Konferenzbeiträge / Atti / Proceedings

# Building Simulation Applications BSA 2024

6<sup>th</sup> IBPSA-Italy Conference Bozen-Bolzano, 26<sup>th</sup>–28<sup>th</sup> June 2024

Edited by Giovanni Pernigotto, Ilaria Ballarini, Francesco Patuzzi, Alessandro Prada, Vincenzo Corrado, Andrea Gasparella

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#### Preface

The sixth edition of the Building Simulation Applications conference, BSA 2024, took place from 26<sup>th</sup> to 28<sup>th</sup> June and was hosted by the Free University of Bozen-Bolzano. The conference is a biannual appointment of IBPSA-Italy, the Italian regional affiliate of IBPSA (International Building Performance Simulation Association).

BSA 2024 featured more than 100 participants and around 275 different authors, with a significant presence of delegates from 18 different countries, in particular from South Korea, Denmark, the United States of America, and India. The conference programme was organised in 13 sessions in three parallel tracks, providing 77 presentations overall, and covering the following topics: characterization of the building stock and special buildings, performance simulation of educational buildings, acoustic studies and simulations, energy efficiency measures and energy flexibility for the existing building stock, IEQ and occupants' behaviour, use of BIM and Machine Learning techniques to support advanced building design and optimization, simulation of the building envelope and hygrothermal analyses, modelling and simulation of HVAC and renewable energy systems, simulation of the building stock and urban-scale analyses, modelling and simulation of case-studies, modelling and simulation of façades and fenestration systems, and new tools and methods for BPS.

The initiatives for students offered in the previous editions of the conference were renewed. The "Student School on Building Performance Simulation Applications", at its fourth edition, dealt with the "Study of the Urban Heat Island effect: from weather data to UBEM simulations with building archetypes". The competition for the "Student best paper award" was organised as well.

An interesting overview on the topic of smart buildings and communities was provided by Panagiota Karava (Purdue University) with the keynote entitled "Smart technology to enable autonomous buildings and connected communities". Ardeshir Mahdavi (Technische Universität Graz) gave a special lecture on the topic of building performance simulation entitled "Building Performance Simulation: Doing things right, or doing the right things?". The third keynote focused on the Zero Emission Building concept, in accordance with the latest recast of the Energy Performance of Building Directive (EPBD): The lecture of Livio Mazzarella (Politecnico di Milano) was entitled "ZEB and CSHPSS: a way to comply with the EPBD requirements using MINSUN 6".

The renewed success of the BSA conference has been demonstrated also by the diversity and by the increase of its participants, which confirms the liveliness of the IBPSA-Italy research community and its international relationships.

Andrea Gasparella Free University of Bozen-Bolzano

#### Analytical Model (SAM 2.0): A New Frontier in Open-Source Building Energy Simulation

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#### Abstract

The Sustainable Analytical Model (SAM), developed by Michał Dengusiak and Jakub Ziolkowski, is an innovative open-source software that broadens the selection of building energy modelling tools written in .NET C#. SAM focuses on enhancing the accuracy and efficiency of energy analysis for architects, engineers, and energy consultants, engaged in the development of energy-efficient buildings. Its open-source nature ensures a wide accessibility, making it an effective tool for bridging the gap between theoretical modelling and practical application. Furthermore, as building design continues to evolve towards more sustainable practices, SAM stands ready to meet these new requirements, providing a customisable, dependable and futuristic platform for energy modelling.

#### 1. Introduction

Open-source tools are gaining greater prevalence within the Architectural, Engineering and Construction (AEC) industry. One example of an opensource toolkit is Sustainable Analytical Model (SAM) which enables specialists to optimise their workflows by tailoring the software tools to their specific needs. SAM can import or create geometry and related data from various sources like Rhino, Revit, etc. to build watertight models. In the creation process, building elements with the material information and spaces with internal conditions, such as thermostats, heat gains and schedules, are attributed to the building. This allows the generation of an analytical model, which is defined as a complete object that can be stored in the JSON format.

#### 2. Background

#### 2.1 Abstract

SAM aims to achieve the goal of the digital twin, where any buildings, with all their associated data, can be replicated, including their HVAC system, or any other custom data decided by the user. The complete development of SAM is defined by the following five key milestones:

#### SAM 1.0 - geometry creation

SAM 2.0 – loads and dynamic simulation (using the generated geometry from SAM 1.0 and attributing it with constructions that consist of materials, and assigning to the spaces the internal condition with their profiles)

SAM 3.0 – HVAC system generation (creating a detailed HVAC system on the attributed model from SAM 2.0 to perform a dynamic simulation) SAM 4.0 – adding HVAC system controls SAM 5.0 – digital twin

In this publication, the focus will primarily be on SAM 1.0 and SAM 2.0. At these stages, SAM facilitates the generation of a building's geometry through the Grasshopper interface and enables the simulation of energy systems; embracing aspects like heating, cooling, and ventilation.

These simulations are performed using external software, such as Ladybug Tools that utilises EnergyPlus and Tas EDSL with its own engine. The latter provides a much more direct and closer integration primarily due to its compatibility with the .NET framework. Furthermore, it also links with a pleth ora of tools and toolkits such as Revit, Topologic, gbXML, Excel, IFC, GEM, and BHoM.

Although SAM is mainly accessed through Grasshopper in Rhino, the SAM\_UI interface was created to enhance the productivity for tasks that are less efficient in this environment. This includes tasks like space renaming, adjusting specific panel constructions, or generating Revit-style 2D floor plans, colorcoded with the specific data. Such features significantly reduce the time and effort required for complex analytical tasks, streamlining the workflow for professionals.

#### 3. Main

SAM 1.0 - focused on geometry - supports multimethod geometry generation. This can then be used to create an Adjacency Cluster. This includes creating detailed 2D outlines of walls at specific level heights, modelling from closed polysurfaces, and generating models from planar panels. It also includes an innovative Revit-style approach in building generation. This is a method for attaining watertight models by extracting the walls per level, performing snapping by aligning elements within a model to precise positions based on a set of predefined rules to a high tolerance and lastly, closing the space by attaching a floor and roof. Unlike other tools that store geometry as 3D elements, SAM represents most of the geometry as 2-dimensional objects with a plane, although still allowing to query its 3D version. This increases the efficiency of the various operations undertaken due to the simpler data management, efficient storage, and optimized computations.

SAM 2.0 is dedicated to dynamic energy simulation and load sizing. The workflow aims to automate the attribution process. Firstly, an Adjacency Cluster is created out of the geometries, for instance, by boundary representation (BREP), as defined in SAM 1.0. Subsequently, SAM offers a broad range of methods to create and assign internal conditions based on predefined strategies. In the last step, an analytical model needs to be created with a material and profile library. Throughout the process, default values are provided to reduce the input required from the user. This approach enables users to initially run simulations on the default settings to validate the model's functionality. Once confirmed, users can then invest time in adding detailed data, saving time and effort.

Objects in SAM can be categorised as either analytical or geometric and are defined in SI units.

#### 3.1 Analytical

For analytical objects, the SAM hierarchy is as follows (Fig. 16), where the majority of objects permit the addition of custom data, making the workflow very customisable and flexible:

**Analytical model**: comprehensive representation of a building that encapsulates all of the necessary attributes. In SAM this consists of the Adjacency Cluster, Location, Materials and Profiles, along with additional model properties.

**Adjacency Cluster:** abstract container for storing the relations between objects including Panels, Spaces, Zones. This is the only object where these connections can be queried, e.g. what panels belong to a given space, or which spaces belong to a zone.

**Zone:** collection of similar properties that spaces share. This allows for an efficient data manipulation, by allowing modifications at zone-level. It is defined by type and name.

**Space**: each space may contain a location (stored as a Point3D) and an Internal Condition. Point3D representing the interior volume within a building, defined by boundary Panels. To query the spatial geometry of the space, e.g., the volume, the panels need to be queried from Adjacency Cluster.

**Internal Condition:** variables affecting the indoor environment such as gains, thermostat settings, or any other custom data related to specialists e.g., acoustic, fire, etc.

**Panel**: instance of a building element. It is defined by the geometry, Construction, Apertures and prop-

erties such as PanelType, for example: internal wall, floor, roof, external wall.

**Aperture**: windows, doors or skylights. It consists of the geometry, ApertureType, ApertureConstruction – which includes the Pane and Frame Construction layers.

#### 3.2 Geometry

SAM analytical objects such as Panels or Apertures are defined by SAM geometry (Fig. 17)

**Face3D:** currently implemented as a three-dimensional closed planar shape, limited by polygonal external and internal edges. It is represented as 2D polygonal edges positioned on a given plane (Fig. 4).

#### External Edge 3D and Internal Edges 3D:

ordered points in 2D space, placed on a given plane. When 3D representation queried, the edges are recalculated from their stored values (Fig 3).

**Polygon2D**: two-dimensional curve with closed, straight segments. It is stored as ordered points in 2D space. (Fig. 1)

**Face2D**: two-dimensional closed shape limited by edges (such as Polygon2D). The External Edges describe the limit of the face, whereas the Internal Edges outline the holes. Face2D that have a single external edge and may have multiple internal edges. This is saved as a collection of Polygon2D (Fig. 2)



#### 3.3 Adjacency Cluster

The Adjacency Cluster (Fig. 5) is a fundamental, yet abstract component that provides the essential functionality and efficiency for organizing and analyzing spatial data within the SAM structure. It stores spaces, zones, panels etc. as well as the relations of these objects within the context of given analytical model (Fig. 6).



Fig. 5 – Adjacency Cluster



Fig. 6 – Adjacency Cluster Relations

The Adjacency Cluster (Fig. 5) will be accessed, in simplified terms, in the SAM structure as a set of two dictionaries. One will include all of the different analytical objects e.g., spaces, panels, etc. The second dictionary consists of the relations between these objects via their GUIDs. This approach allows for an efficient query and modification method.

Currently there are numerous methods to create a watertight Adjacency Cluster, ranging from 2D out-

lines to Revit models, that continuously satisfy the tolerance requirement. The following examples will focus on one of the possible methods, namely: CreateAdjacencyClusterByBrep, and incorporate the input of three distinct BREP boxes, with highlighted internal panels. Each test case undergoes a different transformation of the geometry to demonstrate the capabilities of SAM 1.0.

Initially, the boxes are aligned edge to edge (Fig. 7). Therefore, to refine the geometry, all overlapping surfaces will be merged. Afterwards, the correct PanelTypes are assigned, creating an Adjacency Cluster with three spaces.



Fig. 7 - Three BREP boxes

In the second scenario, the right box was moved along the y-axis (Fig. 8). The overlapping surfaces between the BREPs are split and merged, so that the correct PanelTypes can be recognized by the appropriate location and adjacency.



Fig. 8 - Overlap in Y-axis

This approach is not limited to perfect edge matching and accepts geometries on different levels (Fig. 9).



Fig. 9 - Lower 1m by Z-axis

The method is not limited to adjacent BREPs but also functions on intersecting volumes (Fig. 10). However, in this example, besides the split operation being performed, two additional spaces will be created. Therefore, the resulting AdjacencyCuster will consist of five spaces.



Fig. 10 - Translate -3m by X-axis.

Furthermore, the following modification based on the rotation of the right box along the Z-axis (Fig. 11), shows the versatility of SAM in accepting various geometric inputs.



Fig. 11 – Turn Z-axis

In the final transformation, the right box is moved along the X-axis to completely intersect the two remaining geometries (Fig. 12). This operation creates an Adjacency Cluster with five spaces and correctly recognized PanelTypes, illustrating SAM's adaptability to complex geometry.



Fig. 12 - Transform -7m by X-axis

The provided examples reveal how SAM streamlines the process of geometric model creation, optimizing the efficiency and accelerating the design iteration process. By reducing the required workload from the user in preparing the input geometry, SAM enables engineers to focus on design innovation rather than geometric technicalities. This not only validates SAM as a powerful tool for engineers, but also highlights its potential in optimising the model creation process in AEC applications.

#### 3.4 Analytical Model

An Analytical Model consists of the following:

- AdjacencyCluster
- Materials stored in the MaterialLibrary (a centralized repository with essential information about the e.g., physical and thermal properties of different materials)
- Profiles stored in the ProfileLibrary (a centralized repository for storing assumptions, e.g., in Internal Conditions, where often on an hourly basis the gains, and thermostat settings are saved)
- Location (in latitude/longitude) and address of the model

It is not necessary to provide Materials and Profiles, as SAM has default values, so that only with an Adjacency Cluster, an Analytical Model can be generated. This provides the user with fast feedback on whether the model can be simulated before valuable time is invested into inputting detailed data. Finally, the validated model can be exported in various formats such as IFC, gbMXL and Revit, or directly imported into tools like Honeybee Model or Tas EDSL depending on the needs of the user (Fig. 13 and 14). A model is converted into the different formats below:



Fig. 13 – SAM Analytical Model conversion into different formats (Honeybee, Topologic, gbXML, TasTBD)



Fig. 14 – SAM Analytical Model conversion into different formats (IFC, BHoM)

For instance, the Figure 12 was used to generate the simulation model in Tas EDSL (Fig. 15).



Fig. 15 - Tas Model in Building designer

#### 4. Conclusion

In conclusion, SAM has demonstrated significant potential as an innovative resource for architects, engineers, and energy consultants, especially in designing energy-efficient buildings. By automating geometry creation, SAM reduces user workload, thereby fostering innovation and creativity. Additionally, the default attribution facilitates efficient model testing with preset data, making it an invaluable tool for diverse applications. As an open-source plugin, SAM's transparency and flexibility in storing objects in JSON format promote widespread data access, sharing, and reuse across models.

Looking ahead, the continued development of SAM 3.0 promises to enhance existing workflows, potentially increasing the adoption of HVAC system simulation. SAM 4.0 will enable the exploration of control strategies for HVAC systems, allowing for the evaluation of different approaches. This will help in selecting optimized solutions for HVAC systems, thereby contributing to better building designs and more accurate emissions evaluations, which are crucial for achieving net-zero targets. SAM's capabilities not only streamline the design process but also support sustainable development by providing tools that aid in the creation of energy-efficient and environmentally responsible buildings.

This enhanced functionality and focus on sustainability directly address the need for innovative solutions in the built environment, thereby facilitating the creation of better buildings and supporting the net-zero strategy.

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Fig. 16 – SAM Analytical Model simplified structure



Fig. 17 - SAM Geometry simplified structure

#### Synthetic Indices for Comfort Assessment: An Application to a Historical Building in Catania

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#### Abstract

This article presents a novel methodology that combines energy simulation and the use of advanced comfort indices for assessing thermal comfort in buildings, with a specific focus on a historical office building in Catania (Italy). The research methodology includes detailed modelling in TRNSYS, supported by surveys and on-site measurements of temperature and relative humidity. Then, suitable synthetic indices are introduced that are adaptable to different thermal comfort theories, in line with major standards (ASHRAE 55 and EN 16798-1, namely). This provides a versatile tool for assessing thermal discomfort in historical buildings while easily identifying the rooms where applying possible mitigation strategies is most urgent. This approach also allows us to evaluate the effect of suitable retrofitting options that could achieve good thermal comfort, thus reducing energy consumption and contributing to their adaptation to the evolving climate.

#### 1. Introduction

The analysis of thermal comfort in the built environment is an increasingly prominent topic in engineering and architecture, driven by the need to enhance indoor environmental quality and to reduce the energy consumption in buildings.

The quantification of thermal comfort is critical: many studies have explored various indices, such as Predicted Mean Vote (PMV), Predicted Percentage of Dissatisfied (PPD) (Fanger, 1970), and Standard Effective Temperature (SET) (ANSI and ASHRAE, 2020; Silva et al., 2016; Tartarini and Schiavon, 2020) to assess comfort conditions in buildings. These indices, along with others like Intensity of Thermal Discomfort (ITD), Frequency of Thermal Comfort (FTC), Frequency of Thermal Discomfort (FTD), Fluctuation of thermal Discomfort (FD) (Detommaso et al., 2021; Evola et al., 2015; Sicurella et al., 2012), Passive Discomfort Index (Índice de Desconforto Passivo) (Dos Reis et al., 2022), ASHRAE Likelihood of Dissatisfaction and Nicol et al.'s Overheating Risk (Nicol et al., 2009), provide a solid foundation for optimizing building design and evaluating their operational thermal performance. In the context of historical buildings, these challenges are aggravated by architectural and conservation constraints, thus calling for innovative solutions to align thermal comfort with heritage preservation (Martínez-Molina et al., 2016).

This paper presents a novel approach for evaluating the thermal comfort in buildings over long time spans that integrates dynamic energy simulation with the application of advanced comfort indices to a case study building in Catania. The results also demonstrate that historical buildings, under current climatic conditions, may suffer from thermal discomfort issues, especially in the summer.

#### 2. Material and Methods

#### 2.1 Methodology

In this research, a comprehensive methodology was developed to facilitate the analysis of thermal comfort in historical buildings. The methodology is summarized in the flowchart of Figure 1.

Phase 1 requires detailed information to create a reliable virtual model, including the collection of geometric, morphological and thermophysical data.



Fig. 1 – Workflow of the methodology

The process involves also simplifying the building's geometry and constructing a virtual model using the TRNSYS energy simulation software.

Phase 2 consists in carrying out preliminary experimental measurements, which is instrumental for the validation of the virtual model (phase 3). This step requires the collection of local meteorological data that is then used for a first run of simulations for validation purposes. Data regarding indoor air temperature and relative humidity are also collected to compare them with the simulation results. The validation is based on different error indices (Baggio et al., 2013), whose suggested thresholds (Huerto-Cardenas et al., 2020) are indicated in Table 1: MAE (Mean Absolute Error), RMSE (Root Mean Square Error), r (Pearson's Correlation Coefficient), R<sup>2</sup> (Coefficient of Determination).

Once the model is validated, simulations can be run with the current climate (phase 4), which is done by using the typical meteorological file of the city where the building is placed.

Table 1 – Suggested thresholds for error indices (Huerto-Cardenas et al., 2020)

	MAE	RMSE	r	R <sup>2</sup>
LV 1	≤ 1 [°C - ≤ 5 [	- g/kg] %]	> 0.5	> 0.75
LV 2	≤2 [°C -	- g/kg]		
2,2	$\leq 10$	[%]		

This step also includes the calculation of the Running Mean Outdoor Temperature (RMOT), which is necessary to compute the thermal comfort thresholds in line with the adaptive comfort theory (Humphreys et al., 2015; Yao et al., 2022). After the numerical simulations (phase 5), the outputs are then processed, with a focus on the operative temperature. The methodology requires two different analyses of thermal comfort (phase 6): a first one looks at the time trends of the indoor operative temperature, while the second one relies on the adaptive comfort approach in accordance with the American ASHRAE 55 (ANSI & ASHRAE, 2020) and the European EN 16798-1 (EN 16798-1:2019) standards. This second analysis requires the calculation of three discomfort indices: ITD [°C h], FTD [%] and FD [°C] (Evola et al., 2015; Sicurella et al., 2012), which refer only to those time intervals when the presence of the occupants is expected. More specifically, the ITD quantifies the degree hours by which room temperatures exceed the predefined thermal comfort thresholds:

$$\begin{split} ITD &= \int_{P} \Delta T_{over}(\tau) \cdot d\tau \qquad \text{where} \\ \Delta T_{over}(\tau) &= \begin{cases} T_{op}(\tau) - T_{over} & \text{if} \quad T_{op}(\tau) \geq T_{over} \\ 0 & \text{if} \quad T_{op}(\tau) < T_{over} \end{cases} \end{split}$$

The subscript *over* refers to "*overheating*", i.e. thermal discomfort due to high indoor operative temperatures. The FTD measures the percentage of time within a given period when the indoor thermal comfort conditions are not met; it is determined by dividing the hours in which thermal discomfort is perceived by the total number of occupancy hours. Finally, the FD is the ratio of the ITD to the length of the period when thermal discomfort is perceived:

$$FD = \frac{ITD}{\int_{P} i_{+} \cdot d\tau} \quad \text{where}$$
$$i_{+} = \begin{cases} 1 & if \quad T_{op}(\tau) \ge T_{over} \\ 0 & if \quad T_{op}(\tau) < T_{over} \end{cases}$$

In case of high ITD and low FD, the room is most probably often in the discomfort region, thus a general improvement in the thermal performance of the whole building fabric might be required. On the contrary, a high FD means that discomfort occurs rarely but in an intense way; in this case the problem could be tackled with a single local tailored solution, such as a higher ventilation rate or a more efficient shading device (Sicurella et al., 2012).

#### 2.2 Case Study

The selected case study for this research is an office building belonging to the University of Catania, Italy, built in the first half of the 19<sup>th</sup> century and restored in the past decade. The building's masonry walls are made of volcanic stones and mortar. Wall thicknesses vary across different floors and for internal and external walls.

To create a reliable virtual model, detailed geometric, morphological, and thermophysical data were meticulously gathered. The model creation in TRN-SYS meant simplifying the complex geometry, particularly the windows, which are arched but are modified to an equivalent rectangular shape while retaining the proportion of glazing to frame area.

Afterwards, the U-value of the external walls was measured, and an equivalent thermal conductivity was calculated to treat masonry walls as a uniform material. A detailed analysis of the occupancy rates per unit area in each floor provided also insights into utilization patterns. Validation of the virtual model was then undertaken by measuring indoor temperature and humidity in specific rooms during May and June 2023. Outdoor weather data from a local weather station were supplemented with solar radiation data from an online source, were used in the simulations (SIAS, 2023) (see Figure 2).



Fig. 2 – Outdoor air temperature and solar irradiance from May 31<sup>st</sup> to June 11<sup>th</sup>, 2023

After the construction and successful validation of the model (Huerto-Cardenas et al., 2020), a thermal comfort analysis was carried out. It aimed to identify the rooms with the greatest discomfort and the origins of such discomfort, with a particular focus on summer overheating during the months of June, July, August, and September.

Unlike the fixed comfort bands of non-adaptive theory, the adaptive comfort theory considers timeevolving comfort ranges that are based on outdoor conditions (Humphreys et al., 2015). An essential element in the calculation of adaptive comfort bands is the Running Mean Outdoor Temperature (RMOT), i.e. the mean outdoor temperature over a specified period (Yao et al., 2022). In this paper, RMOT has been calculated through the web tool developed by Tartarini and Schiavon (Tartarini & Schiavon, 2020). This tool allowed us to compute the adaptive comfort bands under different scenarios and considering two specific standards, the ASHRAE 55 and EN 16798-1 namely. ASHRAE 55 includes two performance categories, "80" and "90": "80" denotes comfort levels suitable for 80% of individuals while "90" indicates 90% of people satisfied (ANSI and ASHRAE, 2020). Instead, the EN 16798-1 defines three performance categories: "Category III," "Category II," and "Category I". "Category III" represents lower comfort levels, accepted by a smaller percentage of occupants; "Category I" concerns the highest comfort performance, while "Category II" stands as an intermediate category (EN 16798-1:2019). After calculating the adaptive comfort bands, the operative temperatures of the room were evaluated, examining whether they fell within or exceeded these comfort thresholds. Further analyses quantified discomfort in the thermal zones by using the Intensity of Thermal Discomfort (ITD), Frequency of Thermal Discomfort (FTD), and Fluctuation of thermal Discomfort (FD), specifically during occupancy hours (8 AM to 6 PM).

#### 2.3 Simplification and Modelling of the Case Study Building

The modelling was carried out within the TRNSYS energy simulation software tool (Figure 3 shows an axonometric view of the real virtual building).



Fig. 3 - Case study building and model

To accurately capture the intricacies of the historical building's thermal behaviour, several considerations and simplifications were made. Notably, the thermal zones within the building were defined by merging the rooms sharing common attributes, such as orientation (North, South, East, or West) and function, resulting in 41 thermal zones (the actual number of rooms is 70 instead).

Coherently, internal partitions between rooms pertaining to the same thermal zone were omitted from the geometric model. These thermal zones were, however, manually assigned augmented thermal capacity to compensate for the absence of the massive internal walls. To quantify the thermal capacity of the omitted walls, the computation of volumes of walls included in each thermal zone was carried out, while the specific heat capacity  $(c_p)$  is set to 1 kJ·kg-<sup>1</sup>·K<sup>-1</sup> and the density (ρ) is 2400 kg·m<sup>-3</sup> (Gagliano et al., 2014; UNI 10351:2021; UNI 10355:1994). Wall thicknesses vary across different floors and across internal and external walls. The following measurements were adopted: for external walls facing the street, the masonry thicknesses are 120 cm (ground floor), 105 cm (first floor), 90 cm (second floor), and 75 cm (third floor). In contrast, for external walls facing the courtyard the masonry thicknesses are 90 cm (ground floor), 80 cm (first floor), 70 cm (second floor), and 60 cm (third floor). For internal walls separating individual rooms the thicknesses are 80 cm (ground floor), 65 cm (first floor), 45 cm (second floor), and 30 cm (third floor).

Additionally, architectural features such as light wells on the second and third floors were represented as void spaces. A shading surface was introduced above these light wells, emulating the grilled structure where the thermal systems are placed. Distinct net height measurements were attributed to each floor, because on some floors there are counter ceilings and on other vaults: 5.30 m for the ground

floor, 4.70 m for the first floor, and 5.70 m for both the second and third floors. Many rooms featured vaulted ceilings and non-rectangular doors and windows: these complexities were simplified by approximating rooms as rectangular boxes, but ensuring the same floor surface area and room volume (Elhadad et al., 2020). The same applies to doors and windows, where the simplifications did not affect the glazing and frame surfaces. The building has different types of windows, in terms of frame materials, geometric shape and ratio of opaque and transparent surfaces. Primarily, some windows have wooden frames, with a thickness of 6 cm and a thermal transmittance U = 1.67 W·m<sup>-2</sup>·K<sup>-</sup> <sup>1</sup>, whereas others have metal frames without a thermal break, with a thickness of 7 cm and U = 5.85W·m<sup>-2</sup>·K<sup>-1</sup>. The type of glass employed is consistent across all window types, comprising laminated glass with 8 mm thickness. This glass has thermal transmittance  $U_g = 5.6 \text{ W} \cdot \text{m}^{-2} \cdot \text{K}^{-1}$ , and g = 0.89 (solar heat gain coefficient). As previously written, the diversity of window types encompasses variances in geometric shape and size (Figure 4), leading to a simplification process: Table 2 describes in detail the areas of transparent and opaque surfaces for each type. Furthermore, balconies were simplified: they were merged into a single longer surface. Surrounding buildings were incorporated as shading elements (see Figure 3).



Fig. 4 - Simplification of windows geometry (Type D)

Table 2 - Transparent and opaque surface areas for windows

Туре	Transparent surface area	Opaque surface area	Туре	Transparent surface area	Opaque surface area
	[m <sup>2</sup> ]	[m <sup>2</sup> ]		[m <sup>2</sup> ]	[m <sup>2</sup> ]
А	4.17	2.41	Ι	0.56	0.25
В	4.92	1.20	J	6.46	1.83
С	3.64	2.48	Κ	1.53	1.41
D	4.05	1.97	L	3.30	3.74
Е	2.76	1.72	М	1.72	1.14
F	3.36	2.70	Ν	2.12	2.05
G	2.89	4.08	0	4.64	0.29
Н	2.03	2.13			

The attic space was not included in the model, so the last floor ceiling surfaces were assigned specific boundary conditions for heat exchange with the underlying zones. Subsequently, settings for infiltration were established, specifying an infiltration rate of 0.30 air changes per hour (UNI/TS 11300:2014). The number of luminaires, each hosting two 55 W halogen lamps, is reported in Table 3 for each thermal zone: the lighting schedule is aligned with standard office hours, activated from 7:00 AM to 6:00 PM. Electrical equipment generates 5 W·m<sup>-2</sup> heat gains.

Table 3 – Number of light points for each thermal zone

т.	Light	т.	Light	т.	Light	т.	Light
Zone	points	Zone	points	Zone	points	Zone	points
001	4	101	4	201	8	301	8
002	7	102	4	202	4	302	4
003	23	103	4	203	12	303	12
004	2	104	20	204	16	304	16
005	2	105	10	205	10	305	10
006	10	106	4	206	2	306	2
007	6	107	2	207	11	307	8
008	10	108	6	208	4	308	4
		109	10	209	2	309	2
		110	2	210	2	310	2
		111	4	211	3	311	3

## 2.3.1 Experimental Measurement for modelling and validation purpose

An experimental campaign to measure the U-value of external walls was conducted between 6<sup>th</sup> and 13<sup>th</sup> March 2023 by using a Thermozig heat flow meter, whose technical features are listed in Table 4.

The U-value measurements specifically targeted the walls of selected rooms that were unoccupied due to staff absence. In adherence to (ISO 9869:2014), the selected walls were north-facing, and space heating was turned on during the campaign to increase the indoor-outdoor temperature drop. The duration of the measurements amounted to 167 hours. The results of these measurements revealed that the U-value of the external walls was around 1.15 W·m<sup>-2.</sup>K<sup>-1</sup>. Since the wall thickness is 0.70 m, this corresponds to an equivalent thermal conductivity  $\lambda_{eq} = 1$  W·m<sup>-1.</sup>K<sup>-1</sup>. Between May 31<sup>st</sup> and June 11<sup>th</sup>, 2023, another monitoring campaign was performed in two unoccupied thermal zones, denoted as 203 and 303, located respectively at the second and third floor.

Table 4 – Technical features of Thermozig heat flow meter

	Temperature	Heat Flow
Measuring Range	from -50°C to 125°C	from -300 to 300 W·m <sup>-2</sup> (from -20°C to 60°C)
Resolution	0.01°C	0.01 W·m <sup>-2</sup>
Accuracy	± (0.10+0.0017 t ) °C	± 5% (@T = 20°C)

More specifically, two Wöhler CDL 210 dataloggers (technical features are listed in Table 5) were used for measuring air Temperature and Relative Humidity that were then used to validate the virtual model. A graph of the temperature and relative humidity achieved in the measurement campaign is included in Figure 5.

Table 5 – Technical features of Wöhler CDL 210 datalogger

	Temperature	Relative Humidity
Measuring Range	from -10°C to 60°C	5% to 95%
Resolution	0.1°C	0.1%
Accuracy	± 0.6°C	± 3% for 10% and 90% ± 5% otherwise



Fig. 5 – Temperature and relative humidity values (from May 31<sup>st</sup> to June 11<sup>th</sup>, 2023) (Thermal Zone 203)

#### 2.3.2 Occupancy profiles of rooms

In the simulations, sedentary office workers were considered, with a thermal power of approximately 115 W per person (Sansaniwal et al., 2022). To calculate the total heating load for each thermal zone, this per-person power value was multiplied by the number of workstations and by the actual occupancy rate of workstations (Figure 6). Due to privacy and the lack of more granular data, these calculations were detailed at the floor level rather than at the room level. There are 17 workstations on the ground floor, 31 on the first floor, 34 on the second floor, and 28 on the third floor.



Fig. 6 - Workstations' occupancy rate for each floor

#### 3. Results and Discussion

#### 3.1 Validation of the Virtual Model

As a result of this simulation, air temperature and relative humidity values were obtained and are shown in Figure 5. Moreover, Table 6 and Table 7 show the error index regarding the validation. The error index values were compared with the values suggested by (Huerto-Cardenas et al., 2020) and, as they fall within acceptable ranges, the model shows good agreement with real-world measurements.

Table 6 - Temperature error indices

Thermal Zone	MBE	MAE	RMSE	r	R <sup>2</sup>
	[°C]	[°C]	[°C]		
203	-0.35	0.35	0.38	0.96	0.93
303	-0.14	0.26	0.31	0.92	0.85
able 7 – Rel	lative hum	idity error	indices		
able 7 – Rel Thermal Zone	lative hum MBE	idity error	indices RMSE	r	R <sup>2</sup>
able 7 – Rel Thermal Zone	lative hum MBE [%]	idity error MAE [%]	indices RMSE [%]	r	R <sup>2</sup>
able 7 – Rel Thermal Zone 203	lative hum MBE [%] 0.03	MAE [%] 1.74	Indices RMSE [%] 2.11	<b>r</b> 0.85	<b>R</b> <sup>2</sup>

#### 3.2 Comfort Analysis

By using the validated model, a set of free-floating dynamic simulations was conducted. First, the frequency distribution of the operative temperature was analysed in each thermal zone: Figure 7 reports the results in Zone 204 (second floor, facing West) and Zone 207 (facing East towards the internal courtyard) in June, July, August, and September. These zones show high levels of discomfort: in Zone 204 the most frequent operative temperature range is 31 °C and 33 °C, with a total of almost 550 hours; in Zone 207 the most frequent range is also between 31 °C and 33 °C with a total of over 600 hours, but here we also observe 175 hours above 33 °C.



Fig. 7 - Operative temperature distribution (Zone 204 and 207)

Based on these results only, identifying the thermal zones with the most severe thermal condition is not straightforward, even because the building has 70 rooms divided into 41 thermal zones. This is precisely the point where the utility of the ITD becomes evident: indeed, with a single number it provides a clear indication of both intensity and duration of thermal discomfort.

In this case, the ITD, FTD and FD were computed for each thermal zone against the adaptive comfort bands, whereby the comfort thresholds are not constant with time. In principle, all possible performance categories were considered ("90" and "80" in ASHRAE 55 plus "Category I", "Category II" and "Category III" in EN 16798-1). However, since this is an office building it is reasonable to refer mostly to "Category II" in the EN 16798-1 Standard and "80" in the ASHRAE 55 Standard.

Figure 8 shows the ITD values across all thermal zones, reflecting also the variations within performance categories. These results confirm that the ITD is a valid synthetic index and they emphasize that even when employing the more flexible adaptive comfort approach - several thermal zones may still experience thermal discomfort due to overheating in the absence of cooling systems. For instance, the ITD values in Zone 204 (ITD = 2387) and Zone 207 (ITD = 1876) are high, if compared e.g. with Zone 206 (ITD = 653) and Zone 211 (ITD = 441). There is currently no official reference to a maximum allowed ITD value, but in comparative terms this index immediately identifies the critical rooms where measures are urgently needed to improve thermal comfort. For instance, the rooms on the third floor are on average far less comfortable than on the ground floor.

	ITD_90_HOT	ITD_80_HOT	ITD_cat_i_HOT	ITD_cat_ii_HOT	ITD_cat_iii_HOT
ZONE001	62	0	0	0	0
ZONE002	336	32	31	1	0
ZONE003	1182	425	423	71	6
ZONE004	217	0	0	0	0
ZONE005	673	84	82	0	0
ZONE006	586	48	50	0	0
ZONE007	143	0	0	0	0
ZONE008	98	2	1	0	0
ZONE101	1757	809	807	150	1
ZONE102	1788	844	842	195	9
ZONE103	2483	1367	1371	527	52
ZONE104	3122	1902	1910	941	250
ZONE105	1758	816	818	161	0
ZONE106	888	252	249	1	0
ZONE107	2240	1207	1207	419	22
ZONE108	1370	535	538	44	0
ZONE109	2665	1521	1525	646	122
ZONE110	1186	412	413	13	0
ZONE111	2587	1450	1460	577	86
ZONE201	2025	1021	1019	286	14
ZONE202	2458	1358	1357	500	74
ZONE203	2746	1614	1615	740	193
ZONE204	3660	2385	2391	1347	537
ZONE205	2181	1143	1144	368	14
ZONE206	1556	653	650	95	0
ZONE207	3066	1876	1879	918	230
ZONE208	1993	1015	1017	296	3
ZONE209	2232	1191	1195	419	21
ZONE210	1009	298	296	4	0
ZONE211	1224	441	439	34	0
ZONE301	1932	965	960	288	26
ZONE302	2571	1473	1472	597	139
ZONE303	3642	2400	2404	1357	572
ZONE304	3918	2639	2645	1563	724
ZONE305	2045	1051	1050	313	9
ZONE306	1674	786	780	191	2
ZONE307	3135	1929	1930	954	282
ZONE308	1752	847	845	174	0
ZONE309	1840	896	895	209	2
ZONE310	1196	420	418	22	0
ZONE311	1021	314	309	19	0

Fig. 8 – Intensity of Thermal Discomfort in the 41 thermal zones (purple: ASHRAE 55 - red: EN 16798-1)

Table 8 – Frequency of Thermal Discomfort (Zones 204 and 207)

	FTD - "Ca	tegory II"	FTD - Cate	egory "80"	
	EN 16	5798-1	ASHRAE 55		
	Thermal Thermal		Thermal	Thermal	
	Zone 204	Zone 207	Zone 204	Zone 207	
June	11%	4%	55%	30%	
July	98%	92%	100%	100%	
August	100%	100%	100%	100%	
September	99%	100%	100%	100%	

	FD - "Category II"		FD - Category "80"		
	EN 16798-1		ASHRAE 55		
	Thermal	Thermal	Thermal	Thermal	
	Zone 204	Zone 207	Zone 204	Zone 207	
June	0.5	0.1	0.6	0.4	
July	1.6	1.1	2.6	2.0	
August	2.3	1.5	3.3	2.5	
September	1.4	1.1	2.4	2.1	

Of course, ITD = 0 indicates that a room does not show any overheating issue (Zone 007). Still focusing on Zone 204 and Zone 207, Table 8 and Table 9 report the FTD and FD values, according to "Category II" of EN 16798-1 and Category "80" of ASHRAE 55. The FTD values in Table 8 show that discomfort conditions occur very frequently in both zones, especially in light of the ASHRAE 55 Standard, which is more stringent than "Category II" of EN 16798-1. The FD values are low (Table 9), which suggests steady thermal discomfort.

#### 4. Conclusion

This research developed a simulation framework in TRNSYS to build up and validate a multi-zone model for complex historical buildings with the aim of appraising thermal discomfort in summer. A series of suitable modelling simplifications in terms of geometry and thermal features are introduced in order to keep a reasonable level of detail while reducing the burden of the modelling task. Then, synthetic thermal comfort indices such as the Intensity of Thermal Discomfort (ITD) and the Frequency of Thermal Discomfort (FTD) are applied based on the adaptive comfort theory, to quickly identify the thermal zones that suffer the most from thermal discomfort. The application to a case study in Catania (Southern Italy) proved very effective to easily identify those rooms that urgently call for passive solutions to mitigate indoor overheating, while also informing if discomfort is frequent and steady. The methodology can be extended to other multi-zone buildings even other than offices. Future research is planned to include also the effect of climate change in the simulation framework, by suitably modifying the weather data input.

#### Nomenclature

$c_p$	Specific heat capacity (J·kg <sup>-1</sup> ·K <sup>-1</sup> )		
FD	Fluctuation of thermal Discomfort		
FTD	Frequency of Thermal Discomfort		
ITD	Intensity of Thermal Discomfort		
MAE	Mean Absolute Error		
PMV	Predicted Mean Vote		
PPD	Predicted Percentage of Dissatisfied		
r	Pearson's Correlation Coefficient		
RMSE	Root Mean Square Error		
RMOT	Running Mean Outdoor Temperature (°C)		
$\mathbb{R}^2$	Coefficient of Determination		
Т	Temperature (°C)		
U	Thermal transmittance (W·m <sup>-2·</sup> K <sup>-1</sup> )		
λ	Thermal conductivity (W·m <sup>-1·</sup> K <sup>-1</sup> )		
ρ	Density (kg·m <sup>-3</sup> )		

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#### Data-Driven Digital Twining of Ventilation Systems for Performance Optimization: A University Building Case Study

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#### Abstract

This study introduces the creation and application of a data-driven digital twin for building ventilation systems, focusing on a university building as a case study. It employs a grey-box energy modelling framework to accurately forecast, simulate, and monitor the ventilation system's efficiency under diverse conditions. The study collects a substantial dataset to reflect various usage patterns and environmental influences, which serves to test and validate the component models of the ventilation system. These models are integrated into a digital twin platform, providing a comprehensive overview of the system's performance and critical indicators in real time. The digital twin facilitates informed decision-making for facility managers regarding energy consumption, inefficiency identification, and the recommendation of custom retrofitting actions specific to the building's characteristics and use. The findings confirm that digital twins are effective as a tool to continuously commission and detect anomalies in buildings. The study offers a ventilation modelling and monitoring method capable of recognizing rule-based control behaviours and changes in systems that occur in cycles, like system shifts from winter to summer, and can estimate total air mass flow rate with a correlation exceeding 80%.

#### 1. Introduction

The European Union (EU) is addressing its energy and environmental objectives for 2030 and 2050 by focusing on the building sector, which accounts for nearly 40% of its energy consumption (European commission, 2018). According to the International Energy Agency (IEA), this sector is also responsible for about 36% of total emissions, broken down into residential buildings (22%), non-residential buildings (8%), and construction projects (6%) (IEA, 2019). Digital twin technology is identified as a key innovation for improving building operations, particularly through optimizing ventilation systems which play a crucial role in maintaining indoor air quality and constitute a substantial part of building energy usage.

Recent advancements in computer science have led to the integration of digital technologies like Building Information Models (BIM) and their advanced form, Digital Twins, into building management (Lu et al., 2020). Digital Twins, particularly when combined with sensor data, enhance building energy efficiency through various methods, including model predictive control (MPC) (Smarra et al., 2018) and facilitating real-time energy-saving decisions (Agostinelli et al., 2021). These technologies enable precise and efficient modelling of a building's energy systems. A significant challenge in this field is modelling ventilation systems that must account for the variability in control actions due to different conditions such as seasonality and manual adjustments (Zhang et al., 2022). This research focuses on developing a Digital Twin for the OU44 building at the University of Southern Denmark. The building serves as a live laboratory and is equipped with CO2 sensors and air diffuser damper position sensors. The study combines data-driven and physics-based methods to precisely estimate energy consumption and conditions in specific rooms. This Digital Twin platform offers real-time data on ventilation performance and energy utilization.

The development of the digital twin uses the *Twin4Build* framework (Bjørnskov et al., 2023), which supports grey-box energy modelling of various system components. Additionally, this research investigates continuous monitoring and anomaly detection, addressing the challenges of data collection and system integration in older systems. The findings highlight the profound impact of Digital Twin technology in building management, showcasing through the OU44 case study how such technologies can improve decision-making, enhance monitoring capacity, and adapt to other buildings equipped with basic sensors, demonstrating their broad applicability in the field.

#### 2. Grey Box, Ontology-Based Modelling

Grey-box modelling merges theoretical knowledge and data-driven methods to produce models that balance comprehensibility with accurate system dynamics representation, especially useful for partially understood systems. It incorporates both partial theoretical knowledge and empirical data. Ontology-based modelling enhances this approach by using structured frameworks called ontologies to organize information and define relationships specific to the domain, thereby improving interoperability and facilitating knowledge reuse across different applications. The digital twin concept organizes these models and tools to serve physical asset designers and operators, defining a digital twin as a collection of digital models that predict specific outcomes, supported by a data-acquisition system for real-time physical-digital interaction. A diagram of this model-asset interaction is depicted in Figure 1. The Twin4build framework leverages the SAREF core ontology and its extensions SAREF4BLDG and SAREF4SYST (SAREF, 2020).

It is composed of 5 main classes which provide a streamlined modelling flow:

- Model: Represents the simulation model, composed of 1 or more component models.
- Simulator: Simulates a model instance for a given period.
- Monitor: This class offers methods to analyse estimated and measured data to assess performance and detect anomalies.

- Evaluator: Can evaluate and compare different Model instances based on user-defined quantities of interest.
- Estimator: Provides methods for performing parameter estimation and sensitivity analysis using a model instance and user-defined parameters.



Fig. 1 – Digital twin diagram. It uses sensor data in tandem with digital models to provide a variety of services for building operators and designers (Jradi and Bjørnskov, 2023)

#### 3. Methodology

Figure 2 shows the abstract process carried out to develop the ventilation model. The methodology encompasses an initial phase of characterization and data acquisition, followed by the application of historical data to train a machine learning algorithm. This algorithm is designed to replicate the rule-based control actions for each ventilated room. Subsequently, the approach employs historical data in conjunction with model estimates to conduct parameter estimation and refine the model's accuracy through fine-tuning.

The next sections show a general diagram of the model, with inputs and outputs. Followed by a description of a room model which is replicated for each room inside the ventilation model, the room model contains a controller and a damper model. The controller model attempts to mimic the heterogenous behaviour of the rule-based controller that controls de damper position of each room.





#### 3.1 Ventilation System Model

This study considers one of the 4 nearly identical ventilation systems in the OU44 building. This subsystem provides air to a quarter of the areas on the building, distributed in 20 rooms with demand-controlled ventilation (DCV) and other 10 auxiliary, small rooms like bathrooms and copy rooms with a constant air volume (CAV). These rooms span all 4 levels of the building.



Fig. 3 - Ventilation system model

Figure 3 illustrates a model of the ventilation system. The facility's Building Management System (BMS) monitors  $CO_2$  levels continuously, capturing real-time data every minute from rooms with DCV. This data informs the adjustment of damper positions in each room, which in turn controls the airflow according to a model specific to each room. These airflow calculations are based on the predetermined nominal flow rates designated for each room.

#### 3.1.1 Room model

The individual room model consists of a CO<sub>2</sub>-based controller which uses both CO<sub>2</sub> and time information to provide a damper opening position signal.



Fig. 4 - Room ventilation model

The damper model estimates the air flow through the damper as a function of the damper position. Using the model by Huang (Huang, 2011) in its constrained form, the model has two 2 main parameters: *a* corresponding to a unitless air damping coefficient and  $\dot{m}_{a,max}$  which corresponds to the maximum flow rate of the room damper. The damper's air mass flow rate is described by the equation 1, where the constrains for the coefficients c and b are given by Equations 2 and 3. (3)

$$\dot{m}_a = ae^{bu_d} + c \tag{1}$$

$$c = -a \tag{2}$$

$$b = ln\left(\frac{\dot{m}_{a,max}-c}{a}\right)$$
  
Where:

 $\dot{m}_{a,max}$  is the damper's nominal air mass flow rate (kg/s)

*a* is a damper coefficient (dimensionless).

 $u_d$  is the damper opening position [0-1] (percentage)

The maximum air flow ( $m_{a,max}$ ) rate for each room is taken from the design values given in the buildings blueprints. A fine-tuned value is used for the second parameter (*a*) of the model.

#### 3.1.2 Controller model

One prevalent challenge encountered in modelling ventilation systems of buildings, years after they commence operations, stems from the inconsistency in the control strategy across all rooms within the building, which can fluctuate throughout the year. This variability, compounded by the lack of comprehensive historical data on adjustments and configurations applied to the control system over time, often results in the inadequacy of simple rule-based controllers' models to accurately predict the ventilation system's actual behaviour across the entire building. To address this issue, a data-driven methodology was employed, leveraging artificial neural networks, as shown in Figure 5.



Fig. 5 - Room ventilation controller model

This approach uses both CO<sub>2</sub> concentrations and the rooms' damper positions to train an ANN model which attempts to mimic the behaviour of the rule-based controller assigned to each room.

#### 3.1.3 Data embeddings

To capture the configuration of the ventilation modes for each one of the rooms and to validate the controlling signals each one of the 3 main quantities were adapted for its use in the neural network model. Equation 4 presents the discretization used for the damper position value. A continuous value from 0 to 100 is converted to 20 discrete classes with an integer from 0 to 19 for each. This is the output of the neural network.

$$d = round(\frac{D}{100} \cdot 19) \tag{4}$$

Where d is the discrete value for the damper position used as output of the neural network and D is the original data point [0,100].

Equation 5 describes the normalized CO<sub>2</sub> concentration, with the original values in ppm, a gaussian normalization (Z-score normalization) is made:

$$z = \frac{CO_2 - \mu_{cO2,i}}{4\sigma_{cO2,i}}$$
(5)

Where the mean and standard deviation are calculated with all the data points of each room (*i*) corresponding to the year 2023. The denominator includes four times the sigma value to make it less sensible to outliers. Additionally, making the values smaller and with a 0-mean.

The time variables were divided in three categories: Day of the year, day of the week and time of the day. This division allows the model to have a notion of the effects of seasons, weekdays and day-night cycles which are typically used to define ventilation rule-based controls. To provide insight into the cyclic nature of the first two time-variables, the cyclic embedding presented in Equations 6 and 7 was used.

$$x_{sin} = \sin\left(\frac{2\pi x}{p}\right)$$
(6)  
$$x_{cos} = \cos\left(\frac{2\pi x}{p}\right)$$
(7)

Where x are the original time of day and day of year cyclic features, P is the period of the feature (24 for time of day and 365 for day of year). This representation produces 2 variables per cyclic feature that are fed to the neural network as inputs.

The day of the week feature is encoded using onehot-encoding.

Table 1 -	Hyperparameters	used fo	r the	neural	networks	repre-
senting the	e ventilation contro	oller for e	ach r	oom.		

Hyperparameter	Value
Input size	12
Output size	20
Hidden layer 1 size	50
Hidden layer 2 size	100
Learning rate	0.001
Number of epochs	15
Batch size	64

#### 4. Case Study

A case study using sensor data from a living lab building from the University of Southern Denmark is considered for the implementation of the developed model. This study focuses on the ventilation system of the building. The ventilation system's digital twin aims to provide continuous commissioning services, anomaly detection and insights into the power consumption of the ventilation fan through the estimation of the total air flow rate and room ventilation conditions.

#### 4.1 OU44 Building

Presented in Figure 6, the OU44 building of the University of Southern Denmark is a multi-purpose building equipped with different sensors throughout the building. Specifically, the main rooms and offices measure indoor CO<sub>2</sub> concentrations, a signal that is used in the demand-controlled ventilation system of the building.

The building has 4 nearly identical ventilation subsystems which operate independently. Each one of these is comprised of an Air Handling Unit, ventilation ducts and room air dampers controlled by a centralized controller.



Fig. 6 - Façade of the UO44 building, SDU Odense

The ventilation system, depicted in figure 7, includes a central air handling unit (AHU) that provides demand-controlled ventilation (DCV) to 20 study and multi-purpose rooms, and constant ventilation to 10 auxiliary rooms. The system is managed by a Building Management System (BMS), which controls the ventilation and aggregates data from  $CO_2$  and temperature sensors in each of the 20 main rooms.



Fig. 7 – Block diagram of one of the ventilation subsystems in UO44, VE01

#### 5. Results

#### 5.1 Controller Model

The data-driven approach attempts to capture the rule-based controller behaviour by mimicking the measured controlling actions without having to manually craft a set of controlling rules for each room in the ventilation system. The accuracy of the Artificial Neural Network (ANN) models is evaluated by comparing them to the actual measured positions of dampers in each room. This accuracy is calculated as the percentage of instances where the ANN model's output precisely matches the discretized position of the damper at every timestamp in the test data. The results are presented in Figure 8.



The model training process starts with the data embedding described in section 3.1.3 where the CO2 concentration and time data are pre-processed. Then the data is split into training and test datasets in the following process: Out of the data for the whole year of 2023, the first three weeks of each month are used for training and the remaining days of each month for testing. Additionally, the months of January and February 2024 are used for validation.

The sum of all estimated air mass flows for each one of the rooms is shown in the Figure 9, where the continuous blue line represents sensor data, and the black dotted line are the simulation results for the total air mass flow of the AHU.



Fig. 9 – ANN-based controller estimation for a week during the month of February 2024, RMSE: 0.6581 kg/s Correlation: 0.9335

The accuracy of the ANN-based controllers is evaluated by comparing two key measurements: the Root Mean Square Error (RMSE) calculated using actual measured positions of the dampers and the RMSE calculated using the damper position signals provided by the ANN controllers. This comparison helps assess the error introduced by the ANN controllers. Table 2 presents the comparison of the RMSE obtained when estimating the total system airflow when the control signal is the measured damper position and the estimated air flow using the position signal from the ANN controller model. RMSE calculated with all validation data from 2024.

Table 2 – RMSE and correlation coefficients of mass air flow rate with and without ANN controllers.

Control signal	RMSE [kg/s]	Correlation
Measured	0.6910	0.9684
ANN control	0.6581	0.9335
Difference	0.0329	0.0349

## 5.1.1 Share of air flow from rooms without DCV

The proportion of total airflow to rooms without demand-controlled ventilation was determined by analysing estimated airflow values against measurements from the air handling unit (AHU). The Root Mean Square Error (RMSE) for the initial dataset, covering January 2023, was determined to be 1.566 kg/s. This RMSE is considered indicative of the constant airflow volume in rooms equipped with continuous ventilation. The accuracy of this estimation was further assessed by comparing it against data collected in subsequent periods, as shown in Figure 10.



Fig. 10 – (Top) Original air flow rate estimation. RMSE: 1.6468 Correlation: 0.8241. (Bottom) Adjusted air flow rate estimation: RMSE: 0.5045 Correlation: 0.8241

#### 5.2 Continuous Monitoring

First, the digital twin is implemented for continuous commissioning service of the ventilation system case study. In this regard, the model enables the tracking and identification of irregularities in both the overall ventilation system and within each individual room. This is done by continuously comparing an estimated signal with its measured counterpart, calculating a moving average of the error between the two signals and defining a threshold that would trigger an anomaly signal if surpassed. Figure 11 shows the continuous monitoring of the ventilation system's main air flow rate. Total Air Flow



Fig. 11 – Continuous monitoring of total air handling unit inlet air flow rate from the 5th to the 14th of February 2024

The bottom plot shows the anomaly signal, which is calculated by identifying deviations between the expected and actual damper positions or airflow rates, an anomaly is considered when the error average exceeds 15% for total airflow and 20% for damper positions. In Figure 12, a detailed examination of the monitoring models for all these rooms revealed that the expected control signal deviated in behaviour for 4 rooms. Analysing further, for one of the offices with anomalies, it could be seen that the control signal was manually set to maintain a fully open damper position during work hours, disregarding CO<sub>2</sub> levels. This setup was modified in the following year, as depicted in Figure 13, to allow for adjustments in response to measured CO2 levels, thereby optimizing ventilation performance and indoor air quality.

#### 6. Conclusion

This study utilizes grey-box modeling and ontology-based methods to blend empirical data with theoretical insights for predicting and simulating ventilation system performance under various scenarios.



Fig. 12 - Anomaly signals for the rooms of the ventilation system



Fig. 13 – Anomalous change in the damper controller for Room 10. The behaviour of the controller is different compared to the same period in the previous year

This approach achieves a balance between interpretability and accuracy, optimizing operations without fully depending on complex theoretical processes. It replicates rule-based controllers in larger buildings by training a neural network with control signals, adjusting to cyclic patterns and periodic control strategy changes efficiently. Although effective, it can inadvertently include isolated configuration changes, which could be mitigated with larger datasets.

This research also underscores the challenges in data collection and integration within live buildings, pointing out the difficulties of merging various subsystems into a unified digital twin platform. Future efforts involve incorporating variables such as temperature and humidity to provide a more comprehensive understanding of system performance. Additionally, a promising field of study revolves around exploring forecasting ventilation power consumption and investigating optimization strategies.

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#### Computational Cost Reduction of a Simulation-Based Optimization Process Through Machine Learning Methods: Neural Networks vs. Random Forest

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#### Abstract

Simulation-based optimization (SBO) processes are computationally expensive and the combination with machine learning (ML) methods appears as an alternative capable of reducing computational time consumption without losing the robustness of the solutions. This study compares neural network and random forest algorithms as approaches to replace simulations during the SBO processes. The main objective is to define the best machine learning algorithm and the most reliable ratio between simulations and predictions. The problem was implemented in the Grasshopper + Rhino platform and aimed to minimize the annual energy consumption with artificial conditioning in an office building. Comparing the convergence and reliability of the hybrid processes, the results show that the neural network achieved the best results. The results also show that for this particular/specific problem, the ideal budget comprises 80% of simulations and 20% of predictions, maintaining the results' reliability and reducing the computational cost.

#### 1. Introduction

With the recent technological advances in architectural research, the use of tools capable of producing evaluations and analyses of the performance of buildings has grown, in addition to producing completely new typologies, even before their execution. Parametric modeling, simulations, and optimization are some of these tools. Parametric modeling allows the creation of different building typologies from changes in parameters associated with their characteristics (Farouk et al., 2019). When coupled with simulation tools and optimization techniques, optimal solutions can be obtained satisfying pre-established performance conditions of a building. The coupling among parametric modeling, simulation, and optimization is often called simulation-based optimization (SBO).

In an SBO problem, parametric modeling works to modify the solutions, according to some intelligence implemented by the optimization algorithm, in search of optimal regions of the feasibility space. This search is guided by a fitness function that usually depends on the objective function of the problem and that also requires simulations to be evaluated.

However, SBO processes demand a vast amount of computational time mainly due to the simulations involved. To mitigate this issue, Machine Learning (ML) techniques have been employed since they can predict fitness function values associated with new solutions through real simulation data and produce evaluations faster than traditional methods (Seyedzadeh et al., 2019; Melo et al., 2014). This makes it possible to replace some simulations with predictions acquired by machine learning, training it with the results of simulations previously produced during the SBO process.

The use of machine learning techniques for prediction shows promise in optimization problems due to the intrinsic nature of optimization algorithms, which often generate and evaluate multiple solutions while searching for the optimal solution. This process results in the creation of a database containing solutions previously evaluated by the exact function of the problem. This database represents a valuable resource for training machine learning
techniques, allowing the prediction of new solutions without the need to evaluate each one for its exact function throughout the optimization process. This approach offers the potential to significantly reduce the time and resources required to solve optimization problems that demand high computational costs.

In the past years, several studies have shown the capability of Artificial Neural Networks (ANN) and Random Forest (RF) to aid in solving architecture and engineering problems. One in particular (Bui, Nguyen, Ngo, and Nguyen-Xuan, 2020) estimated the amount of energy used for various activities within a building, such as heating and cooling (energy consumption), using the hybridization of the ANN model with the firefly optimization algorithm (EFA). The performance of EFA-ANN was validated by comparing the obtained results with other methods, such as iteratively reweighted least squares (IRLS), ensemble model, smart artificial firefly colony algorithm-based support vector regression (SAFCA-SVR), extreme learning machine (ELM), which presented best results, and the lowest Root Mean Square Error (RMSE) values. Further, (Zekić-Sušac et al., 2021) used Random Forest, ANN and classification and regression tree (CART) to predict the cost of energy consumed in public buildings. The results have shown that the approach integrating random forest with the Boruta algorithm has produced a higher accuracy.

The neural network was created to mimic concepts from the neurobiological field, and it works through 3 main elements: inputs, hidden layers, and outputs. The inputs correspond to the parameters of the problem being analyzed. The layers are formed by nodes, structures where each input value is associated with a weight through mathematical functions and sent to the next layer (Gurney, 1997). Finally, outputs represent the predicted value of the response variable.

In contrast, Random Forest is a collection of randomized decision trees (Kam Ho, 1995). These decision trees are a machine learning technique that works as a tree structure by repeatedly dividing the given data into smaller subsets until only one data remains in each subset. The inner and final sets are known as nodes and leaf nodes. Then for the final results, it calculates the average predicted values of all independent trees.

Both methods need training and parameter tuning to improve the quality of their responses. Therefore, it is necessary to separate the database into two parts, one for training and the other for testing. The algorithm is exposed to the training part, where it learns patterns that will be applied in the test part to predict the response variable (Mahesh, 2019). The choice of these sets impacts the final quality of predictions. Typically, 80% of the data are used for training and the remaining 20% for testing, as such separation ratio has been theoretically proved to deliver good results (Gholamy et al., 2018). Then, the response variable predicted by the method is compared with the actual values from the database, and depending on the performance of the method, its parameters are adjusted.

The main parameters for the neural network are the number of iterations, nodes, and layers. For the random forest they are the numbers of independent trees and its depth. As suggested by (Karsoliya, 2012), the parameters are obtained by performing robust tests with database samples using different configurations in order to obtain better results.

Therefore, this study aims to evaluate and compare two ML methods, Neural Network and Random Forest, when coupled to an SBO process to indicate which one offers the best performance in predicting the energy consumption of an office building and also discover which is the best percentage of simulations replaced by prediction without losing the quality of the results.

# 2. Methodology and Simulation

# 2.1 The Simulation-Based Optimization Problem

A simulation-based optimization problem was selected based on the research of previous authors (Wetter & Wright, 2004), and it seeks to minimize the primary energy consumption based on the annual thermal loads of a single thermal zone that represents an office building (Fig.1). The building model combined the East and West offices (grey shade in Fig.1) into a single thermal zone and added the corridor as internal mass.



Fig. 1 – 3D Model of the office building. Source: Wetter, M., Wright, J., 2004

The SBO problem quantifies the impact of four parameters: building orientation  $(180^{\circ} \text{ to } -180^{\circ})$ ; transmittance of shading elements (0.2 to 0.8); and width of the openings to the east and west (0.1 to 5.9 m).

We used the Grasshopper for Rhino SBO implementation from (Waibel et al., 2019). The implementation uses EnergyPlus for the building performance simulation. We analyzed the problem based on TMY2 weather data for Seattle, Washington, USA.

We used the RBFOpt mono-objective optimization algorithm (Costa and Nannicini, 2018). The single objective method is an optimization approach that focuses on minimizing or maximizing a single objecttive value. It is available in the Opossum optimization engine, as it stands out from previous work (Waibel et al., 2019). As for this paper, the minimizing method was chosen, and its parameters were used by default. A maximum of 10000 iterations and evaluations, with local search available and 2000 maximum cycles. Additionally, the generation of 700 solutions served as a stopping criterion for each run of the SBO.

# 2.2 The Machine Learning Methods

Due to the nature of how these ML techniques work and the need for a previous database to be created, it requires a certain number of solutions through simulations to be made. The size and quality of this database directly impacts the performance of the ML.

In this work, the first solutions generated by the optimization algorithm and evaluated by the exact function of the problem constitute the database used to train the machine learning techniques. To answer

one of the questions in this research about the best proportion of solutions evaluated by the exact function compared to those that will be predicted by the ML technique, 5 divisions of the database were proposed to be investigated. We started from 50% simulated and used as a database, and the others 50% were predicted. Then in each split 10% was added to the simulated percentage until the last split, which was 90% simulated and 10% predicted. The Python language was used to code the algorithm of both ML techniques. To implement the neural network and random forest in the Grasshopper environment, the GHPythonRemote plugin was used (Cuvilliers and Mueller, 2022). This plugin allows the connection of external Python instances to Grasshopper, enabling the use of several code libraries that once were not available. For this problem, the Python programming library Scikitlearn (Sklearn) was used on both ANN and RF.

In the case of ANN, the MLPRegressor parameters were kept as default, with the exception of the number of hidden layers and neurons, which were set to 30, and the maximum iterations equal to 4000. Increasing the number of layers can enhance the model's capacity, yet this can only be done to a certain extent, since rather than extracting meaningful patterns, the model may start to 'overfit' the data. For RF, the RandomForestRegressor from Sklearn, the only specified parameters were the maximum depth of the tree, set to 15, and the number of trees in the forest, set to 100. This follows the same concept of the neurons and layers from ANN, where higher numbers can increase the model's quality but up to a certain threshold, to avoid overfitting.

Consequently, the workflow of the SBO processes coupled with ML techniques is presented as in Figure 2. The optimizer engine generates new solutions, by changing the values of the variables, and their Fitness Function values F(x) are obtained through simulations by EnergyPlus. These solutions are stored in a database until the desired number of simulations is reached, as defined by the simulation/prediction ratio used. This process is represented by green arrows. Then, all the values of the variables and the respective answers found by simulation up to now, serve as a database to feed the machine learning technique. From now on, the ML is the one that will provide F(x) to the optimizer engine, with the workflow represented in red and black arrows in Fig. 2.



Fig. 2 – Workflow on the cases without ML technique (green arrows), and with hybrid application (red arrows)

# 2.3 The Analysis

To produce statistics, 25 runs were done for each percentage ratio for each of the ML methods. The coupling process of the simulation with the optimization happens in the evaluation of the fitness function of the solutions, composed of the building energy consumption.

A base case was used for comparisons disregarding the ML techniques and obtaining the values of all solutions by simulation. Adding this case to the other 5 that mix simulation and prediction, a total of  $6 \times 25$  runs of SBO process were carried out, evaluating 700 x 25 x 5 solutions in each of the ML techniques.

After that, in order to compare the methods, we first assessed the performance of both methods by tracing the average of the convergence of the solutions found. Then, we evaluated the root mean squared error (RMSE) values of some results produced by the ML technique, selected according to a random sampling of 30 solutions. Finally, we compared the optimal results obtained at the end of each run through boxplots.

#### 3. Results and Discussions

Undoubtedly, in terms of computational resource expenditure, solutions whose fitness is predicted require much less computational time. On average, for the problem in this paper, the computational time for predicting the fitness of a solution is 75% faster than by simulation, as the first takes around 818 milliseconds and the second 3.4 seconds.

Figure 3 presents the convergence values for NN and RF application. Both exhibit similar behavior, by repeating the values at the end of the process and all percentage combinations do not differ significantly, since all reached the value of 133 kWh/m<sup>2</sup>. Even so, the combination of 90% of simulated cases with 10% predicted by ML, obtained the best response with a consumption metric of 133.19 kwh/m<sup>2</sup> for NN and 133.11 kwh/m<sup>2</sup> for RF. Furthermore, in both applications, the 60/40 and 80/20 processes are the closest to the 100% simulated results, represented in red.





When evaluating the difference between the responses acquired by prediction and the same by simulation, it can be seen in the Figure 4 that the values of the RMSE are generally low, not exceeding the margin of 1.65 kwh/m<sup>2</sup> on the percentage 50/50 for NN and 1.62 kWh/m<sup>2</sup> for RF. The 80/20 process that obtained the lowest RMSE value is also the one that came closest to the real-case convergence curve (Figure 3).

In practical terms, it is safe to say that all percentages had an acceptable performance regarding the quality of the responses found through the prediction with the ML techniques.



Fig 4 – RMSE values for each percentage in both techniques results

The figure below presents the best results acquired in all 25 runs of each of the percentages. Through the boxplot, it is noticed that the percentage 60/40 stands out, obtaining the lowest median for neural networks, whose results are presented with a black outlayer. Although, the minimum value of 129.886 kwh/m<sup>2</sup> that was acquired through the neural network initially qualifies it as the best result among all processes. However, when performing more detailed analysis and simulating with the same parameters supplied to the neural network, it was noticed that the response obtained by simulation was greater than that predicted by the model. Consequently, the value of 129.886 kwh/m<sup>2</sup> cannot be considered the lowest among all the percentages. Meanwhile, it is possible to observe that the 90/10 process obtained the lowest median for Random Forest, followed by 80/20, which also had the lowest dispersion. As for the other processes, in addition to a higher median value, they present a greater dispersion.



Fig. 5 – Boxplot of best results for each percentage with both techniques

# 4. Conclusion

This study aimed to evaluate two methods of ML and also discover the best percentage of simulations replaced by prediction without compromising the quality of the results. The results presented here, for both ANN and RF, demonstrate a significant reduction in the computational cost without affecting the optimization process's performance. For all the percentages used, the RMSE values varied between 0.74 kwh/m<sup>2</sup> to 1.65 kwh/m<sup>2</sup> for NN and 0,59 kwh/m<sup>2</sup> to 1,62 kwh/m<sup>2</sup> for RF.

As for the convergence from both methods, it is shown that the neural network, in all its processes, converged close to 200 solutions (Figure 3). In the RF, however, this convergence takes more time to happen, indicating that the neural network processes could have been stopped much earlier, further minimising the computational cost and outperforming the random forest application.

Additionally, the optimal values presented in the convergence graph are similar to the curve of the results of the 100% simulated case. For the artificial neural network, the configuration closest to this was 80/20, where 80% of the solutions are simulated and 20% are predicted. The same happens in random forest application, where 80/20 not only is the closest to the 100% simulated case but also has the lowest RMSE value of 0.47 kwh/m<sup>2</sup> and the second lowest median of all processes. Therefore, this is indicative that 80/20 is the best percentage, for both machine learning techniques presented in this study.

In conclusion, both techniques presented a reduction in computational cost, obtaining the best results in the 80/20 division and low RMSE values. However, the neural network proved to be more suitable for this problem, considering that it converged faster, which would allow us to reduce the number of solutions needed for the problem. Still, further research should apply these same comparisons to SBO problems with multiple objectives. This will help to reassert the best technique choice for a hybrid method and significantly reduce the computational cost spent on solving SBO problems.

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3

# Normalization Method of Building's Actual Energy Consumption for Normalized Building Energy Benchmarking

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#### Abstract

Energy use intensity (EUI, kWh/m<sup>2</sup>·yr) has been widely used in the building industry for building energy benchmarking. However, this EUI-based building energy benchmarking could lead to a biased assessment because it overlooks other influential factors such as operational schedule, occupancy, plug-load, setpoint temperature, and weather (hereafter referred to as operational factors). To overcome the issue, the authors propose a normalization process for the building's actual energy consumption considering the aforementioned factors. In this study, a concept of normalization coefficients was introduced based on the relationship between the operational factors and the change in energy consumption. The eXtreme Gradient Boost regression (XGBoost) models were used for deriving normalization coefficients that can convert the actual heating and cooling EUIs into the normalized EUIs per building under the operational factors. Validation studies demonstrated that the conversion of actual EUIs into normalized EUIs using these coefficients can contribute to fair building energy benchmarking. In other words, the proposed normalization approach holds promise for achieving more objective building energy performance benchmarking.

#### 1. Introduction

Objective building energy benchmarking can play an important role in making decisions to improve building energy efficiency and supporting government agencies and policymakers in their efforts to reduce greenhouse gas emissions (Piscitelli et al., 2024). Building energy benchmarking is a process that diagnoses the energy performance of a building compared to peer groups generally established by building types or climate zones. In conventional energy benchmarking systems, energy use intensity (EUI, kWh/m<sup>2</sup>·yr) defined as energy use per unit floor area has been widely utilized as a performance indicator for building energy benchmarking. However, it has been acknowledged that EUI can be an 'unfair' metric because it overlooks other influential factors such as operational schedule, occupancy, plug-load, setpoint temperature, and weather (Bogin et al., 2024). Thus, this EUI-based building energy benchmarking could lead to a biased assessment regarding distinguishing energyefficient from energy-inefficient buildings. Other trials have been undertaken to develop energy use per worker in office buildings, and energy use per bed in hotels, but they have proved to be unsatisfactory (Arjunan et al., 2022). Therefore, for more objective building energy benchmarking, it is imperative to normalize actual energy consumption over operational schedule, occupancy, plug-load, setpoint temperature, weather (hereafter referred to as operational factors).

As part of the building energy benchmarking, many efforts have been made to define 'peer building group'. Recently, data-driven models considering multiple influential factors have been introduced. For example, by the use of multiple linear regression (MLR) models, actual energy consumption is *neutralized* depending on building type, climate, or building's thermal attributes, etc. (Dahlan et al., 2022; Kükrer et al., 2023; Gupta et al., 2023). Unsupervised clustering methods are adopted to define peer groups according to building types, climate zones, or building energy usage patterns and attributes (Gao & Malkawi, 2014; Zhan et al., 2020). The aforementioned studies are focused on developing a 'peer building group' and then comparing my target building to the peers.

Rather than taking that approach, this study introduces an EUI normalization process. The normalization methodology considers the combined influences of diverse operational factors such as the operational factors as well as a combination of them. With the introduction of the normalization, we aim to assess the 'pure energy performance level' of buildings.

With this in mind, this study proposes a benchmarking approach utilizing normalization coefficients established by the relationship between operational factors and EUI. The eXtreme Gradient Boost regression (XGBoost) models were used for deriving normalization coefficients for heating and cooling EUIs. The normalization coefficients can convert the actual heating and cooling EUIs into the normalized EUIs per building under the operational factors.

As validation studies, comparative analyses between actual EUIs and normalized EUIs were carried out. It was substantiated that buildings with an identical design exhibit similar normalized energy consumption. The proposed normalization method is expected to reduce the so-called performance gap. In other words, the results indicate that normalized EUI can be a promising candidate for more objective benchmarking of building energy performance.

# 2. Methodology

# 2.1 Data Collection

For a reference building, a three-story medium office building developed by the US DOE (Deru et al., 2011) was selected (Fig. 1). The gross floor area of the building is 4,500 m<sup>2</sup> with a window-to-wall ratio (WWR) of approximately 33.3%. The aspect ratio of the building is 0.6. Based on the building energy code compliance in South Korea (MOTIE, 2023), the thermal insulation values for the external walls, floor, and roof of the building were set as 0.48 W/(m<sup>2</sup>·K), 1.81 W/(m<sup>2</sup>·K), and 1.81 W/(m<sup>2</sup>·K), respectively. The window U-value and SHGC were set to 2.0 W/(m<sup>2</sup>·K) and 0.38, respectively. Lighting power density was set to 8.1 W/m<sup>2</sup>, and the infiltration rate was set to 0.5 ACH. Also, the building was modelled with an 'Ideal Loads Air System' instead of detailed HVAC systems.

After developing the reference building model as a 'baseline', the authors used Latin hypercube sampling (LHS) in order to generate 200 medium office buildings with different operating conditions (Mckay et al., 2000). The operating conditions were regarded as the key factors affecting the building's operational energy consumption, independent of the building's thermal properties. The factors included operational schedule (starting hour, operation hours), occupant and appliance densities, heating and cooling setpoint temperatures. Additionally, weather data from 90 locations in South Korea, were collected (KMA, 2022), and the meteorological characteristics of each location were analysed in terms of heating and cooling degree-days (HDD, CDD). A total of 18,000 simulation runs were conducted (=200 operation conditions times 90 locations). The details of the factors are tabulated in Table 1.



Fig. 1 – Building energy normalization process (E<sub>sample</sub>: Energy consumption of a sample building, E<sub>reference</sub>: Energy consumption of a reference building, EUI<sub>actual</sub>: actual EUI of a building, EUI<sub>normalized</sub>: normalized EUI by a normalization coefficient)

As the output variables of the sample buildings, we collected the annual heating and cooling energy consumptions (kWh/m2·yr) exclusive of domestic hot water because heating and cooling energy are closely correlated with building thermal performance. In addition, the reference building's energy consumption was calculated based on the reference operating conditions that are referred to ASHRAE standard 90.1 (2022) and Seoul weather data. These conditions include a starting time of 9:00 AM, 8 hours of operation, an occupant density of 0.16 person/m<sup>2</sup>, appliance density of 8.61 W/m<sup>2</sup>, and heating and cooling setpoint temperatures of 20 °C and 26 °C, respectively. Additionally, Seoul weather data exhibits HDD of 2,730 K d and CDD of 903 K d. Note that we used the reference building's energy consumption as the numerator and the sample energy consumption as the denominator (Fig. 1).

# 2.2 Surrogate Model

Based on the EnergyPlus simulation runs, we trained an XGBoost regression model as a surrogate model for obtaining the normalization coefficients. XGBoost is an efficient implementation of gradient boosting based on decision trees (Chen & Guestrin, 2016). XGBoost builds a series of decision trees iteratively, where each tree corrects the errors of the previous one, thereby improving the overall model's prediction accuracy.

The input variables of the XGBoost regression models are shown in Table 1. Two XGBoost models

were constructed to derive heating and cooling normalization coefficients, respectively. A total of 18,000 input-output pairs obtained from the presimulated EnergyPlus samples were partitioned into training and testing sets, or 7:3 (12,600:5,400). In other words, the models were trained with 12,600 training datasets, and the models' accuracies were tested against 5,400 testing datasets.

Table 1 – List of influential factors used in the normalization process

Factors	Unit	Range	Reference
Starting hour	h	[7, 10]	Building audit reports
Operation hours	h	[8, 14]	Building audit reports
Occupant density	people/ m²	[0.075, 0.25]	ASHRAE (2021)
Appliance density	W/m <sup>2</sup>	[2.7, 16.1]	ASHRAE (2021)
Heating setpoint temperature	°C	[18.5, 21.5]	Building audit reports
Cooling setpoint temperature	°C	[24.5, 27.5]	Building audit reports
Heating degree- days	-	[1,393 <i>,</i> 3,492]	KMA (2022)
Cooling degree- days	-	[452, 1,118]	KMA (2022)

#### 2.3 Normalization Process

As illustrated in Fig. 1, the proposed normalization coefficient is defined as Eq. (1).

$$C = E_{reference} / E_{sample} \tag{1}$$

where  $E_{reference}$  denotes the energy consumption of a reference building under the reference operating and weather conditions (Section 2.1), while  $E_{sample}$  represents the energy consumption of a sample building under different operating and weather conditions.

The coefficients can be regarded as a lumped number that can account for dynamically interwoven effects of the aforementioned operational factors. Thus, a normalization coefficient greater than 1.0 means that the sample building whose thermal performance is equal to the reference building consumes less energy than that of the reference building because of the aforementioned factors, e.g. operation hours, occupant density, setpoint temperatures, weather, etc.

Then,  $EUI_{actual}$ , the actual energy use of a target building, can be converted into  $EUI_{normalized}$ , normalized energy use as shown in Eq. (2).

$$EUI_{normalized} = EUI_{actual} \times C \tag{2}$$

This normalization process can be exemplified as shown in Table 2. The normalization coefficients are likely to contribute to objective building energy benchmarking.

Table 2 - Normalization example

	EUI (kWh/m²·yr)
Ereference	100
Esample	120
С	0.83
EUIactual	150
EUInormalized	125.0

# 2.4 Two Validation Studies

In order to ascertain the validity of the normalization coefficients proposed in this study, it is necessary to collect measured energy data from a variety of existing buildings. However, collecting such data demands significant costs and time. Therefore, the authors conducted two validation studies using a series of simulation results.

- Validation study #1 (buildings' identical thermal performance under different operations)

We derived the normalization coefficients for 18,000 buildings with identical architectural designs ('can be regarded as identical thermal performance') but varying operation hours and plugloads in different locations. Then, three types of EUIs were calculated from 18,000 buildings.

The first EUIs are obtained from the reference operating conditions and defined as the true EUI (EUI<sub>true</sub>). The second EUIs are calculated according to the building's actual operating conditions and defined as the actual EUI (EUI<sub>actual</sub>). Finally, the third EUIs were calculated based on the normalization coefficients and defined as the normalized EUI (EUI<sub>normalized</sub>). Then, two differences in EUIs were calculated: one is  $\varepsilon_{actual}$  between the EUI<sub>true</sub> and EUI<sub>actual</sub>, and the other is  $\varepsilon_{normalized}$  between the EUI<sub>true</sub> and the EUI<sub>normalized</sub>.

- Validation study #2 (buildings' different thermal performance under different operations)

We generated 1,000 buildings with different architectural designs under varying operating conditions. In order to generate 1,000 different buildings, the authors conducted LHS with seven architectural design variables as tabulated in Table 3. Similar to the validation study #1, a comparative analysis was performed using three types of EUIs (EUI<sub>true</sub>, EUI<sub>actual</sub>, EUI<sub>normalized</sub>) and two mean absolute percentage errors (MAPE) as the evaluation metrics. The first is MAPE between the EUI<sub>true</sub> and EUI<sub>actual</sub>, while the second is MAPE between the EUI<sub>true</sub> and the EUI<sub>normalized</sub>. Then, a correlation analysis was conducted between the EUI<sub>true</sub> and the EUI<sub>actual</sub>, as well as between the EUI<sub>true</sub> and the EUI<sub>normalized</sub>, using the coefficient of determination (R<sup>2</sup>).

#### 2.5 Benchmarking Case Study

In contrast to the validation studies (Section 2.4), we developed a benchmarking case study. For this purpose, we developed four different buildings (denoted by Blds. #1-#4) having different WWR and window U-values. The four buildings have different operating conditions. Bld. #1 represents far superior thermal performance having a WWR of 0.2 and a window U-value of 1.5 W/(m<sup>2</sup>·K). Blds. #2-#4 were designed to have proportionally higher WWR and window U-values than Bld. #1. In other words, Blds. #2-#4 represent far inferior thermal performance. The details of the four buildings and benchmarking results will be addressed in Section 3.4.

Table 3 – List of design variables and ranges

Variable	Unit	Range	Reference
Gross floor area	m²	[450, 22,500]	0.1-5 ratio of the reference building
Aspect ratio	-	[0.06, 3]	0.1-5 ratio of the reference building
Number of floors	-	[2, 10]	Building audit reports
Wall U-value	W/m²·K	[0.15, 0.6]	Building audit reports; MOLIT (2023)
Window U-value	W/m²·K	[1.5, 3.5]	Building audit reports; MOLIT (2023)
Window-to- wall ratio	-	[0.2, 0.8]	Building audit reports
Window SHGC	-	[0.3, 0.7]	Building audit reports; ASHRAE (2021)

# 3. Results

#### 3.1 Surrogate Model Accuracies

In order to evaluate the accuracies of the surrogate models, three metrics including the root mean squared error (RMSE), the coefficient of variation of root mean squared errors (CVRMSE), and the coefficient of determination ( $R^2$ ) were used on the testing datasets (Table 4). The calculated RMSE, CVRMSE and  $R^2$  scores are 0.03, 2.5% and 0.99 for heating normalization coefficients (*C*<sub>heat</sub>), and 0.09, 8.3% and 0.98 for cooling normalization coefficients (*C*<sub>cool</sub>), respectively. In addition, Fig. 2 shows the comparison between the simulation and prediction results. These results indicate high accuracies of the models in predicting normalization coefficients for heating and cooling EUIs.

Table 4 –	Surrogate	model	accuracies
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Output	RMSE (-)	CVRMSE (%)	R <sup>2</sup> (-)
Cheat	0.03	2.5	0.99
Ccool	0.09	8.3	0.98
6 5 4 1 0 0 1	Heating 2 3 4 5 Simulation	12 10 10 6 6 6	Cooling 4 6 8 10 12 Simulation

Fig. 2 – Simulation vs. surrogate model predictions (left: heating, right: cooling)

#### 3.2 Calculated Cheat and Ccool vs. EUI

Fig. 3 shows the comparison results between the normalization coefficient and EUI<sub>actual</sub> using the training datasets of the surrogate models. The relationship between the two variables appears to be inversely proportional. The variability in EUI<sub>actual</sub> demonstrates that even buildings with identical thermal performance can exhibit a significant difference depending on the operating conditions. The range of cooling normalization coefficients is wider compared to that of heating, suggesting that cooling EUI is more sensitive to variations in operating conditions.

As exemplified in Table 2, the buildings with the normalization coefficients of less than 1.0 fulfil demanding operating conditions such as long operation hours, low indoor temperature in summer, severe weather locations, etc. Thus, these buildings are likely to be wrongly assessed as poor energy performance buildings, and vice versa for the buildings with normalization coefficients greater than 1.0.



Fig. 3 – Normalization coefficients (C) vs.  $EUI_{actual}$  (above: heating, bottom: cooling)

#### 3.3 Validation Study #1

Fig. 4 shows the distributions of  $\epsilon_{actual}$  (the difference between EUItrue and EUIactual) and Enormalized (the difference between EUItrue and EUInormalized) for 18,000 buildings that have identical thermal performance under varying operational conditions. For heating  $\epsilon_{\text{actual,}}$  the minimum and maximum -79.9 kWh/(m<sup>2</sup>·yr) values were and 43.8 kWh/(m<sup>2</sup>·yr), respectively. In contrast, for heating Enormalized, the minimum and maximum values were -4.7 kWh/(m<sup>2</sup>·yr) and 6.4 kWh/(m<sup>2</sup>·yr), respectively. Regarding cooling *eactual*, the minimum and maximum values were -85.8 kWh/(m<sup>2</sup>·yr) and 27.5 kWh/(m<sup>2</sup>·yr), respectively. In contrast, for cooling  $\varepsilon_{normalized}$ , the minimum and maximum values were -9.1 kWh/(m<sup>2</sup>·yr) and 7.5 kWh/(m<sup>2</sup>·yr), respectively. As shown in Fig. 4, the distribution of  $\varepsilon_{normalized}$  is quite marginal compared to  $\varepsilon_{actual}$ .



Fig. 4 – Distributions of  $\epsilon_{actual}$  and  $\epsilon_{normalized}$  (above: heating, bottom: cooling)

#### 3.4 Validation Study #2

As mentioned earlier in Section 2.4, Figs. 5-6 and Table 5 show the results of validation study #2. The MAPEs between EUI<sub>true</sub> and EUI<sub>actual</sub> are 25.4% and 45.4% for heating and cooling, respectively, while the MAPEs between EUI<sub>true</sub> and EUI<sub>normalized</sub> are only 5.6% and 11.2% for heating and cooling, respectively. In addition, both relationships between EUI<sub>true</sub> and EUI<sub>actual</sub> for heating and cooling had lower R<sup>2</sup> scores of 0.35 and 0.22, respectively, while the relationships between EUI<sub>true</sub> and EUI<sub>normalized</sub> for heating and cooling had lower R<sup>2</sup> scores of 0.35 and 0.22, respectively, while the relationships between EUI<sub>true</sub> and EUI<sub>normalized</sub> for heating and cooling had far higher R<sup>2</sup> scores of 0.89 and 0.62, respectively. This means that the normalization coefficients can reduce any possible biased assessment of the actual EUIs.



Fig. 5 – Comparison of heating EUI<sub>true</sub> vs. EUI<sub>actual</sub>, EUI<sub>normalized</sub>



Fig. 6 – Comparison of cooling  $EUI_{true}$  vs.  $EUI_{actual}$ ,  $EUI_{normalized}$ 

Table 5 - Comparative analysis results

Dependent	variable	MAPE (%)	R <sup>2</sup> (-)
Heating	EUIactual	25.4	0.35
	EUInormalized	5.6	0.89
Cooling	EUIactual	45.4	0.22
	EUInormalized	11.2	0.62

#### 3.5 Benchmarking Results

As mentioned earlier in Section 2.5, Table 6 shows the four buildings and benchmarking results. EUI<sub>true</sub> represents energy use under the reference operating conditions. heating EUI<sub>actual</sub> reflects biased rankings. However, heating EUI<sub>normalized</sub> are close to EUI<sub>true</sub>, and renders more objective benchmarking than EUI<sub>actual</sub>.

Similarly, the variances in cooling EUI<sub>true</sub> among the four buildings were negligible. Nevertheless, cooling EUI<sub>actual</sub> shows substantial differences between the four buildings, while cooling EUI<sub>normalized</sub> shows significantly smaller differences. Based on Table 5, it can be highlighted that EUI<sub>normalized</sub> can serve as a promising candidate for a more objective benchmarking of building energy performance.

# 4. Conclusion

This study introduced a normalized building energy benchmarking approach. The proposed normalization coefficients were established to account for the variation in EUI influenced by operational factors (starting time, operation hours, occupancy, plug-load, setpoint temperature, weather).

Table 6 – Benchmarking results

Building #		#1	#2	#3	#4
Architectural	WWR (-)	0.2	0.4	0.6	0.8
designs	Window U (W/(m <sup>2</sup> ·K))	1.5	2.2	2.8	3.5
Heating	EUI <sub>true</sub> (kWh/(m²·yr))	54.1	56.0	58.5	61.5
	EUI <sub>actual</sub> (kWh/(m²·yr))	39.0	77.3	62.2	42.7
	EUInormalized (kWh/(m²·yr))	54.1	58.6	59.6	62.3
Cooling	EUI <sub>true</sub> (kWh/(m²·yr))	30.0	29.5	28.8	28.1
	EUI <sub>actual</sub> (kWh/(m²·yr))	22.1	77.8	77.0	71.0
	EUInormalized (kWh/(m²·yr))	28.0	30.2	28.3	26.6

The heating and cooling normalization coefficients were generated using XGBoost models constructed based on a reference medium office building by US DOE. Two validation studies demonstrated the conversion of actual EUIs into normalized EUIs can enable more objective building energy benchmarking (Sections 3.3-3.4). Moreover, the approach proved effective for buildings with different thermal performance and architectural designs (Section 3.5).

Conclusively, the proposed normalization coefficients are likely to mitigate potential biases against actual EUIs and contribute to better building energy benchmarking. Additionally, the proposed normalization approach may be considered as an alternative for reducing the performance gap between measured and predicted energy use. As a further study, we aim to apply the concept of normalization coefficients to several existing buildings selected from Korean building energy database. The outcomes of this study will be beneficial for advancing objective building energy performance benchmarking methods and fostering performance-based thinking within the IBPSA community.

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# Simulator for Predicting Vertical Illuminance of Window With External Venetian Blind

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#### Abstract

Many studies have shown that by installing external Venetian blinds on the transparent envelope and utilizing daylight efficiently, we can reduce cooling and heating load and lighting energy and improve thermal and visual comfort. Among many studies, most of them use light sensors or whole-building simulation tools to derive and control illuminance that affects the indoor luminous environment. However, this requires the cost of sensor installation and a large amount of information and modeling effort for simulation. In addition, it is difficult to understand the relationship between the inflow of visible light, the slat angle of blind, and illuminance. Therefore, this study proposes a stand-alone daylighting simulator based on artificial neural network using the visible transmittance of the window with external Venetian blind. Using the developed simulator, it is possible to easily predict indoor vertical illuminance under changing external environment by reflecting natural light inflows with only some information of the system and major environmental factors without sensor installation or simulation modeling effort.

In addition, due to the advantages of this simplicity, it can be easily used for model predictive control (MPC).

#### 1. Introduction

In order to reduce cooling and lighting energy and improve occupant's thermal and visual comfort, many studies have been conducted to efficiently use transmitted daylight through an external Venetian blind (EVB) with transparent building envelopes. Many researchers have analyzed the effects of EVB on the thermal and light environment of buildings (Carletti et al., 2016; Fedorczak-Cisak et al., 2019) and analyzed the uncertainty and sensitivity of energy and visual performance due to various factors (window-to-wall ratio, glazing type, slat angles etc.) (Singh et al., 2016; Huo et al., 2021a). Moreover, based on the influence and analvsis of these external Venetian blinds, many studies are being actively conducted to reduce the heating and cooling load and lighting energy of the building, and improve the visual comfort through the control of the slat angle of EVB (Huo et al., 2021b; Baghoolizadeh et al., 2023). Carletti et al. (2006) installed EVB in a full-scale test room and monitored temperature and illuminance through



Fig. 1 - Simulator for indoor daylit environment: As-is vs. To-be

thermometers and luxmeters, arguing that the different configurations of the Venetian blind can keep the mean radiant temperature lower and maintain a good level of internal illuminance. Fedorczak-Cisak et al. (2019) installed EVB in the office space and observed temperature and humidity through sensors (temperature, humidity, air velocity) during the transition season when the heating and cooling system did not operate, showing that the use of blinds reduced discomfort hours by 92% compared to rooms without EVB. Huo et al. (2021b) modeled a venetian blind with EnergyPlus, and evaluated the shading performance when EVB was installed in different climate regions in China. The results show that there is a maximum building energy saving potential per unit window area of EVB when the window is westward and has low WWR (window-to-wall ratio) and slat angle of EVB is 0°. Baghoolizadeh et al. (2023) conducted multi-objective optimization (energy consumption, visual & thermal comfort) of Venetian blinds in office buildings with EnergyPlus and NSGA-II algorithm. They showed that in the shading position (interior vs. exterior), the external blinds were optimally selected for all seasons, so the external blinds performed better than the internal blinds in terms of solar and luminous control, e.g. the smaller the slat angle of EVB, the better the visual comfort but the higher the lighting energy.

According to many other studies (Jung & Kim, 2010; Shin et al., 2011; Park et al., 2012; Kim & Kim, 2015) when inducing and controlling the illuminance according to the slat angle of the EVB, the illuminance at a specific point is directly measured through a light sensor or derived using a simulation tool (EnergyPlus, Desktop Radiance 2.0, TRN-SYS). However, this requires detailed and extensive information (dimension and material properties for zone and window & blind, etc.) for modeling process. Also, it is difficult to understand a clear interrelationship between the inflowing luminous flux (direct and diffuse solar radiation), which greatly affects indoor illuminance, and the slat angle of EVB (the control variable) and illuminance (subject to the control variable). For implementing optimal control of EVB, e.g. determining an optimal slat angle, accurate prediction of daylighting transmission in terms of the slat angle is a prerequisite. If this relationship can be explained in a simple simulation toolbox per se, it becomes easier and more convenient to implement MPC of EVB. In addition, such simulator must be developed as a 'stand-alone' fashion so that it can be independent from a room model or a zone model for its wide application in optimal control of daylighting system. Therefore, this study proposes a 'stand-alone' daylighting simulator that predicts the vertical illuminance passing through the EVB + double glazing window system (EVBW) under varying external environment and the slat angle of the blind. The proposed simulator predicts illuminance based on the inflowing luminous flux.

# 2. Daylight Simulator Methodology

#### 2.1 Key Information

1. In general, we perceive the luminous flux as the lumens [lm] or illuminance  $[lm/m^2]$  caused by solar irradiance  $[W/m^2]$  from the sun with a certain amount luminous efficacy [lm/W].

2. When daylight is introduced into interior zone, the luminous efficacy varies depending on the climatic and sky conditions (Littlefair, 1988; Umar & Chaiwiwatworakul, 2018). Therefore, we must acknowledge that luminous efficacy is not always constant and the luminous efficacies of direct and diffuse radiations are different from each other (Chaiwiwatworakul & Chirarattananon, 2013; Perez et al., 1990).

3. Solar altitude is a major factor that affects the luminous efficacies of direct and diffuse radiations (Aghimien et al., 2021).

#### 2.2 Visible Transmittance

Visible transmittance (VT) is a fraction of the visible spectrum of sunlight through the glazing of a window, weighted with respect to the photopic response of the human eye. When there is only a window, VT is used as one value, and only one reference value is presented for normal incidence in ASHRAE Fundamentals (ASHRAE, 2021). However, when EVB is installed in the window, VT is calculated by three categories: dir-dir, dir-dif, and dif-dif. Dir-dir transmittance is the ratio of the incident beam radiation without distribution due to collision with slats when passing through the shading device (Figure 2 (a)). Dir-dif transmittance is used when the source is a beam incident radiation but outgoing radiation is diffuse due to collision with slats (Figure 2 (b)). Dif-dif transmittance is the ratio of the outgoing and incident radiant energy where the incident and outgoing radiation is diffuse (Figure 2 (c)) (Curcija et al., 2018). For overall VT estimation through the EVBW system, we need to consider the aforementioned three VT values (VT<sub>dir-dir</sub>, VT<sub>dir-dif</sub>, VT<sub>dif-dif</sub>). These three VT values depend on solar position and slat angle of EVB, and accordingly, the ratio of direct (Idir) and diffuse (Idif) radiations entering the interior can be found.



Fig. 2 – Visible transmittance according to the incidence and inflow of direct and diffuse solar radiation ((a)  $VT_{dir-dir},$  (b)  $VT_{dir-dif},$  (c)  $VT_{dir-dif})$ 

#### 2.3 ANN Model

An artificial neural network (ANN) model was used to develop the aforementioned daylighting simulator. ANN is constructed based on a multilayer perceptron between the input layer and the output layer, and there are multiple nodes in each layer. ANN predicts output variables by learning the correlation between input and output variables through weight parameter updates between nodes that minimize errors between the model's output and measured values through backpropagation methods (Raza & Khosravi, 2015; Ra et al., 2017). Although the number of hidden layers can affect the accuracy of the ANN model, there are no clear rules for determining the best number of hidden layer units (Han et al., 2012). Therefore, the input and output variables of the virtual daylighting simulator developed in this study were selected in consideration of the characteristics of light according to the slat angle, solar radiation and the solar position when the EVB was installed. The input parameters are a slat angle, environmental conditions (direct & diffuse solar radiation, zenith angle), and variables depending on the slat angle (three VT values (Figure 2), opening ratio, and the rate of horizontal diffuse solar radiation reaching the vertical wall). For reference, the zenith angle is set to  $(90^{\circ} - \text{solar altitude}, (^{\circ}))$ , so the influence of the solar altitude can be reflected in the zenith angle. In addition, the sky condition (clearness) is also considered along with direct and diffuse radiation (Perez et al., 1990). The output parameter is the vertical illuminance of the EVBW system.

Table 1 – ANN	l parameters
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The number of hidden layers	2
The number of nodes (each layer)	(40, 100, 100, 40)
epoch	500

To collect input data for ANN learning, we generated an EVB and double-window model using pyWincalc (Kohler et al., 2019), a Windows-CalcEngine (LBNL, 2016)'s python package developed by LBNL (Lawrence Berkeley National Laboratory). The specifications and properties of slat of EVB are tabulated in Table 2. The slat angle of 0° is the state in which the blind slat is horizontal, and the slat is positive when facing the sky and negative when facing the ground. The double window consisted of clear glazing 6mm + argon gas 12 mm + clear glazing 6mm and was 1 m x 1 m in width and height (Figure 3). The EVBW system was set to the south facing. Environmental conditions were selected from 9 am to 4 pm in the summer solstice, autumn equinox, and winter solstice by referring to the EnergyPlus weather data (EPW) of Seoul that reflect changes in the solar position and sky condition according to season and time. Then, for each time point, we discretized the slat angles at 10° intervals in the range of -80° - 80° and derived three VT values.

The three VT values show different characteristics because the inflow of direct and diffuse radiation varies depending on the solar position and slat angle.  $VT_{dir-dir}$  shows a large value when the profile angle defined by the azimuth and altitude angles of the sun and the slat angle are parallel.  $VT_{dir-dif}$  is affected by the profile angle of the sun and the proportion covered by the slats. Also, since diffuse radiation does not have a specific orientation, it is not affected by the solar position and only the difference according to the slat angle. Therefore,  $VT_{dir$  $dif}$  is the largest at 0°, where diffuse radiation can be transmitted the most, and decreases to a symmetrical form based on 0°.



Fig. 3 – Double window with external Venetian blind and slat angle

Table 2 – Specification and properties of external Venetian blind slats

Slat property	Value
Slat width	50 mm
Slat spacing	50 mm
Slat thickness	15 mm
Transmittance	0.0
Reflectance	0.47
Distance from the window	100 mm

Next, to collect output data for ANN learning, we generated a zone (5 m x 5 m x 3.4 m) for simulation and the same EVBW system as pyWincalc (dimension, material properties etc.) using Climate Studio, a light simulation tool developed by Solemma (Figure 4). Thereafter, as with the collection of input data, we discretized  $10^{\circ}$  intervals (- $80^{\circ} - 80^{\circ}$ ) and conducted a total of 408 simulation runs (3 days x 8 hours x 17 slat angles) under the same environmental conditions. Then, we measured the vertical illuminance for the vertical surface grid immediately behind the system.



Fig. 4 - Lighting simulation using ClimateStudio

Based on the pyWincalc and the ClimateStudio simulation runs, we trained an ANN model. The accuracy of the ANN model was 13.0% based on Coefficient of Variance of Root Mean Square Error (CVRMSE), showing a prominent accuracy.

#### 2.4 Validation

To validate the developed 'stand-alone' daylighting simulator, the author compared with ClimateStudio simulation results for an office room under an arbitrary summer, autumn equinox and winter day under one hour and 17 slat angles (total 51 cases = 3 days x 1 hour x 17 slat angles). The CVRMSEs between the 'stand-alone' daylighting simulator and a 'whole-building' ClimateStudio simulation runs were 9.1% in summer (Figure 5 (a)), 11.1% in autumn (Figure 5 (b)), and 9.3% in winter (Figure 5 (c)), respectively. The predicted illuminance in all seasons showed high accuracy, which means that the proposed daylighting simulator can account for the visible light transmittance according to the solar position and slat angle and accordingly, the vertical illuminance passing through the system can be well predicted.



#### Model Predictive Control (MPC)

The energy use of large buildings is mainly dominated by cooling and lighting, and it is important to supply adequate daylighting and accordingly reduce cooling and lighting energy. To realize this, many studies have been conducted on optimal control of external venetian blind. In this regard, the authors applied the virtual daylighting simulator to MPC study for a given office space.

To quantify transmitted solar energy through EVBW system, Q<sub>solar</sub> was introduced (Reddy et al. 2016). Please note that the direct and diffuse solar heat gain coefficients (SHGC<sub>dir</sub>, SHGC<sub>dif</sub>) can vary according to the slat angle and solar position, and the amount of direct and diffuse radiation (Equation 1).

$$Q_{solar} = SHGC_{dir} \bullet I_{dir} + SHGC_{dif} \bullet I_{dif}$$
(1)

In addition, it is assumed that the transmitted daylight can be quantified by the vertical illuminance ( $E_{vg}$ ) measured at the interior surface of inner glazing of EVBW. Accordingly, the objective function in MPC is to minimize  $Q_{solar}$  and maximize  $E_{vg}$  in cooling season, while to maximize both  $Q_{solar}$  and  $E_{vg}$  in winter. The constraints were set to have  $E_{vg}$ below 2,000 lux to avoid excessive glare in occupant's position about 1.1m away from the window by referring to the research of Karlsen et al. (2015). Optimal slat angles in summer and winter days were found through the exhaustive search method at intervals of 10° from -80° to 80°. The baseline was assumed to have the slat angle of 0°. The cost functions in summer and winter are as follows:

$arg minJ = -E_{vg}$	$+ Q_{solar}$	(summer)	(2)
$arg minJ = -E_{vg}$	- Q <sub>solar</sub>	(winter)	(3)
s.t. Evg	$\leq 2,000 \text{ lux}$		

Table 3 shows the results of summer control. In case of relatively large diffuse radiation (9 am, 2 pm) between 9 am and 4 pm, 0° was selected as the optimal angle because VTdif-dif of 0° is maximum (Figure 6 (b)) so large introduction of diffuse radiation maximized Evg (9 am: 344 lm/m<sup>2</sup>, 2 pm: 492 lm/m<sup>2</sup>). If the slat angle is negative, Q<sub>solar</sub> can be reduced because SHGCdir and SHGCdif tend to decrease. Accordingly, VT and  $E_{vg}$  also decrease. Therefore, 0° was optimally selected according to the cost function in summer. When direct radiation was greater than diffuse solar radiation (10 am, 11 am, 12 pm, 1 pm, 4 pm), -20° was selected as the optimal angle because it reduced SHGC<sub>dir</sub> (Figure 6 (c)), although the values of VTdir-dif and VTdif-dif tend to decrease (Figure 6 (a), (b)), Table 3). When diffuse radiation was greatest but direct radiation was relatively small (3 pm), 10° was selected as the optimal angle. Compared to 0°, the values of SHGC<sub>dir</sub> and SHGC<sub>dif</sub> at 10° are larger (Figure 6 (c), (d)), so Qsolar was increased (10°: 187 W/m<sup>2</sup>, 0°: 154 W/m<sup>2</sup>). But, by choosing 10° with a high VT<sub>dir-dif</sub> value (Figure 6 (a)),  $E_{vg}$  was increased (10°: 497 lm/m<sup>2</sup>, 0°:  $410 \text{ lm/m}^2$ ).



Similarly, Table 4 shows the results of winter control. Due to the low solar altitude, the introduction of direct solar radiation through the slat angle can be far greater than that in summer. Accordingly, VTdir-dir is large (max: 0.75, range: 0.0-0.75) (Figure 7 (a)). Therefore, Evg could easily exceed 2,000 lx depending on the slat angle. When the solar altitude is low and direct and diffuse radiation were relatively low, the slat angles of 20° (9 am, 4 pm) and 30° (10 am) were selected as optimal. The profile angle according to the azimuth and altitude of the sun at those hours is between 15° and 30°. Therefore, when the slat angle is parallel to the profile angle at 20° or 30°, the values of SHGCdir, SHGCdif and VT<sub>dir-dir</sub> are large (Figure 7 (a), (b), (c)), so more direct and diffuse radiation were introduced com-

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pared to the baseline (0°). Thus, both  $Q_{solar}$  and  $E_{vg}$  become greater (Table 4). When direct and diffuse radiations are large (11 am, 12 pm, 1 pm, 2 pm, 3 pm), -10° was selected as the optimal angle. At 0°,  $VT_{dif-dif}$  is the maximum at every hour, but  $E_{vg}$  becomes beyond 2,000 lx. Therefore, compared to 0°, the values of SHGC<sub>dir</sub> and SHGC<sub>dif</sub> at the slat angle of -10° are smaller (Figure 7 (b), (c)). Also,  $E_{vg}$  does not exceed 2,000 lx with reduced  $VT_{dir-dir}$  and  $VT_{dif-dif}$  (Figure 7 (a), Figure 6 (b), Table 4). Please note that Figure 6 (b) represents both seasons (summer, winter).



Fig. 7 - VT and SHGC values in winter (using pyWincalc)

# 4. Conclusion

In this study, an artificial neural network-based 'stand-alone' daylighting simulator was developed to predict vertical illuminance passing through a double window with external Venetian blinds. The novelty of the proposed simulator is the advantage of being 'stand-alone' because it relies on minimal information regarding the EVBW system and environmental factors (direct and diffuse solar radiation, zenith angle). As a result of verification under various environmental conditions, this daylighting simulator can easily predict the vertical illuminance at the interior surface of glazing by accurately calculating transmitted solar radiation through the EVBW system with the use of three VT values (VT<sub>dir-dir</sub>, VT<sub>dif-dif</sub>, VT<sub>dif-dif</sub>) as a function of the slat angle. Therefore, this study contributes to overcoming the issue of capturing the dynamic relationship between the slat angle, transmitted direct and solar radiation through the transparent envelope, and any relevant illuminance. In addition, as part of MPC, the daylighting simulator was utilized for optimal control of EVB considering the heat and light transmission based on  $Q_{\text{solar}}$  and  $E_{\text{vg}}$  derived from the simulator. It is promising that the 'standalone' daylighting simulator could be freely applicable to MPC. As a further study, the authors will investigate how the daylighting simulator could be beneficially used for in-site experiments including a validation study between the predicted and measured illuminance values.

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# Nomenclature

# Symbols

ANN	Artificial neural network	
$E_{vg}$	vertical illuminance (lm/m <sup>2</sup> )	
EVB	External Venetian blind	
EVBW	EVB + double glazing window system	
I <sub>dir</sub>	direct solar radiation (W/m <sup>2</sup> )	
$I_{\mathrm{dif}}$	diffuse solar radiation (W/m <sup>2</sup> )	
$Q_{solar}$	transmitted solar energy through	
	EVBW (W/m <sup>2</sup> )	
SHGC <sub>dir</sub>	direct solar heat gain coefficient (-)	
SHGC <sub>dif</sub>	diffuse solar heat gain coefficient (-)	
VT	Visible transmittance	

VT <sub>dir-dir</sub>	direct-direct visible transmittance (-)
VT <sub>dir-dif</sub>	direct-diffuse visible transmittance (-)
VT <sub>dif-dif</sub>	diffuse-diffuse visible transmittance
	(-)

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Time	I <sub>beam</sub> (W/m²)	I <sub>dif</sub> (W/m²)	Baseline (slat angle=0°)		MPC		
			Transmitted Q <sub>solar</sub> (W/m <sup>2</sup> )	E <sub>vg</sub> (lm/m²)	Q <sub>solar</sub> (W/m <sup>2</sup> )	E <sub>vg</sub> (lm/m²)	Optimal slat angle (°)
9am	129	280	119	344	119	344	0°
10am	690	199	157	390	114	388	-20°
11am	450	149	105	436	76	417	-20°
12pm	520	165	119	455	86	444	-20°
1pm	560	181	128	478	93	447	-20°
2pm	747	259	176	492	176	492	0°
3pm	222	395	154	410	187	497	10°
4pm	696	202	166	344	118	311	-20°
Total	-		1,124	3,349	969	3,340	-

Table 3 – Results of MPC using the daylighting simulator (Summer)

Table 4 – Results of MPC using the daylighting simulator (Winter)

Time	I <sub>beam</sub> (W/m²)	I <sub>dif</sub> (W/m²)	Baseline (slat angle=0°)		MPC		
			Transmitted Q <sub>solar</sub> (W/m <sup>2</sup> )	E <sub>vg</sub> (lm/m²)	Q <sub>solar</sub> (W/m²)	E <sub>vg</sub> (lm/m²)	Optimal slat angle (°)
9am	78	46	66	399	80	1,095	20°
10am	423	120	260	1,487	346	1,964	30°
11am	500	76	266	2,616	208	1,991	-10°
12pm	620	120	305	2,878	233	1,416	-10°
1pm	720	150	358	2,849	271	1,448	-10°
2pm	700	200	406	2,616	322	1,642	-10°
3pm	650	95	364	2,356	290	1,921	-10°
4pm	452	93	288	1,304	358	1,795	20°
Total		-	2,313	16,505	2,108	13,272	-

# Modelling Solar Disability Glare Reflected off Modern Building Facades

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#### Abstract

Buildings can be examined during concept design to identify potential for sunlight to reflect off exterior cladding surfaces and create traffic disability glare onto surrounding roadways. Historically most assessment methodologies calculate veiling luminance hazard at roadway receiver locations assuming specular type reflections off glazing. A population dosage of veiling luminance is proposed in this study as a limiting measure of solar disability glare exposure to passing traffic. Modern facades are increasingly adopting metal sheet cladding products displaying both specular and highly diffuse reflective properties. In-house software has been developed to perform solar reflection calculations off a range of specular and diffuse reflective surface finishes. The program generates view-based luminance renderings at traffic receiver locations. Subsequently, a custom script evaluates the renderings and determines annual disability glare metrics including retinal irradiance, glare source angle and background luminance for comparison with existing disability glare criteria. Threshold increment is calculated from modelled veiling and background luminance as a measure of reduction in contrast due to disability glare. Case studies are reviewed where façade solar reflections flagged during early design as a traffic disability glare population dosage risk were successfully mitigated with façade treatments. Implications of facade solar reflectivity mitigation for building energy consumption are discussed.

#### 1. Introduction

Sun disability glare occurs when direct or reflected sunlight is projected onto the retina of the human eye causing poor visibility. When driving it interferes with contrast, sharpness perception and vision acuity. Most motorists have experienced disability glare associated with driving directly toward a sunrise or sunset and these occurrences have been directly linked to grim accident and fatality statistics, e.g., (Mitra, 2014; Sun et al., 2017; Redelmeier et al., 2017; The Sunday Times, 2014). In terms of driver liability however the "Act of God" sun glare defence has been overruled in several legal cases given there should be some driver expectation of low altitude sun glare hazard being a natural event, e.g., (Dubois Law Group, 2012). It has been argued the driver should anticipate the hazard and take precautions by reducing speed, lowering sun visor, wearing sunglasses etc. Solar reflections from building facades however can be unexpected and come from unnatural and unexpected directions. Emergency doctrine may be a defence for a driver impacted by these unnatural solar reflections resulting from an "Act of the Designer".

Increasing urbanization in many cities is leading to higher traffic volumes exposed to reflected solar disability glare hazard and therefore increased community risk. As buildings become taller, so too do the distances over which low altitude reflected sun can cast onto surrounding roadways thereby increasing population dosage of reflected solar disability glare events.

Buildings can be examined during concept design to identify and quantify disability glare hazard onto surrounding roadways. Unfortunately, there has been little in the way of solar disability glare criterion for city planning consent authorities to prescribe and a need to further develop criteria and tools is recognised, e.g., (Danks et al., 2016; Glanville et al., 2024). Some of the earliest traffic glare assessment methodologies developed calculate Holladay veiling luminance  $L_v$  at receiver locations assuming specular type façade reflections.

#### 2. Specular Solar Reflections

Building glazing products typically have specular solar reflectivity properties whereby the angle of incident sun ray onto the glass is equal to reflected solar ray angle. A popular methodology to identify and quantify disability glare associated with specular solar reflections from glazed facades was developed by (Hassall, 1991). Hassall's methodology calculates the diurnal and seasonal solar path at any given location (longitude and latitude) and calculates specular reflections off the subject building façade orientation onto surrounding roadway receiver locations. Glazing reflectivity properties are incorporated into the analysis as obtained from available product data or photometric tests. Human eve sensitivity of the motorist is then quantified by the Holladay formula in Eq.1.

 $L_{v} = \frac{kE_{G}}{\theta^{2}}$ (1)

Holladay calculates a veiling luminance hazard  $L_v$  experienced by a driver of sufficient intensity to scatter the retinal image; appearing like a 'veil' placed in front of the observer's line of sight. Hassall nominates 500 cd/m<sup>2</sup> as a reasonable magnitude of limiting veiling luminance.

E<sub>G</sub> is the illumination of reflected glare onto the corneal plane and k (typically in the order 10) accounts for variables such as age and colour of the subject's eye, (Adrian, 1989; CIE 140, 2019; Jurado-Piña et al., 2009; Vos, 2003). Central to the calculation of veiling luminance is the angle between the glare source and the driver's line of sight  $\theta$ . A narrow angle  $\theta$ coinciding with a glare source closely aligned to the driver's *required* line of vision will result in a high veiling luminance value and is to be avoided or mitigated. Pedestrians are not usually restricted to the same line of sight requirement imposed on a highspeed moving vehicle and can normally divert their line of sight to increase the angle  $\theta$ .

A Population Dosage (cd.s/m<sup>2</sup>) to passing traffic per solar reflection event per day is proposed as a limit, being the product of veiling luminance (cd/m<sup>2</sup>), exposed road length (m) divided by traffic average speed (m/s), all multiplied by the number of vehicles exposed to the glare event per day (number of moving vehicles passing per unit time multiplied by glare event duration) and fraction of time with clear skies; these shifting variables integrated over the duration of a reflection event per day. As a rule of thumb, a value of approximately 1x10<sup>6</sup> cd.s/m<sup>2</sup> constant luminance or greater per day for a reflection event implies a high population dosage to passing traffic.

#### 3. Diffuse Solar Reflections

Modern facades are increasingly adopting metal sheet cladding products displaying both specular and highly diffuse reflective properties, e.g. (BHP, 2022). Diffuse reflections occur when sun rays reflecting off a rough surface are scattered in many directions.

Disability glare impact of both specular and diffuse solar reflections can be quantified using potential ocular impacts and assessed against criteria developed by (Ho et al., 2011). The Ho criteria has been used to assess solar reflections from roof and ground mounted photovoltaic panels at airport locations cast onto landing aircraft and is adapted in this study to assess glare hazard onto roadways surrounding buildings with facade materials such as metal cladding.

The Ho methodology assesses the ocular hazard caused by glint or glare as a function of the intensity of the glare upon the eye (retinal irradiance)  $E_r$  in  $W/m^2$  and the subtended glare source angle  $\omega$  being the extent to which the glare occupies the receptor's field of vision, dependent on size and distance of the reflector glare source. The severity of the ocular hazard can be assessed against three criteria levels as will be discussed in Section 5.1.1.

In-house software has been developed by CPP based on an open-source ray tracing engine, RADI-ANCE, to perform solar reflection calculations off a range of user specified surface finishes with flat to complex curvatures. Commercially available ClimateStudio software uses the RADIANCE engine and generates view-based luminance High-Dynamic Range (HDR) renderings at specific locations which could impact road users. A Stereographic Fisheye setting is typically used to produce the views and render luminance during daytime at set time intervals (typically 1 minute) throughout the solar year (ClimateStudioDocs.com, 2024). These annual HDR images for user nominated high-risk driver locations/orientation are processed using RADIANCE's internal tool Evalglare (Radiance-Online.org, 2020). CPP's custom software parallelises and automates the Evalglare processing of thousands of high-quality luminance images to identify façade locations and times of the year causing maximum driver impact. CPP's software system is tuned to filter glare sources and approaching driver fields of view as discussed further in Section 5.1.1. Using the principle of 'Reverse' photometry (Nilsson, 2009) whereby viewing is the reverse of radiating, glare source luminance is taken as the glare source on the eye plane and multiplied by glare source size  $\Omega$  in steradians (sr) which are also extracted from the HDR images of daylight simulations; a similar approach has also been adopted by (Jakubiec et al., 2014). The subtended angle of the glare source  $\omega$  in rad is obtained from the relationship:

$$\omega = 2\cos^{-1}\left(1 - \frac{\Omega}{2\pi}\right) \tag{2}$$

Luminance efficacy K is used to convert light from photometric to radiometric values for irradiance analysis (e.g. 100 lm/W for a morning clear-sky scenario). Corneal irradiance  $E_c$  in  $W/m^2$  is converted to retinal irradiance  $E_r$  through the following relationship with reference to Fig. 1:

$$E_{\rm r} = \tau E_{\rm c} \left(\frac{d\dot{p}}{d_{\rm r}^2}\right) \tag{3}$$

Where the eye focal length f=0.017 m, glare source size  $\omega$  in rad, diameter of the image projected onto the retina  $d_r$  in m ( $f\omega$ ), ocular transmission coefficient  $\tau$ =0.5, and pupil diameter  $d_p$ =0.002 m.



Fig. 1 – Section through the eye demonstrating a glare source projected onto the retina

# 4. Contrast

Rod receptors on the retina of the eye at low light levels within the scotopic and into mesopic luminance range provide little colour response, provide low visual acuity but are highly sensitive to brightness and contrast (Armas et al., 2007). Hence contrast is an important measure of solar disability glare risk for a driver in mesopic dusk/dawn conditions and in some highly overcast or overshadowed daytime conditions. Threshold contrast for a target is given by:

$$C_{\rm b} = \left(\frac{\Delta L}{L_{\rm b}}\right) \tag{4}$$

Where:  $\Delta L = L_t - L_b$ 

(5)

L<sub>t</sub> is the target luminance and L<sub>b</sub> is the background luminance. Threshold contrast or Weber fraction (telescope $\Theta$ ptics.net, 2023) varies with the type of physiological response. Extensive experiments were conducted by (Blackwell, 1946) to determine Contrast Threshold of the human eye under a variety of background luminance conditions. From this work a threshold contrast C<sub>b</sub>  $\approx$  0.016 would be suitable in the upper mesopic range up to background luminance with values of the order 10<sup>2</sup>-10<sup>3</sup> cd/m<sup>2</sup>. Adding a veiling glare source L<sub>v</sub> to both the target and background has the effect of reducing the effective contrast below threshold, Eq. 6:

$$C_{g} = \frac{(L_{t} + L_{v}) - (L_{b} + L_{v})}{L_{b} + L_{v}} = \frac{L_{t} - L_{b}}{L_{b} + L_{v}}$$
(6)

Scattering of light passing through atmospheric pollutants and windscreen media (dirt, water droplets, damage, and internal reflections) can be added to the veiling glare (Schreuder, 1991; Lundkvist et al., 1987).

Threshold Increment (TI) is defined as 'the measure of disability glare expressed as the percentage increase in contrast required between an object and its background for it to be seen equally well with the source of glare present', (AS/NZS4282:2019). Within the scotopic to mesopic range limits of the code a 'higher value of TI corresponds to greater disability glare.'

From the equations above it can be shown:

$$TI(\%) = \left(1 - \frac{C_g}{C_b}\right) \times 100 \tag{7}$$

Fechner (telescopeOptics.net, 2023) noted departure from the Weber law at the extremes of perceived brightness including retinal saturation at high luminance. In many instances the saturating background luminance associated with a low altitude solar disc will be in the same line of sight as a coinciding glancing façade reflection. In such conditions the low altitude sun can cast disability glare onto an approaching driver well exceeding a veiling luminance of 500 cd/m<sup>2</sup>. With reference to the TI definition above however, the increase in contrast required between an object and the high background luminance due to the solar disc in the line of sight will not change significantly due to the veiling luminance of the facade reflection contribution. The facade contribution makes little difference to the driver disability glare event and hence a low TI value results. In this saturation luminance scenario, the low TI value would be misleading in terms of a disability glare marker, however the low value demonstrates the negligible contribution from the building façade.

# 5. Case Studies

#### 5.1 Perpendicular Reflections

Incident solar rays near perpendicular to a flat glazing plane with specular reflectivity properties will reflect solar rays with a veiling luminance of magnitude proportional to the visible light reflectivity coefficient of the glazing product.

#### 5.1.1 Material selection for mitigation

CPP completed a solar disability glare study for the ICC Theatre in Sydney, Australia during the early planning stages. Mid-winter early morning rays were identified to strike the vertical east glazed façade with low altitude reflections back onto Pier Street westbound traffic travelling on an inclined roadway toward the site, Fig. 2 (photo taken at nearby footpath location). Veiling luminance was predicted to be in the order 1100 cd/m<sup>2</sup> at approaching roadway locations using CPP in-house software following the Hassall methodology. The highest reflections were calculated off the southern end of the east façade initially modelled with a 10 % visible light reflectivity coefficient glazing product.



Fig. 2 – Winter solstice morning solar reflection off Theatre east facade glazing - photograph courtesy Sydney Morning Herald

A Population Dosage (cd.s/m<sup>2</sup>) of approximately  $1 \times 10^{6}$  cd.s/m<sup>2</sup> constant luminance per day was estimated for this reflection event and implies significant solar disability glare exposure to passing traffic.

View-based luminance renderings where prepared for further assessment of the 10 % visible light reflectivity coefficient glazing product against the Ho criteria. Multiple potential reflective glare surfaces inside the driver's view field were assessed for both specular and diffuse reflections. Initial assessment of disability glare ignores the sky, direct sun, and the environment behind it to assess the net glare impact of the development. The software filters out these background contributions and calculates average luminance across an area exceeding a threshold luminance; the same area also defines subtended source angle. The initial result is plotted against the Ho criteria in Fig. 3. The severity of the ocular hazard criteria is divided into three levels with the results in this example being marginally high at the low end of 'Potential for After-Images'.

Glazing product selection with a low visible light reflectivity coefficient can be effective at mitigating these near perpendicular reflections. Reducing the visible light reflectivity coefficient of the glazing from 10 % to just below 5 % will reduce veiling luminance from 1100 cd/m<sup>2</sup> to the 500 cd/m<sup>2</sup> Hassall criteria and reduces reflections toward the Ho criteria for '*Low Potential for After Images*'



Fig. 3 – Potential impacts of retinal irradiance vs subtended source angle criteria by Ho et al. Result for winter solstice morning solar reflection off east facade glazing at roadway viewing position

View-based luminance renderings are illustrated in Fig. 4 with background contributions included. Concern remained in terms of contrast for an approaching driver during this mesopic dawn event, even with a <5 % visible light reflectivity coefficient performance glazing product. In this example the software computes  $L_{20} = 1530$  cd/m<sup>2</sup> background luminance as an area average in the 20° driver's field of view (white circle in Fig. 4). Solving Eq. 4 to 7 above for a veiling luminance meeting the Hassall limit  $L_v = 500$  cd/m<sup>2</sup> gives a TI of 29 % being marginally greater than suggested TI limits of 15-20 %, e.g., (Armas et al., 2007; AS/NZS1158.5:2014; AS/NZS 4282:2023).



Fig. 4 – Winter solstice morning solar reflection off east facade glazing. View based luminance rendering at roadway viewing position

Hence an alternative material was sought with a low reflectivity coefficient and diffuse reflective characteristics. A metal mesh product was selected for the southernmost 20 m of the east façade where there was greatest potential to reflect the morning sun toward the Pier Street roadway, Fig. 5. The material has predominantly diffuse reflective properties producing reflections well below the codified TI limits.



Fig. 5 – Winter solstice morning solar reflection off east facade metal cladding mesh. Photograph taken at the same simulated roadway viewing position

Energy consumption for heating and cooling of a glazed facade building such as the ICC Theatre will be heavily dependent upon glass selection. The full spectrum of solar radiation reaching the facades will be either reflected by the glass (as measured by the solar energy reflectivity coefficient), transmitted directly into the building interior through the glass, or absorbed by the glass then re-released on the inner and outer glass surfaces. For most glazing products there is a close proportionality between the visible light reflectivity coefficient of the outer glass surface (important for glare studies) and the solar energy reflectivity coefficient. A low visible light reflectivity coefficient therefore generally means more solar radiation arriving at the glazing will penetrate the building and provide passive solar heating; being heavily dependent on the glass absorptance properties. Similarly, there will be some correlation between a higher visible light reflectivity coefficient glazing and lower cooling loads. Selection of specific glazing properties and products to reduce overall heating and cooling loads is best made in conjunction with building energy simulation modelling.

#### 5.1.2 Façade orientation for mitigation

Glazed balcony balustrades to a mid-rise Sydney apartment building were predicted to cast solar reflections toward oncoming traffic simultaneously over an extended stretch of highway in another example illustrated in Fig. 6. At location 1 to the northeast of the balustrades, peak reflections with high veiling luminance were predicted during early morning traffic periods in early and late winter over a 100 m length of roadway representing a high population disability glare dosage. The straight length of roadway impacted was parallel to the reflected rays and inclined 1.6° toward the site resulting in very low  $\theta$  values and hence high veiling luminance  $L_v$  over an extended receiver roadway length, limited almost only by building height.



Fig. 6 – Perpendicular reflection example – mitigation by glazing reorientation

In this example a simple reorientation of the northeast facing balustrade glazing by just 10° anticlockwise was sufficient to prevent the low altitude sun reflecting onto the this stretch of roadway.

#### 5.2 Glancing Reflections

Most glazing products will exhibit reflective properties of an ideal mirror when the incident and reflected solar rays are near parallel to the façade plane, i.e., a glancing reflection. Hence a glazed façade cannot be safeguarded just through low-reflectivity glass product selection and each building needs to be assessed considering façade orientation and alignment relative to oncoming traffic.

#### 5.2.1 Opaque fins for mitigation

Glancing solar reflections are illustrated in Fig. 7 for an early morning event at a Sydney location. The tall building façade is 25 m wide in plan and casts reflections towards drivers approaching the site from the west whereby the low altitude rising solar disc will approach the same line of sight as a coinciding glancing façade reflection. Planning authorities may require a low veiling luminance contribution from the facades of proposed buildings despite high pre-existing background luminance  $L_b$  as was discussed in Section 4.



Fig. 7 - Glancing reflection example - mitigation by using vertical fins

In Fig. 7 it is the reflected rays closest to parallel to the façade that cast the highest veiling luminance onto eastbound drivers, and these can be readily blocked using opaque vertical fins placed perpendicular to the façade plane as illustrated in Fig. 7. At location 1 to the west of the façade the peak veiling luminance reflection occurs just after sunrise in the mid-seasonal months at an angle  $\Phi 1$ reflected off a point on the façade 16 m above ground level. The disability glare exceeds 500 cd/m2 for 8 minutes over a 25 m length of flat roadway centred on location 1 and represents a population dosage risk during high volume traffic (similar but symmetrically reverse glancing solar reflections occur during afternoon traffic). Vertical fins placed with a fin depth to spacing ratio of 1:10 as illustrated in Fig. 7 are sufficient to block incident and reflected rays of angle  $\Phi 1$  or shallower. At location 2 the same reflection event peaks half an hour later and here the fins are not deep enough to block a larger angle  $\Phi$ 2. At this location the veiling luminance magnitude is significantly lower however due to a lager  $\Phi 2$  value contributing to the denominator of Eq. 1. Furthermore, by blocking the earlier reflections the population dosage for the event is also significantly reduced.

In practice a series of much shallower fins having the same depth to spacing ratio can be implemented; the fins themselves should have a low-reflective finish. Alternatively, some forms of façade articulation can provide the same blockage effect, e.g. ratio of a punch window recess depth to window width. Solar shading associated with reflection mitigation can also be used to advantage in reducing building energy consumption particularly for cooling, e.g., angling vertical fins to shade low altitude summer sun.

# 6. Conclusions

This paper has reviewed an existing methodology to calculate traffic disability glare at roadway receiver locations resulting from specular type solar reflections off building glazing and proposes a population dosage of veiling luminance as a limiting measure of solar disability glare exposure to passing traffic.

In-house software has been developed to perform solar reflection calculations off a range of specular and diffuse reflective surface finishes. The program generates view-based luminance renderings at traffic receiver locations. Subsequently, a custom script evaluates the renderings and determines annual disability glare metrics for comparison with existing disability glare criteria.

Threshold increment is calculated from the modelled veiling and background luminance as a measure of reduction in contrast due to disability glare. Case studies are reviewed where façade solar reflections flagged during early design as a traffic disability glare population dosage risk were successfully mitigated with façade treatments. Implications of facade solar reflectivity mitigation for building energy consumption are discussed.

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#### Nomenclature

#### Symbols

Cb	Threshold contrast		
dr	Diameter of an image projected onto		
	the retina (m)		
dp	Davlight adjusted pupil diameter		
- 1	(m)		
Eg	Corneal plane illuminance (lux or lm/		
Ec	Corneal plane irradiance (W/m²)		
Er	Retinal plane irradiance (W/m <sup>2</sup> )		
f	Eye focal length (~0.017 m)		
k	10 by convention		
Κ	Luminous efficacy (lm/W)		
L <sub>b</sub>	Background luminance (cd/m <sup>2</sup> )		
Lt	Target luminance (cd/m <sup>2</sup> )		
$L_{\rm v}$	Veiling luminance (cd/m <sup>2</sup> )		
θ	Angle between the glare source and		
	a receiver line of sight (°)		
τ	Ocular transmission coefficient		
Φ	Specular incident and reflected		
	angle relative to façade in plan (°)		
Ω	Subtended angle of glare source in		
	steradians (sr)		
ω	Subtended angle of glare source in		
	radians (rad)		

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# Energy Modelling and Calibration of a Controlled Environment Agriculture Space in a Cold Climate Using Building Performance Simulation Tools

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#### Abstract

This paper presents the energy modelling and calibration of a small-scale experimental greenhouse using building performance simulation tools in a cold climate. The greenhouse is modelled in EnergyPlus using the OpenStudio interface. Evidence-based calibration is then performed using the available construction information. Subsequently, an automated off-line calibration of influent energy model parameters yielded a NMBE of 1.90 % and a CV-RMSE of 5.75 % over monthly energy data. The modelling and calibration conducted in this paper also helped identify knowledge gaps in controlled environment agriculture (CEA) energy modelling using building performance simulation (BPS) tools.

# 1. Introduction

The Quebec greenhouse sector, covering 313 hectares (3.13 km<sup>2</sup>), accounts for approximately 1 TWh of annual thermal energy consumption, with around 300 GWh sourced from electricity. With Quebec's government plan to expand greenhouse production, there is a prompt focus on increasing the use of electric energy in the sector. However, as industries strive to decarbonise their production, the demand for low-carbon electricity escalates, resulting in unprecedented pressure on the grid.

Electricity in Quebec, Canada, is primarily produced from very low-carbon renewable sources, mainly hydroelectric dams, owned by Hydro-Québec, a public utility. The greenhouse sector benefits from a reduced rate (6.164 ¢CND·kWh<sup>-1</sup>) for the electricity used for crop lighting and production space heating. This rate becomes interruptible for about 100 hours per year during cold weather events, with a higher peak rate applied during those specific periods (58.168 ¢CND·kWh<sup>-1</sup>). As such, tools are needed to estimate the impacts and propose mitigation strategies for efficient electrification of the greenhouse sector.

Building Performance Simulation (BPS) tools have recently gained popularity for predicting peak energy demand and energy consumption of controlled environment agriculture (CEA) production spaces, including greenhouses and high-density controlled environment agriculture (CEA-HD) production spaces such as vertical farms (e.g., Graamans et al., 2018). The heat balance at the crop canopy level, necessary for proper hygrothermal load prediction in these production spaces, has also been recently implemented into BPS tools. The literature provides limited information regarding the prediction performance of CEA space models developed using BPS tools. Also, the methodology used to calibrate these models has been sparsely addressed in the existing literature (Beaulac et al., 2023).

In this paper, a building energy model of a smallscale experimental greenhouse is developed using design information and in-situ experimental data using the BPS software EnergyPlus. Measurements of the indoor environment conditions and operating data of the energy systems of the CEA production space are used to calibrate the developed BPS model. The data was gathered for an empty greenhouse, i.e., without crops, as the initial step to reduce the number of variables to be calibrated. Finally, the calibrated BPS CEA model prediction is assessed and analysed. This study provides insights into BPS CEA modelling and calibration using case study data gathered in a northern climate.

# 2. Description Of The Small-Scale Experimental Greenhouse

The small-scale experimental greenhouse is 6.1 m long by 3.7 m wide and 4.3 m high. The aluminium structure sits on a 0.8 m high by 0.2 m thick concrete wall, as illustrated in Fig. 1 (a). The south-facing windows are double-paned 16 mm glass windows (RSI=0.33 m<sup>2</sup>·K·W<sup>-1</sup>,  $\tau$ =0.9,  $\rho$ =0.08), and the north-facing façade consists of 16 mm polycarbonate panels (RSI=3.2 m<sup>2</sup>·K·W<sup>-1</sup>, τ=0.62, φ=0.08). Two operable vents are located on the glass roof. A 1510 L·s-1 exhaust fan with gravity louvres is located in the gable end opposite the doors, and two operated louvres are beside the entrance door. The electric heating system has a 9 kW boiler that supplies two hydronic circuits, each with 77.7 m of 15.9 mm (5/8") tubing. In addition to the hydronic floor, a 5 kW, 165 L·s<sup>-1</sup> fan coil unit (FCU) is installed in the greenhouse. The lighting system consists of ten LED luminaires (Sollum SF05A – 340 W, 780 µmol·s<sup>-1</sup>). For the 2022 year, the total energy consumption was 32 149 kWh with a 15-minute peak electrical demand of 14.8 kW. The heating degree-days for the greenhouse location in ASHRAE climate Zone 6A are 4837 (Base 18 ºC).

# 3. Approach And Method

The proposed modelling and calibration methodology includes three successive steps: (1) energy model development, (2) evidence-based calibration and (3) additional model parameter estimation. The methodology is applied to a small-scale experimental greenhouse as a case study to test the proposed approach.

# 3.1 Energy Model Development

The greenhouse geometry was modelled using the OpenStudio plugin for Sketchup. The different energy model attributes were then specified in the OpenStudio (Guglielmetti et al., 2011) interface to EnergyPlus (Crawley et al., 2001). The hydronic floor system was modelled as a hot water loop with a «LowTemperatureRadiant:ConstantFlow» object and the FCU as a «UnitHeater». The photoperiod was set from 04:00 to 20:00, and the lighting system availability was adjusted according to an availability schedule throughout the year. The availability schedule was implemented to take into account periods when systems were disconnected due to ongoing commissioning related work in the greenhouse. An availability schedule was also implemented for the FCU for the same purpose. Fig. 1 (b) illustrates the building energy model geometry compared to the experimental greenhouse.

The infiltration was modelled according to Eq.1 where *I* is the total zone air changes per hour (ACH),  $I_D$  is the design ACH,  $T_z$  is the thermal zone air temperature (°C),  $T_{\infty}$  is the outside air temperature (°C) and  $U_{\infty}$  is the wind speed (m·s<sup>-1</sup>).

$$I = I_D \cdot (A + B \cdot |T_z - T_{\infty}| + C \cdot U_{\infty} + C \cdot U_{\infty}^2) \quad (1)$$



Fig. 1 - (a) Experimental small-scale greenhouse and (b) Building energy model (BEM)

Furthermore, the natural ventilation model used for the two roof operable vents is described by the quadrature sum of the wind-driven ventilation (Eq.2) and the stack-driven ventilation (Eq. 3), where  $Q_w$  is the wind-driven volumetric air flow rate (m<sup>3</sup>·s<sup>-1</sup>),  $C_w$  the opening effectiveness,  $A_{op}$  the opening area (m<sup>2</sup>),  $U_{\infty}$  the local wind speed (m·s<sup>-1</sup>),  $Q_s$  the stack driven airflow rate (m<sup>3</sup>·s<sup>-1</sup>),  $C_D$  the discharge coefficient, g the gravitational acceleration (m<sup>2</sup>·s<sup>-1</sup>),  $\Delta H_{NPL}$  is the height from midpoint of lower opening to the neutral pressure level (m).

$$Q_w = C_w A_{op} U_\infty \tag{2}$$

$$Q_s = C_D A_{op} \sqrt{2g\Delta H_{NPL}(|T_z - T_{\infty}|/T_z)}$$
(3)

#### 3.2 Evidence-Based Calibration

The attributes of the greenhouse EnergyPlus model were specified using the principles of evidencebased energy model calibration, which is based on data collection and analysis (Raftery et al., 2011). Based on measurements, the lighting system power level was lowered from 3 400 W to 3 200 W. The heating setpoint was set at 15 °C for the thermal zone and 18 °C for the mean air temperature control of the hydronic heating radiant slab-on-grade system.

Data was gathered for 2022 using an independent acquisition system (Yokogawa GM10) that measures temperature, humidity inside the greenhouse, and hot water flow rate. Three current transducers are connected to a second acquisition system (EGauge EG4130) to monitor the electric energy consumption of the boiler, the fancoil, and the artificial lighting.

Unfortunately, the local weather station data was corrupted for a significant portion of 2022. The ERA5 reanalysis weather (Hersbach et al., 2020) and Copernicus Atmosphere Monitoring Service (CAMS) radiation service (Schroedter-Homscheidt et al., 2016) were used to generate the actual weather year (AWY) weather files. The boiler capacity was first adjusted based on measurements. The electric boiler is located in a technical shed next to the smallscale experimental greenhouse. A fraction of the boiler heating capacity dissipates inside the technical shed. The electrical boiler's thermal efficiency was adjusted to account for this. This was completed by comparing the thermal energy provided by the hydronic circuit to the greenhouse with the electrical energy consumption of the boiler. Regression analysis of the thermal energy against the electrical energy yielded a thermal efficiency of 88.35 % (R<sup>2</sup> of 0.98), as illustrated in Fig. 2. This ensured that the appropriate amount of thermal energy was supplied to the zone and that the total boiler electrical energy was adequately modelled.



Fig. 2 – Measured boiler thermal energy as a function of measured boiler electrical energy  $% \left( {{{\rm{F}}_{\rm{F}}}} \right)$ 

A blower door test yielded a 310 L·s<sup>-1</sup> infiltration airflow rate at 50 Pascals. According to Eq. 4, the initial infiltration was thus set at 0.7 air changes per hour (ACH).

$$ACH_{Natural} \approx \frac{ACH_{50}}{20} \approx 0.7$$
 (4)

The calibration of the model was assessed using specific metrics, such as those proposed by ASHRAE Guideline 14-2014 (American Society of Heating and Engineers, 2014). This guideline states that a building energy model is deemed calibrated if the net mean bias error (NMBE) is below 5 % and the coefficient of variation of the root-mean-square error (CV-RMSE-) is below 15 % using monthly data, as defined by Eq. 5 and 6, respectively.

$$_{\text{NMBE}} = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)}{(n-p) \times \bar{y}} \times 100$$
(5)

$$CV-RMSE = \left[\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{(n-p)}\right]^{1/2} / \bar{y} \times 100$$
(6)

#### 3.3 Model Parameter Estimation

Following the evidence-based calibration, additional parameters were estimated using an optimisation algorithm sometimes classified as an automated off-line calibration technique. The bottom slab thickness, the polystyrene insulation thickness, the concrete thermal conductivity and the infiltration model parameters were estimated using ExCaliBem (Sansregret et al., 2014), an interface to the Genopt optimisation program (Wetter, 2001). The optimisation algorithm used is the hybrid particle swarm optimisation and Hooke-Jeeves generalised pattern search (GPSPSOCCHJ).

The optimisation problem used to estimate these parameters is stated in Eq. 7 with the two quadratic loss functions (Eq. 8 and 9). The objective function (Eq. 7) was computed over the monthly FCU energy, the monthly boiler energy and the total monthly energy in addition to the hourly FCU energy, boiler energy and temperature profiles for three periods of 2022: (1) February 12<sup>th</sup> to February 28<sup>th</sup>, (2) September 21<sup>st</sup> to October 5<sup>th</sup> and (3) December 12<sup>th</sup> to December 28<sup>th</sup>. These periods were selected to cover operating conditions where different systems were active: period (1) includes the FCU and hydronic floor, period (2) comprises the hydronic floor and operable vents, and period (3) involves only the hydronic floor.

$$f(\mathbf{x}) = \frac{|NMBE| + CVRMSE}{C}$$
(7)

$$g_1(\mathbf{x}) = \max(0, |NMBE| - 5)^2$$
 (8)

$$g_2(\mathbf{x}) = \max(0, CVRMSE - 15)^2$$
 (9)

The parameters of the parameter vector (x) are listed in Table 1, including their initial value, lower bound, upper bound, and step size. The initial values for the infiltration model (Eq. 1) were set using the values suggested by BLAST (Herron et al., 1981). The concrete thermal properties were taken from the ASHRAE fundamentals handbook (American Society of Heating and Engineers, 2021) (q=2240 kg·m<sup>-3</sup>, c<sub>p</sub>=900 J·kg<sup>-1</sup>·K<sup>-1</sup>). The concrete slab is 0.75 m deep at its thickest point and is at least 3 inches (0.076 m) deep under the radiant hydronic slab.

#### 4. Results

Table 1 presents the parameter estimates obtained using the optimisation algorithm. Fig. 3 presents the measured and simulated monthly energy consumption of the FCU, boiler, and lighting system. The energy model is deemed calibrated at a monthly level according to ASHRAE Guideline-14 with a NMBE of 1.90 % and a CV-RMSE of 5.75 %.

Initial Lower Upper Step Estimated Parameter value bound bound Size Value  $k_{Slab}$  (W·m<sup>-1</sup>·K<sup>-1</sup>) 2.0 1.3 2.6 0.11.56 0.750 0.076 0.750 0.001 0.5822  $L_{Slab}$  (m)  $k_{ins} (W \cdot m^{-1} \cdot K^{-1})$ 0.029 0.029 25 0.001 15.43 Α 10 0.01 0.606 0 6.66 B (K<sup>-1</sup>) 0.03606 0 0.50 0.0001 0.06263 C (s·m<sup>-1</sup>) 0 0.50 0.0001 0.4292 0.117 D (s<sup>2</sup>·m<sup>2</sup>) 0 0.005 0.0001 0.0018344 0.000 0 10 0.01  $\Delta H_{NPL}$  (m) 4.2 6.95  $C_w$ 0.5 0 1 0.01 0.9938  $C_D$ 0.5 0 1 0.01 0.54938

Table 1 - Estimated parameter initial value, lower bound, upper bound, step size and estimated value.



Fig. 3 – Monthly measured and simulated energy use for the year 2022

Fig. 4 and Fig. 5 show the measured and simulated hourly temperatures and relative humidity, respectively. Upon analysis of the data, it appeared that the temperature measured inside the greenhouse seemed unusually high for certain measured data points (Fig. 4). The likely explanation for this was that the installed thermocouples were left unshielded for the 2022 calendar year, leading to elevated readings during sunny periods.



Fig. 4 – Simulated and measured air temperature inside the greenhouse in 2022

Also, upon inspecting the left portion of Fig. 4, it is

evident that the heating systems' capacity was insufficient during part of 2022, as the measured temperature dropped below the lower safety setpoint of 15 °C. Since the heating system's capacity was modelled according to the design data, the model also demonstrated temperatures that fell below the safety setpoint programmed into the heating systems, as depicted in Fig. 4. Additional heating capacity is being installed to resolve this issue.



Fig. 5 – Simulated and measured relative humidity inside the greenhouse in 2022  $\,$


Fig. 6 – Hourly measured and simulated FCU, boiler and lighting energy use from February 14th 2022 to February 27th 2022

Prediction performance metrics were not computed on temperature and humidity measurements, as they are shown to be flawed. Hence, Fig. 4 and Fig. 5 are provided as a general indication of the agreement between simulated and measured temperature and relative humidity data. Further work will be undertaken to provide the scientific community with accurately calibrated energy models.

Fig. 6 presents the hourly energy consumption profiles of the energy systems for a typical week where the FCU, the hydronic floor system and the lighting systems are in operation. The energy consumption of the lighting system follows a regular pattern and can easily be modelled using a power level and a schedule. Improvements are still needed in modelling the hydronic floor and the FCU. These two systems did not use the same sensor for control, which is believed to contribute to the discrepancies between the measured and simulated data. The control system will be adjusted to link the operation of both systems based on the same sensor reading.

#### 5. Discussion

The presented results highlight the importance of being cautious when selecting the parameters, as the optimisation problem could become ill-posed, resulting in considerably different parameter esti-

mates with even small changes in the objective function. Conducting a sensitivity analysis to identify the influential parameters, rather than relying on the heuristic method, would be valuable in developing a more robust calibration approach. The parameters of the infiltration model estimated using the meta-heuristic optimisation algorithm could be verified through tracer gas decay experiments using the procedure described in ASTM E741-11. Conducting these experiments under various weather conditions would yield the necessary data to derive empirical correlation coefficients for the greenhouse-specific infiltration model. This could be repeated in greenhouses with different shapes, dimensions, and constructions to support the development of reference values for future modellers.

The estimated opening effectiveness ( $C_w$ ) values obtained through the optimisation algorithm should be validated in future studies, as such high opening effectiveness is unusual. This could be attributed to the combination of a small-scale greenhouse with relatively large roof vent openings.

Improvement to the weather data used could also be achieved by using a dedicated site weather station. This additional data source will include many onsite measurements such as outdoor temperature, relative humidity (Campbell Scientific HMP45C), carbon dioxide (Vaisala GMP343), wind speed and direction (05103VK-L), global shortwave irradiance (EKO MS-80SH pyranometer), barometric pressure (Campbell Scientific CS100) and rain and snow (R.M. Young 52202). Furthermore, microclimate measurements within the greenhouse will be added, such as temperature (Apogee TS-100), radiation-shielded thermocouples, relative humidity, carbon dioxide, net radiometers (apogee SN-522-SS), PAR (apogee SQ-500-SS) and ePAR (apogee SQ-610-SS) are installed.

Once the data with crops inside the greenhouse becomes available, the calibration of the greenhouse energy model should be revised, integrating a canopy-level heat balance algorithm. This integration will consider the sensible and latent heat exchanges between the crops and the greenhouse microclimate.

## 6. Conclusion

This paper presents the calibration results of a building energy model for controlled environment agriculture (CEA) using real-world measurements from a highly instrumented small-scale experimental greenhouse. Further analysis of the simulated and measured temperature profiles should offer additional insights into the model calibration approach. The next step will involve gathering data on crop hygrothermal loads within the greenhouse, integrating the crop leaf-level energy balance into the simulation engine and continuing the calibration process.

#### Nomenclature

#### Symbols

$A_{op}$	opening area (m <sup>2</sup> )
$C_D$	discharge coefficient
C <sub>w</sub>	opening effectiveness
ŷ	estimated data
A 11	midpoint height from the lower opening
$\Delta H_{NPL}$	to the neutral pressure level (m)
Ι	infiltration flow rate (ACH)
Q	volumetric flow rate (m <sup>3</sup> ·s <sup>-1</sup> )
Т	temperature (°C)

- Uwind speed (m·s<sup>-1</sup>)ggravitational acceleration (m<sup>2</sup>·s<sup>-1</sup>)nnumber of data pointspnumber of parameters
- y measured data

#### Subscripts/Superscripts

$\infty$	outside
D	design
s	stack-driven
W	wind-driven
Z	zone

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## Microclimate Conditions in the SS. Salvatore Church of Bologna

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#### Abstract

This paper analyses the microclimate conditions in the Church of Santissimo Salvatore in Bologna and their influence on the acoustics of the Church and the sound of the pipe organ. It is commonly acknowledged that the variation of air temperature, median radiant temperature, relative and absolute humidity could provoke thermal expansions of metals which are used for the organ pipes. This paper analyses a monitoring campaign which lasted one year in which temperature and relative humidity were stored with a data logger. Moreover, the paper shows the effect in the variation of the microclimate conditions in the church by simulating different numbers of people in the church and different thermal conditions outdoor. Finally, the paper reports the variations of the acoustic parameters simulating the new values of temperature, relative humidity and air velocity.

#### 1. Introduction

While historical buildings are extremely valuable, managing their environs may be difficult. This is mostly because restoring them can be expensive and complex, especially when it comes to major buildings like churches. Visible areas are typically given priority in current restoration projects, leaving many older materials unrepaired or only partially restored. This leads to a lack of progress in confronting invisible parts of indoor environmental control. Many churches experience rapid temperature variations as a result of overheating, and severe effects on their interiors are also a result of lack of control over external factors. This creates problems for both the preservation of these areas' valuable cultural heritage and the proper use of their cultural value. Microclimate investigations in Italian churches have been reported in several studies (Aste et al., 2019; Poljak & Ponechal, 2023; Aste et al., 2016). However, it can be said that there is still insufficient information to discuss practical measures for appropriate operation and preservation effectively.

Organ tuning is typically influenced by temperature. Metal pipes not only expand with environmental changes but also, as the air temperature inside the pipes fluctuates, the speed of sound changes significantly, affecting the pitch of the organ pipes. A temperature variation of 10 degrees can result in approximately a one-third semitone change. It might be argued that discussing the appropriate preservation and best use of historical organs is difficult without first managing interior settings properly.

Thermo-hygrometric variables are one of the various variables that influence acoustic parameters. The impact of temperature and humidity has been examined in the realm of voice alarm systems (Gomez-Agustina et al., 2014), and in voice reproduction systems (Yang & Moon 2018). Their findings indicated that higher temperatures and humidity levels led to an increase in reverberation time, particularly at high frequencies (Yan & Tronchin, 2025). Consequently, parameters associated with speech were observed to decrease as temperatures and humidity values rose. In our previous research, experimental and statistical analysis was conducted on the influence of temperature, humidity, and air velocity to room acoustic parameters and showed the formulas for calculating each acoustic parameter (Tronchin, 2021).

## A Brief History and Case Study Overview

Italian churches are rich cultural assets, but investigations trying to identify and best use their distinctive worth remain behind due to their complexity. Not every place can recreate the music of that era on-site. Though Bologna is the only place in Italy with a significant concentration of Renaissance to early Baroque organs, there have been almost no recent studies on organs, acoustics, churches as musical surroundings, and microclimates for preservation.

The Santissimo Salvatore Church (via Cesare Battisti, 18, 40123 Bologna) originated as the Canonici Regolari monastery in the fourteenth century. It developed into a large monastery with a bell tower, a church, a theater, an extensive library, and three courtyards in the fifteenth century. The church was fully renovated in the early years of the 17th century, constructing the current building. Magnificent works of art from the 12th to the 16th centuries, including works by Guercino and others, are housed inside the church (Fini, 2007). Designed between 1605 and 1623 by architect Tommaso Martelli with assistance from Padre Giovanni Ambrogio Mazenta, who also worked on Bologna's San Pietro Cathedral, the present church edifice is one of the city's largest and is distinguished by its early Baroque style (Zaccanti, 1995). The church's main construction was damaged by lightning and battle in the 18th and 19th centuries, but it has since undergone multiple renovations to return to its former shape as his masterwork. The church underwent its most recent restoration in 2000. Without the dome, the church's interior measurements are roughly 60 meters long, 28 meters wide, and 26 meters tall. Inside, there is a single, spacious nave with eight side chapels, massive pillars, a large number of windows, and four raised balconies for music, as well as two antique organs from that era.

This church's importance stems from the fact that it is Bologna's oldest originally intact musical setting, created in the early Baroque era especially for separated choirs. In fact, it produces a reverberant ambiance that provides a rich background for religious music.

## 3. Methods and Tools

#### 3.1 Measurements of the Microclimate

To better understand the real environment in which the organ is located, the temperature and relative humidity in the church were observed using small data loggers (RC-51H by Elitech, London, UK) at intervals of 10-15 minutes throughout the year 2023. On the front of one organ (in cornu epistolae: 9.3 meters above floor level on the eastern wall of the southern transept) long-term measurements were made. The outside condition was derived from data from the Arpae (https://www.arpae.it/) regional weather station located in the heart of Bologna.



Fig. 1 – Data logger on the front of organ

## 3.2 Indoor and Outdoor Thermal Simulation Conditions

The program IES.VE (www.iesve.com/) was used to simulate the church's interior setting. The most recent weather data for Bologna was obtained from climate.onebuilding.org; it was last updated in 2021. A simplified internal structure model of the church was created in IES.VE, all internal environmental parameters were computed based on the external condition. Using Apache, the temperature and humidity for the entire year were computed, and at specific periods, MicroFlo-CFD was used to simulate air velocity. Due to variations in the population (0, 10, 100, and 500), the daily hours were fixed from 8:00 to 18:00. The output data for each parameter from the simulation was obtained hourly.



Fig. 2 – Simulation 3D model of the church in IES.VE software

#### 3.3 Modelling of Acoustic Parameters

Regression equations derived from prior study data on the link between temperature, relative humidity, and air velocity and acoustic parameters were used to do this (Tronchin, 2021). Every octave band has a different coefficient value. Temperature readings of 26.88 to 31.77 degrees Celsius (mean 30.28), humidity values of 37.8 to 54.7 % (mean 43.52 %), and air velocity values of 0 to 0.56 m/s (mean 0.15 m/s) were the range of measurement data used in this formula. The values of the input variables match the variation in the mean values.

$$y = A + B_{1}(\Delta t) + B_{2}(\Delta t)^{2} + B_{3}(\Delta t)^{3} + C_{1}(\Delta u) + C_{2}(\Delta u)^{2} + C_{3}(\Delta u)^{3} + (1)$$
  
$$D_{1}(\Delta v) + D_{2}(\Delta v)^{2} + D_{3}(\Delta v)^{3}$$

Using Apache data, the acoustic parameters for the full year were calculated without taking into account the values D1 to D3, which presuppose a zeroair velocity. Air velocity measurements ranging from D1 to D3 were included in order to evaluate the impact of occupancy.

Table 1 – Regression Coefficient for Reverberation Time T30

Input variable	-	Δt	Δt2	∆t3
Coefficients	А	B_1	B_2	B_3
125Hz	2.417			
250Hz	2.95			-0.006
500Hz	2.813			
1000Hz	2.891	-0.033		0.001
2000Hz	2.737	-0.012	-0.007	
4000Hz	2.152			0.002

Input variable	Δu	Δu2	∆u3	Δv	∆v2	Δv3
Coefficients	C_1	C_2	C_3	D_1	D_2	D_3
125Hz	-0.018					
250Hz	0	-0.003				
500Hz						4.437
1000Hz	-0.005			0.244	-	
					0.684	
2000Hz			0	0.116		-0.604
4000Hz	0.006	0		0.076	-0.24	

#### 4. Results and Discussion

## 4.1 Measurement and Simulation of Both Indoor and Outdoor Environments

It seems that 2021 was marginally colder than 2023 based on a comparison of the meteorological data from both years (Table 2). But beyond this discrepancy, it becomes clear that the simulations and the real observations diverge significantly.

Table 2 – Annual Air Temperature and Relative Humidity of Indoor and Outdoor

	Air Temperature (°C)				
	Average	Min	Max	Range	
Meas. Church interior 2023	19.7	9.8	28.7	18.9	
Meas. Exterior 2023	17.1	-1.2	40.1	41.3	
Calc. Church interior 2021	16.8	0.11	34.4	34.29	
Meas. Exterior 2021	14.8	-5	36	41	
	Relative Humidity (%)				
	Average	Min	Max	Range	
Meas. Church interior 2023	56.1	35.5	70.2	34.7	
Meas. Exterior 2023	62.3	11	99	88	
Calc. Church interior 2021	60.7	13.79	99.94	86.15	
Meas. Exterior 2021	69.6	14	100	86	



Fig. 3 – Microclimate measured and simulated: Temperature and relative humidity (a) measured in the church with the regional weather station data (Bologna idrografico in 2023) (b)(c) Simulation in IES.VE software with the weather station data (Bologna Marconi in 2021)

While the sensors placed within the actual church show relatively mild movements, the simulated temperature and humidity fluctuations nearly match those outside (Fig. 3). While the simulations displayed data from the room's centre, the actual measurements were made at the organ's location.

#### 4.2 Variations with People Occupancy

The simulated annual temperature and relative humidity are displayed here under the influence of population occupancy, and their patterns were nearly constant throughout the year. With 500 participants, the larger results revealed a few minor variations (Fig. 4). While seasonal variations in humidity occur, the amplitude of temperature swings stayed largely stable year-round at a maximum of 1.6 degrees. The simulation indicated that during the winter, the impact of human presence on humidity was larger.

Table 3 – Difference between no people and 500 people

	Average	Min	Max	Range
Difference of	0.83	0.28	1.64	1.36
Air Temperature (°C)				
Difference of	-0.46	-4.01	11.91	15.92

Relative Humidity (%)



Fig. 4 – Temperature and relative humidity simulated in IES.VE, and Enlargements

#### 4.3 Analysis of Indoor Acoustics

The acoustic parameter T30 (Reverberation Time) variation for entire data and particular chosen times

for examining the impact of occupancy were computed (Fig. 5), as it happens for simulations on theatres (Bevilaqua et al., 2024). Depending on frequency, the annual variances showed notably different tendencies. Even though the church is much larger than it was in the previous report, two of the six values—roughly ranging from two to 3.5—were deemed appropriate for the reverberation value (Fig. 5a). The other four values, however, fluctuated over a very wide range (Fig. 5b–c).



Fig. 5 – Acoustic parameter T30 calculated from the simulation data. (a)(b)(c) thought one-year, (d)(e) Variations with people occupancy

In several timings depicting the greatest temperature change and the greatest relative humidity between zero people and 500 people, the simulated variations of the T30 value were shown (Fig. 5d-e). When compared to annual variations, the range of value changes caused by occupancy was not very great.

#### 5. Conclusions

For the purpose of preserving cultural heritage, it is necessary to evaluate the impact of interior environmental variables on acoustic parameters because air stratification and thermo-hygrometric conditions in tall historical structures are challenging to model. This study shed new light on the intricate relationships that exist between old churches' interior microclimate, organ pipe acoustics, and cultural heritage preservation. More real-world thermo-hygrometric behaviors were recorded than in prior modeling attempts thanks to long-term observation of temperature and humidity distributions in the Church of Santissimo Salvatore in Bologna. A greater knowledge of how underlying physical elements like temperature and humidity affect acoustic characteristics was attained by the integrated approach that combined field data with thermal and acoustic simulations. The real measurements and the modeling simulation showed noticeably different trends for the indoor temperature and humidity over the course of the year. The year-round changes in the acoustic parameters, which were computed, were extraordinarily broad. Overall, the findings show that in order to properly evaluate the effects on cultural heritage assets that are sensitive to indoor environmental conditions, such as pipe organs, and are housed in locations with limited capacity to regulate temperature, like tall historical buildings, detailed measured microclimate data are necessary. The preservation of both tangible and intangible cultural assets could be advanced by more research using this methodology on other case studies.

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## The Impact of Thermal Zone Resolution on the Energy Simulation Results of Complex Buildings

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#### Abstract

Strategic reduction of thermal zoning granularity in energy performance simulation may be advantageous in high-resolution queries involving large and complexbuilt objects in view of time and effort reduction potential. However, the proper choice of thermal zones' granularity is also dependent on the nature and purpose of performance queries. In this context, this paper explores the influence of the thermal zones' resolution on buildings' estimated heating and cooling loads. To this end, the illustrative instance of a multi-zone building is selected and made subject to varying levels of thermal zoning resolution.

#### 1. Introduction and Background

Simulation of complex-built entities (e.g., large buildings with a multitude of differentially tempered zones, campuses, or entire urban neighbourhoods) requires considerable resources in terms of time, effort, and computing power. Hence, a number of past studies have explored various strategies to simplify or reduce the computational domain. However, the steadily increasing efficiency of computational algorithms and hardware means have been suggested to render such efforts less critical. Nonetheless, in certain instances, strategic reduction of the simulation models' complexity and the corresponding required computational resources may be useful, or even necessary.

This necessity seems less controversial in cases of vast simulation domains such as urban energy computing applications. Thereby, measures such as utilization of reduced models or the adaptation of the hour-glass methodology have been shown to have the potential to be effective (Ghiassi & Mahdavi, 2017). But reductive measures may be reasonable even in the less extensive case of complex multi-zonal building objects. Therefore, it is not only the spatial extension and complexity of the objects (size of the building, number of zones) that motivate reductive measures, but also the nature of more recent trends in simulating system dynamics and human behaviour (Malik et al., 2022). For instance, stochastic simulation routines and highresolution agent-based modelling of occupants' movements and actions in buildings can result in a rapid increase of simulation models' complexity, which in turn leads to a surge of required computational load for data generation and processing.

Hence, strategic reduction of the simulation domain may be advantageous in simulation-based high-resolution queries that involve: *a*) large and complex built objects, *b*) multi-zonal thermodynamic processes, *c*) multiple dynamically operated control systems and devices, and *d*) complex patterns of occupants' presence, movement, and control actions.

A further reason to reflect on the granularity of simulation models relates to the fit-for-purpose discussion (Gaetani et al., 2023; Mahdavi & Tahmasebi, 2016). The idea is that the performance simulation strategies in general and the selected level of simulation model granularity in particular should take the nature and purpose of performance queries into consideration. Of relevance are here factors such as the stage of the design process (i.e., early versus late) and purpose of the query (e.g., demonstration of code compliance versus sizing of mechanical equipment for heating, cooling, and ventilation). Moreover, it has been also plausibly argued that the fidelity of simulation results does not necessarily improve in tandem with increased complexity and granularity of the simulation model. In fact, the relationship between detail level of simulation model input parameters and the uncertainty associated with simulation results is nonlinear (Alonso, 1968; Magni et al., 2022).

In this context, the present contribution addresses one of the features of the simulation models of complex buildings that can influence the required time and effort for obtaining the target computational results. To this end, the focus is on the energy simulation domain and the influence of the thermal zones' resolution on the computed values of the building performance indicators, including those pertaining to buildings' heating and cooling loads.

The thermal zones in simulation models may have divergent thermally relevant characteristics, such as maintained ambient temperatures and illuminance levels, as well as occupancy-related assumptions (patterns of occupants' presence and behaviour in buildings).

To explore the implications of zonal resolution, the illustrative instance of a multi-zone building is selected and made subject to a full-domain and fairly detailed dynamic thermal simulation, thus establishing the benchmark case. Subsequently, multiple alternative models with varying levels of zonal fusion are generated and simulated. The process is repeated for multiple locations to obtain a first impression regarding potential dependencies of the results' variance on the external climatic conditions.

The results are compared to the benchmark using the respective values of the aforementioned performance indicators. Hence, the variation of obtained results can be studied, as smaller zonal units are successively fused into larger units.

The paper concludes with reflections on the degree to which the zoning granularity may be suggested to be worthy of critical consideration.

## 2. A Case Study

#### 2.1 Overview

To explore the impact of thermal zoning granularity on the simulated values of typical energy performance indicators (i.e., heating and cooling loads), a generic office building was used as the case in point. Section 2.2. describes the building model (typical floor plan and basic construction properties). The examined zoning granularity levels are described in Section 2.3. Section 2.4. provides the details of the performed simulation runs.

#### 2.2 The Building Model

Fig.1 shows the schematic illustration of the selected office building's regular plan. It consists of 16 double-occupancy office rooms, four central meeting and service rooms, as well as vertical (elevators, stairs) and horizonal (corridor) circulation areas.

The thermal transmittance of the building's external walls is assumed to be 0.3 W.m<sup>-2</sup>.K<sup>-1</sup>. Windows' thermal transmittance is assumed to be 1.0 W.m<sup>-</sup> <sup>2</sup>.K<sup>-1</sup> and the window glazing is assumed to have a shading coefficient of 0.5.

The window to wall area ratio is assumed to be 40%. The air change rate in the office area during the occupancy hours is assumed to be 1  $h^{-1}$ , otherwise 0.2  $h^{-1}$ .



Fig. 1 – Schematic depiction of the regular plan of the selected office building  $% \left( {{{\rm{D}}_{{\rm{B}}}} \right)$ 

#### 2.3 Four Levels of Zoning Granularity

Four thermal zoning schemes (labelled Z1 to Z4) are considered for the parametric simulation runs (see Table 1). In the case of the highest granularity (Z1), each of the 16 perimeter offices is assumed to have its own user-determined ambient temperature during the occupancy hours (ranging from 18 to 26°C). In the case of the next zoning scheme (Z2), adjacent offices were fused into one, resulting in a total of 8 office zones. The conditions in these zones (ambient temperature, reference task illuminance, air change rate, occupancy period) were assumed to represent the average values of the two zones they emerged from. This process was repeated in case of the zoning scheme Z3, resulting in four office zones. Finally, in the case of zoning scheme Z4, all office areas were fused into one uniformly conditioned zone.

Table 1 – Overview of the four thermal zoning schemes (Z1 to Z4) (see Fig. 1 for the room labels)

Z1	Z2	Z3	Z4
Р	A + B		
D			
С	C + D	A + D + C + D	
F			
Ι	P+O		
А		$\mathbf{D} + \mathbf{O} + \mathbf{N} + \mathbf{M}$	A + B + C + D
М	N + M	$\Gamma + O + N + M$	+
J			P + O + N + M
В	L + K		- I + K + I + I
Е		$\mathbf{I} + \mathbf{V} + \mathbf{I} + \mathbf{I}$	L + K + J + I
Κ	J + I	L + K + J + I	' F + F + G + H
G			LIIGIII
Н	G+H		
0		E+E+C+U	
L	E + F	L+F+G+II	
Ν			
R	Q + R		
Т		O B S T	O + D + C + T
S	S + T	Q+K+5+1	Q+K+5+1
Q			

#### 2.4 Parametric Runs

Simulations were conducted for the aforementioned four zoning schemes. Three locations in Europe with different climatic conditions were considered as the site of the building. The motivation was to see if the impact of the zoning granularity is consistent across different climatic conditions. Toward this end, weather files for three cities were applied, namely Oslo (Norway), Vienna (Austria), and Palermo (Italy). Oslo and Palermo display rather high heating and cooling loads respectively, whereas Vienna has an intermediate position. Simulation results were expressed in terms of the values of annual heating and cooling loads.

#### Results and Discussion

Table 2 entails the numeric values of computed performance indicators (annual heating and cooling loads) for the four simulated thermal zoning schemes (Z1 to Z4) and the three locations.

To make the comparison of results for different zoning schemes easier, Table 3 includes the relative deviations of the results of the zoning schemes Z2, Z3, and Z4 from those of the zoning scheme Z1, which is used here as a kind of benchmark. As the values associated with zoning scheme Z1 are the highest in all cases, the values in Table 3 represent, in percentage, the underestimation of Z1 loads by zoning schemes 2 to 4.

The results, as summarized in Tables 2 and 3 warrant certain observations:

Computed values of performance indicators are different for different levels of resolutions. Specifically, the higher the resolution of the zoning scheme, the larger are the values of both heating and cooling loads.

Table 2 – Values of computed energy performance indicators (annual heating and cooling loads) for the four simulated thermal zoning schemes (Z1 to Z4) and the three locations

Indicator	Zoning	Vienna	Oslo	Palermo
	Z1	75.0	108.6	22.0
Annual head	Z2	65.9	97.4	17.5
[kWh.m <sup>-2</sup> .a <sup>-1</sup> ]	Z3	62.2	92.3	16.3
	Z4	61.4	91.7	15.6
	Z1	24.0	9.2	77.0
Annual	Z2	19.2	6.9	64.7
[kWh.m <sup>-2</sup> .a <sup>-1</sup> ]	Z3	17.4	6.2	61.0
	Z4	16.3	5.9	58.6

The magnitude of deviation that can be considered significant (or non-negligible) may be debatable.

But if one considers a threshold of 10% deviation as significant, then the results point to nonnegligible degrees of deviation. One has to be of course careful when arguing based on relative deviation data, as respective percentages are typically higher for smaller absolute values of the commodity under consideration. For instance, in the present case, lower (i.e., 5 - 20), medium (i.e., 60 - 65), and higher (i.e., 90 - 95) absolute annual loads in kWh.m<sup>-2</sup>.a<sup>-1</sup> correspond respectively to higher (i.e., 20 - 25), medium (i.e., 12 - 25), and lower (i.e., 10 -15) relative deviations in percentage.

As the results in Tables 2 and 3 are purely simulation-based, it is not meaningful to evaluate them in terms of their "correctness" or accuracy. In fact, as it was alluded to before, higher zonal resolution is not necessarily constituent of more reliable predictions. However, this specific case study appears to suggest that the results obtained from a highresolution zoning scheme are on the "safe side", as they are underestimated by the schemes of lower resolution.

There are multiple potential reasons and mechanisms responsible for the resolution-dependent discrepancies of the results. Despite the effort to normalize factors other than the zoning size, multiple details of the simulation models do inadvertently differ. In fact, it is difficult to preserve certain zone properties in the course of zonal fusion, including, for instance, the thermal mass effects of the partition elements between the zones as well as the schedule-dependent thermal loads associated with internal gains and ventilation loads.

Table 3 – Relative deviation (in %) of the computed energy performance indicators (annual heating and cooling loads) of zoning schemes Z2 to Z4 from the respective results of zoning schemes Z1 for the three locations

Indicator	Zoning	Vienna	Oslo	Palermo
	Z2	12	10	20
Annual heating load	Z3	17	15	26
	Z4	18	16	29
	Z2	20	25	12
Annual cooling load	Z3	27	33	21
	Z4	32	36	24

Nonetheless, the consistency of the observed tendency in the present study points to one potentially responsible factor for at least part of the observed deviations: Assignment of a thermal node in a numeric simulation model to a larger zone implies a within-zone thermal balance, hence effectively covering part of the required heating or cooling load provision. This masking effect yields seemingly lower load, which would not result in models with higher zonal resolution.

#### 4. Conclusion

The investigation presented in this paper was motivated by the potential implications of the strategic reduction of thermal zoning granularity in energy performance simulation, particularly in case of large and complex buildings. Decisions on zoning resolution could be ostensibly informed by considerations related to both *i*) the efficiency and effectiveness of the simulation process and *ii*) the nature and purpose of performance queries.

To illustrate this matter, the influence of the thermal zones' resolution on the computed heating and cooling loads of an office building was studied via parametric simulation. The results point to nonnegligible effects of the resolution of the building's thermal zones on computed annual heating and cooling loads.

The loads displayed, independent of the climatic context considered, higher values for simulation models with higher zonal granularity. Whereas this finding does not necessarily imply that higher zonal resolution translates into higher reliability, it does suggest that results obtained through such high-resolution models may be on the conservative side. Representing large thermal zones through single nodes in the numeric simulation increases the tendency toward within-zone thermal balance, thus resulting in lower estimation of required heating and cooling loads.

Future studies need to further examine and validate these results through consideration of a larger number and more detailed building models with regard to building typologies, environmental control systems, operation regimes, and contextual parameters. Likewise, a more comprehensive set of thermally relevant building performance measures must be taken into consideration, including energy use estimates and thermal state indicators relevant to passive mode of building operation. Moreover, studies of thermal zoning resolution and its implications for the building simulation results must take applicable practical considerations into account, including the orientation of building and the type and operation methods of the building's des-

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ignated building systems. Finally, investigations of the kind presented in this paper have the potential to inform ongoing and future developments toward the automated generation of thermal zone configuration and the selection and sizing of environmental control systems and components.

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## Development and Calibration of an Urban Building Energy Model for the City of Padua

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#### Abstract

Research about Urban Building Energy Models (UBEMs) has undergone a significant increase in recent years. In most of the papers in the scientific literature, researchers claim that UBEMs can be used by policy makers and other stakeholders to evaluate and plan energy efficiency measures at urban scale. Despite their good purpose, researchers are still the main users of these tools. This work tries to make a step forward by calibrating an UBEM on real energy consumption data from 489 residential buildings of Padua (Italy), and to use the calibrated model to assess two energy efficiency measures on the considered sample of buildings. Results show that calibrating only two coefficients is sufficient to obtain an accurate model with a limited computation effort. The analysis of two renovation scenarios suggests that deep retrofits on the biggest consumers is an effective strategy to abate CO2 emissions at urban level.

#### 1. Introduction

Urban building energy models (UBEMs) allow researchers, urban planners, architects, and policymakers to simulate and assess the energy performance of individual buildings, neighbourhoods, or entire cities (Cerezo Davila et al., 2016). Thus, UBEMs serve as valuable tools for developing strategies to mitigate the environmental impact of buildings, reduce greenhouse gas emissions, and improve the resilience of the urban environment.

Previous research has shown that simplified building models based on the electrical analogy offer an efficient compromise between low computation time and high accuracy (Zarrella et al., 2020). Indeed, using detailed dynamic building models for large scale simulations would not be justified given the uncertainty associated with operational, geometrical and physical input parameters, which can undermine the reliability of UBEM simulations (Prataviera et al., 2022).

When energy consumption data are available at individual building level, a possible solution consists in calibrating the building parameters so that the error between measured and calculated energy consumption is minimized (Chen et al., 2020). Bayesian calibration is a commonly used technique to adjust building models' parameters and reduce their error against metered energy consumption (Sokol et al., 2017). Dilsiz et al., 2023, provide the ranking for different climates and building forms so researchers can choose the top 3-4 parameters to calibrate instead of running a sensitivity analysis (Dilsiz et al., 2023). The accuracy of urban energy prediction with annual temporal resolution can be significantly increased if calibration is performed by using building-level data (Dilsiz et al., 2023). The same study found that using monthly data to calibrate uncertain input parameters is not improving the accuracy of UBEM simulations.

This paper presents the lessons learnt during the development and calibration of the urban building energy model for the city of Padua (Italy), which are essential steps towards the implementation of a reliable digital model for its building stock.

The calibrated model is then used to assess the impact of two retrofit measures in terms of  $\rm CO_2$  emissions.

## 2. Model

The simulations were carried out using EUReCA (Prataviera et al., 2021), an UBEM based on two lumped capacitance models: the one-capacitance model by ISO 13790 Standard and the two-capacitance model proposed by VDI 6007 Standard, shown in Fig. 1.

The underlying building models were compared in detail in a previous study (Vivian et al., 2017).

The tool creates the lumped parameter model and calculates the energy consumption of the buildings starting from a georeferenced dataset (a GeoJSON file). The dataset includes geometrical variables, i.e. polygons representing the buildings' footprints, height, as well as parameters about the building envelope, the heating and cooling systems and other parameters associated through predefined archetypes that are valid for Italian residential buildings. Internal heat gains were taken from Standards (European Committee for Standardization, 2019).



Fig. 1 - Representation of the equivalent electrical circuit of the 7R2C model proposed by VDI 6007

## 3. Case Study

#### 3.1 The City of Padua

This work focuses on the analysis of 489 buildings located in Padua, shown with red shapes in Fig. 2. Padua is an Italian city located in the in the eastern part of the Po Valley and belonging to the Veneto Region, with coordinates 45.4° N and 11.9° E and a population of about 210 000 inhabitants.

Italy's climate is divided into six zones depending on the number of heating degree-days, calculated using a conventional indoor air temperature of 20°C (*D.P.R. n. 412* 1993). Padua belongs to climatic zone E, with 2383 degree-days per year. This zone corresponds to a temperate climate without dry season, with hot summer, i.e. to Cfa climate (Peel et al., 2007).



Fig. 2 - Padua's map from the Urban Atlas Building Height dataset. In red the buildings considered in this work

The considered sample of buildings is entirely composed by residential apartment blocks, spread within the whole city centre. As such, the considered case study is a realistic representation of Padua's residential building stock in terms of building envelopes and geometrical characteristics. Gas consumption data are available for all the buildings considered for 2020, 372 buildings for 2021 and 370 buildings for 2022.

#### 4. Methods

The model development consists of two parts: model initialization and model calibration. The first part includes preparing the input data and making a quality check on building geometries. In this part, the nominal parameters of the RC models were calculated, and a first simulation run was performed. In the second part, the building parameters were than adjusted to minimize the error between simulated and measured gas consumption data. Finally, the calibrated building models were used to simulate different refurbishment scenarios.

#### 4.1 Model Initialization

In the first phase, the geometrical footprints are imported from OpenStreetMap and converted into the GeoJSON format. The buildings for which gas consumption data were available were selected and each building was associated with an archetype based on the alleged period of construction. The periods considered are pre-1945, 1945-1976, 1976-1991, 1991-2005 and post-2005. These periods were chosen to separate buildings according to the energy efficiency laws (L.373/76, L.10/91 and D.lgs. 192/2005) in force during their construction. Building heights were obtained from satellite data (European Environment Agency, 2022).

Adiabatic surfaces were selected for those buildings adjacent to other buildings, which occurred frequently for buildings in the city centre. An initial screening of all 489 buildings was important to associate archetypes, and spot geometrical mismatches between shapefiles and aerial images.

#### 4.2 Model Calibration

The calibration relied on annual gas consumption data of all 489 buildings, distributed in almost every district of the city. The buildings for which gas consumption was available are the red ones in Fig. 2. Two parameters for each building were iteratively changed until the mean square error between calculated and actual gas consumption data were minimized. Based on the results of a previous paper (Prataviera et al., 2022), the two most influential parameters selected for the calibration were the indoor temperature setpoint  $T_{set}$  and the surface area of the external building walls. The latter was changed using a multiplier called  $f_{walls}$ . These two parameters emerged as the most influential ones from a sensitivity analysis carried out on nine input parameters that are typically used as inputs for UBEM simulations. The domain of these two variables in the calibration process are 17 - 22 °C for  $T_{set}$  and 0.75 - 1.25for  $f_{walls}$ . The optimization was implemented using the Trust Region Reflective algorithm (Branch et al., 1999), as formulated in the least\_squares method included in scipy's optimization library (Virtanen et al., 2020). The model's accuracy was evaluated using different indicators, described in the following Equations.

$$CV_{RMSE} = \sqrt{\sum_{i=1}^{n} e_i^2 / n} / \mu \tag{1}$$

$$CV_{MAE} = \sum_{i=1}^{n} |e_i| / n / \mu$$
(2)

where  $e_i$  represents the absolute error between simulation and real gas energy consumption for the *i*-th building, n is the total number of buildings, and  $\mu$  the average measured gas consumption.

#### 4.3 Scenario Analysis

After calibrating the models, two renovation scenarios were analyzed:

- Scenario 1: Building envelope renovation, including thermal insulation of the external walls, roof, and ground floor, as well as the replacement of windows.
- Scenario 2: scenario 1 with additional replacement of existing gas boilers with air-source heat pumps.

The analysis was focused mainly on the reduction of CO<sub>2</sub> emissions. The study considered an emission factor of 0.260 kg/kWh for the electricity consumed and 1.983 kg/Nm<sup>3</sup> for natural gas.

#### 5. Results

Urban building energy models (UBEMs) allow researchers, urban planners, architects, and policymakers to simulate and assess the energy performance of individual buildings, neighbourhoods, or entire cities.

#### 5.1 Accuracy of the Initial Model

Fig. 3 shows the distribution of the errors in the simulated gas consumption compared to the measured ones. It can be observed that the model clearly overestimates gas consumption, as the distribution is skewed towards positive errors, counting 53 buildings above a 50% overestimation. According to sample checks within the dataset, this overestimation of the model depends on few factors, mainly linked to geometrical and zoning assumptions; for instance, the footprint from GIS data sources is often larger than real building dimensions and buildings can be partially unheated. Despite these deviations, the model is able to approximate the annual gas consumption with an acceptable error (between -30% and +30%) for 345 out of 489 buildings, i.e. for 70% of the sample. Here, "acceptable" error should be considered in light of the uncertainties that characterize UBEM's input parameters (operational, geometric and physical parameters of the buildings). A previous study has shown that urban simulations with standard inputs can lead to deviations up to 50% for residential buildings (Prataviera et al., 2022).



Fig. 3 – Distribution of the errors in the annual gas consumption before model calibration

#### 5.2 Model Accuracy After Calibration

The calibration of the building model parameters was carried out using the gas consumption data of 2020 as a training dataset. The calibrated building models (i.e. the same models with updated temperature setpoint and external wall coefficient) were then used to simulate the gas consumption of the buildings during two consecutive heating seasons, i.e. during years 2021 and 2022. Since for those years gas consumption data was available only for a subset of the sample (372 buildings for 2021 and 370 buildings for 2022), Fig. 4 shows the distribution of the errors using the percentage of buildings considered.

As expected, the best result is obtained on the training dataset (year 2020), with 92.2% of the buildings with errors of the simulated gas consumption included between -30% and +30%. The remaining 7.8% fails to be calibrated due to the limits imposed to the two coefficients, which were kept close to nominal values ( $T_{set} = 20$  °C and  $f_{walls} = 1$ ) to preserve the physical sense of the simulations. For years 2021 and 2022 the percentage drops to 84.1% and 84.9%, respectively. The metered data from 2020 could be biased by the increased occupancy of residential buildings due to COVID's lockdowns. Therefore, it is expected that calibrating and testing the model using gas consumption data without this disturbance would produce lower errors.



Fig. 4 - Distribution of the errors in the annual gas consumption after model calibration

Fig. 5 shows the calibrated parameters (temperature setpoint of the indoor air and external wall coefficient) obtained with two exit criteria of the optimization loop, where each dot represents a calibrated building model. Blue dots refer to parameters that were calibrated with tighter tolerance (10-4 relative error between consecutive iterations) compared to red dots, that used a wider tolerance (10-2). As the figure shows, the calibration algorithm tends to use  $f_{walls}$  as first parameter to calibrate the model, and only when the area reduction/increase is not sufficient, then the setpoint temperature changes. Such behaviour is clear from the concavity of the curve, and it is due to a larger effect of the external wall area on the gas consumption, compared to the heating setpoint temperature.



Fig. 5 - Calibrated parameters with different exit criteria

Table 1 shows the accuracy of the model and the computation time of the calibration as a function of the tolerance.

Table 1 – Accuracy indicators and computation time

Tolerance	CV <sub>MAE</sub>	CV <sub>RMSE</sub>	Comp. time (min)
10 <sup>-4</sup>	19.0%	46.1%	209.1
10 <sup>-3</sup>	19.0%	46.1%	181.7
10 <sup>-2</sup>	20.2%	46.8%	147.4

Both from the latter table and from Fig. 5, it is clear that the tolerance does not strongly influence calibration results. Indeed, blue and red points are almost aligned and the  $CV_{RMSE}$  and  $CV_{MAE}$  indicators do not significantly change. Nonetheless, it is worth mentioning that using a tolerance of 10-2 seems to be the best choice due to the way lower computational time to reach the calibration (30% less computation time compared to 10<sup>-4</sup>). Fig. 6 shows the calibrated parameters when the search domain is extended from 0.75-1.25 to 0.4-1.6 for the external wall coefficient and from 17-22 °C to 10-30 °C for the indoor air temperature setpoint. Extending the boundaries of the optimization domain reduces the errors of the model (for instance, CV<sub>MAE</sub> drops to 9.7% compared to the values shown in Table 1) but introduces the problem of model interpretability. Fig. 6 shows the values of the calibrated coefficients when the search domain is extended beyond the previously set limits: the setpoint temperature of indoor air can be in a range between 10 °C and 30 °C and the external wall coefficient can be in a range between 0.4 and 1.6. The external wall coefficient compensates the uncertainty associated to different parameters, and in particular the surface area and the thermal transmittance of external building components. Such uncertainty is difficult to quantify a priori. On the other hand, the setpoint temperature of indoor air is a parameter for which it is easier to guess an acceptable range. Indeed, it is difficult to imagine setpoint temperatures higher than 24 °C and lower than 16 °C in the heating season. The buildings for which the calibrated parameters fall in this range are 59, i.e. approximately 12% of the entire sample. Therefore, the model can be considered physically meaningful for 88% of the sample. This share drops to 81% if the physically acceptable range of the setpoint temperature is reduced to 17-23 °C.



Fig. 6 - Calibrated parameters on extended domain

Fig. 6 also shows that the archetype selected for a certain building does not correlate significantly with the calibrated parameters. Indeed, the buildings are distributed over the whole calibration range regardless of the archetype.

#### 5.3 Scenario Analysis

Fig. 7 shows the amount of CO<sub>2</sub> emissions of the considered sample of buildings in three scenarios: a base scenario and the extreme renovation scenarios described in Section 4.3. The black line represents the base scenario without efficiency measures and can be read either on the left axis (absolute CO<sub>2</sub> emissions) and on the right axis (CO<sub>2</sub> emissions

compared to the total). The orange and green lines represent the effect of the corresponding building renovation scenarios on the overall CO2 emissions of the considered building sample. These lines should be read on the right axis, as shown by the arrows. This chart is particularly useful because it allows us to rapidly find the number of buildings that must be renovated to achieve a certain decarbonization objective. For instance, cutting 40% of CO2 emissions (i.e. 60% of CO2 emissions post-renovation on the right axis) requires 251 building renovations in Scenario 1 or 89 building renovations in Scenario 2. The lower number of building renovations needed to achieve the same goal can be explained by the fact that Scenario 2 involves a deeper retrofit: besides the thermal insulation of the building envelope, this scenario includes the replacement of the existing gas boilers with air-source heat pumps for space heating. Consequently, the maximum CO<sub>2</sub> emissions reduction that can be achieved by Scenario 2 is higher than that of Scenario 1: if all buildings underwent renovation, CO<sub>2</sub> emissions would be 47.1% of today's emissions in Scenario 1 and only 21.2% in Scenario 2.



Fig. 7 - Decarbonization chart for different renovation scenarios

#### Discussion

The initial development of the Urban Building Energy Model, including the visual check of the buildings, was crucial to initialize the building model parameters. Since this was the most time-consuming activity of the project, automating this activity by means of machine learning techniques would be

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crucial for a rapid and cost-effective implementation of UBEMs to large building stocks. A preliminary simulation with the initial parameters revealed that, in most cases, the simulation overestimates the buildings' gas consumption for space heating. The distribution of the residuals is skewed towards positive values, with errors often exceeding +70% compared to measured data declared by the gas distribution company.

Although it is not able to guarantee global optimality, the proposed calibration process was able to reduce these errors significantly. The root mean squared error over the entire sample was more than halved, and the corresponding distribution of the residuals was shifted towards a normal distribution. This significant improvement was obtained within reasonable computation time (approximately 1 hour for each 100 buildings using a 12th Gen Intel(R) Core(TM) i7-12700H processor at 2.30 GHz), which is another important feature to allow scalability, given that each objective function evaluation needs to perform a simulation of the entire sample of buildings.

Since calibration is a numerical process, the parameters obtained must be verified to check that they preserve the physical interpretability of the model. Finally, the calibrated Urban Building Energy Model was used to study the effects of energy renovation scenarios on the CO2 emissions of the considered sample of buildings. Although not directly shown in the graphs, this analysis allows to determine the impact of the renovation of specific buildings. In other words, this analysis does not assume an average consumption of the considered building sample but refers specifically to 489 buildings of the city of Padua. The same analysis could be scaled on a larger sample and enriched with more renovation scenarios, thus making a significant step forward to plan data-aware urban energy policies. This is particularly important for a city like Padua, which is located in a highly polluted area and is constantly ranked among the most polluted cities in Europe (European Commission. Joint Research Centre, 2021). Introducing investment and operating costs in this analysis would be very useful to pinpoint the most effective efficiency measures for a given budget. Introducing more efficiency measures and considering techno-economic indicators could therefore be an interesting line of research for future developments, with direct implication for policy makers and administrators.

## 7. Conclusion

This paper has presented the set-up of an Urban Building Energy Model and its practical use for the city of Padua (Italy). The model set-up showed that using open source data for building geometry leads to overestimate the heated volume of the buildings, and that a simple calibration of two parameters significantly improves the model's accuracy within reasonable computation times.

The analysis of renovation scenarios shows the importance of deep retrofits on the biggest consumers to achieve ambitious decarbonization targets at city level.

Future studies will extend the sample of buildings and the set of possible efficiency measures, including both heating and cooling season.

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## ClustEnergy OpTool: An Open Tool for Assessing the Energy Flexibility Provided by Clusters of Buildings

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#### Abstract

Over the past 25 years there has been a significant growth in final electricity consumption, and this is expected to increase due to greater electrification and continued integration of Renewable Energy Sources (RESs). This trend can lead to imbalances and sustained strains on power grids during surpluses and peak demand. To address these challenges, through flexible strategies, building thermal demand can be managed in response to the grid requirements. In this field, moving from the individual building level to the cluster level allows for a greater reserve of displaced energy for grid balancing. However, planning the flexible resources needed for energy management of clusters of buildings can still be difficult. Therefore, a tool to evaluate flexibility scenarios can be useful. Thus, the aim of this paper is to introduce ClustEnergy OpTool, an open tool for estimating the energy demand of a user-defined cluster of buildings under different demand management strategies. The user can compose the cluster by choosing from different building archetypes served by Heat Pumps (HPs) to meet the thermal demand for space heating, cooling and DHW. Buildings can be equipped with PV and subject to a given price signal. Then, by selecting different ways to flexible manage the cluster energy demand (e.g., peak-shaving or demand-shifting, price signal-based management), the tool can estimate the energy shifted, peak displacement, PV self-consumption and electricity bill reductions, both at cluster and individual building level.

#### 1. Introduction

Final electricity consumption has increased over the years, recording in 2019 a 37.8% increase since 1994 (IEA, 2021). With many policies moving toward sustainable energy models, this upward trend is ex-

pected to continue, as electrification (e.g., replacement of traditional boilers with Heat Pumps (HPs)) plays a key role in decarbonization efforts (Boa Morte et al., 2023). To cover the growing demand for electricity, there is a widespread installation of distributed energy resources (DERs, e.g., renewables and energy storage), leading to a decentralized energy supply (Abd Alla et al., 2022). However, the nonprogrammable nature of major renewable sources can lead to imbalances and prolonged stress on power grids. To address these challenges, it is necessary to provide flexible energy demand management. In this scenario, buildings can play an important role. By exploiting the energy flexibility provided by building thermal loads, electrical demand can be controlled in response to power grid requirements. To activate the energy flexibility, several modes are available in buildings. These are: building thermal inertia, water tanks, optimal control, and Demand Response (DR) strategies (such as, peak-shaving and demand-shifting) (Arteconi et al., 2018). Within this domain, the need for a large reserve of energy flexibility may involve moving from a single building level to a larger scale, such as a cluster of buildings (Vigna et al., 2018). In a cluster of buildings, a set of energy flexibility providers are coordinated through a single network to mutually influence their energy response and manage aggregate consumption loads. However, quantifying the reserve of flexibility offered by clusters of buildings can still be difficult due to the complexity of integrating diverse energy systems and the dynamic nature of RESs (Vigna et al., 2018). Several methods and indicators are proposed to quantify the energy flexibility offered by a cluster of buildings (Awan et al., 2023; Wang et al., 2018), even if a well-established practice is not yet available. In this sense, the aim of this paper is to present ClustEnergy OpTool (Mugnini et al., 2024) an open tool in Python (Python, 1991) based on several user-configurable functions for supporting the evaluation of energy flexibility provided by clusters of buildings. As an extension of a preliminary version proposed by (Mugnini et al., 2021), this work proposes new functionalities and additional settings to represent a greater range of scenarios. It is added, for instance, the implementation of space cooling and DHW production and PV systems. Moreover, when implementing demand management strategies, the user can set an electricity price signal. Finally, more detailed utilization profiles are considered when estimating the electricity demand of the cluster, to further diversify the thermal demand of buildings. The tool demonstrates reliability in estimating energy requirements, validated with the ANSI/ASHRAE 140 standard (i.e., BESTEST (ASHRAE, 2020)). Then, after selecting building archetypes for a reference location, ClustEnergy OpTool users can define various DR scenarios to assess the cluster flexibility reserve, supporting decision-makers in optimizing energy resource allocation. To this end, based on the selected DR strategy, the tool enables estimation of energy displacement, peak displacement, distributed or collective PV self-consumption, and electricity bill cost reduction (both at cluster and individual building level). Therefore, the following section describes the methodology (Section 2) of the released version of ClustEnergy OpTool (Mugnini et al., 2024) followed by an application example (Section 3).

## 2. Methodology

As mentioned, the purpose of this paper is to present the released version of ClustEnergy Optool, an open tool useful for estimating energy flexibility offered by a cluster of buildings. Based on the methodology proposed by Mugnini et al. (Mugnini et al., 2021), Fig. 1 shows the operation of the tool describing the various functional blocks (i.e., user-set parameters, outputs, and database) along with the control logic. The following subsections aim to describe the operation methodology of the tool. Section 2.1 describes the thermal demand modelling for individual buildings. The optimization problem is described in Section 2.2, while Section 2.3 focuses on the thermal generation system for space heating (SH) and space cooling (SC). Section 2.4, on the other hand, describes the demand for DHW production. Sections 2.5 and 2.6 explain, respectively, useful utilization models for load diversity within the cluster and forcing signals (i.e., PV generation and price profiles) to perform load shifting strategies. Section 2.7 illustrates the optimal control to activate the energy flexibility through the selected DR strategy. Finally, Section 2.8 lists the performance indicators in output. An example of tool application is provided in Section 3.

#### 2.1 Building Modelling and Aggregation

After selecting a reference location and simulation period, a crucial step is defining a representative cluster. To this end, ClustEnergy OpTool adopts an archetype approach to represent buildings with different age classes (Mugnini et al., 2021). Based on data provided by the Tabula Project (Corrado et al., 2012), Single-Family Houses (SFHs) are considered. In addition, being an open-source tool, the user can implement modifications to include other building types (e.g., Multi-Family Houses) related to different climate zones and countries. Then, the energy demand of individual buildings is represented based on the thermoelectric analogy (e.g., Resistance (R) and Capacitance (C) networks). For instance, thermally insulated dwellings are shown in Fig. 2, that presents a differentiation of the inner and outer layers from the insulating layer. For the emission system, the contribution of air systems is directly applied to the thermal node of indoor air (Tin in Fig. 2). However, in underfloor heating systems, the thermal contribution is applied to the innermost thermal node of the floor (T<sub>f,in,ap</sub> in Fig. 2) representing the inner layers from the tubes (Mugnini et al., 2021).



Fig. 1 - Schematic of ClustEnergy OpTool operation



Fig. 2 – RC network model of a thermally insulated building with air emission system ( $Q_{th}$  applied to the indoor air thermal node) and underfloor heating system ( $Q_{th}$  applied to the to the innermost thermal node of the floor)

Heat gains from solar radiation and indoor sources (e.g., occupancy, lighting, and appliances) are distributed on nodes representing building components in accordance with the validation standard ANSI/ASHRAE 140 - Informative Annex B7 (ASHRAE, 2020). Finally, RC parameters useful for building modeling are identified using a white box approach (Mugnini et al., 2021). Therefore, the energy dynamics of buildings can be represented through a state-space model formulation.

## 2.2 Optimization Problem Formulation

To calculate thermal loads ( $Q_{th}$ ) to be provided as input to the state-space model formulation (Fig. 2), a Linear Programming (LP) problem is proposed. Thermal loads are minimized to maintain the indoor air temperature ( $T_{in}$ ) in the user-set thermostat range (Baseline Case, BL). The LP problem is formulated as follows:

$$\min \sum_{t=1}^{n} Q_{th,BL}(t) \tag{1}$$

Subject to the following constraints and bounds:

- $\forall t: T_{in}(t) \le T_{setpoint}(t) + \Delta T_{upper}$ (2)
- $\forall t: \ T_{in}(t) \ge T_{setpoint}(t) \Delta T_{lower}$ (3)
- $\forall t: 0 \le Q_{th}(t) \le Q_{th,max}(t) \tag{4}$

Where  $T_{setpoint}$  represents the user-set temperature in the thermostat.  $\Delta T_{upper}$  and  $\Delta T_{lower}$  represent the upper and lower thermostat tolerances set by the user, respectively. While  $Q_{th,max}$  represents the thermal capacity of the HP as the outdoor air temperature varies.

#### 2.3 Space Heating and Cooling System

After defining a cluster of buildings, it is important to define the characteristics of the thermal generation system for SH and SC. According to the problem formulation in Section 2.2, the energy dynamics of buildings are represented by constraints on indoor air temperature (Eq. 2 and 3), while the input thermal power becomes a decision variable bounded to the HPs capacities (Eq. 4). Consequently, electric consumption loads for SH or SC to be managed in the DR strategies become:

$$P_{ele,th,BL}(t) = Q_{th}(t)/COP_{th}(t)$$
(5)

where COPth represents the Coefficient of Perfor-(COP) mance of the HP. Accordingly,  $P_{ele,th,BL}(t)$  represents the trend in electric power consumption during the baseline (BL) scenario useful for comparison with the DR scenario, as explained later. By choosing from available sizes, the tool considers the performance characteristics of real HPs extracted from datasheets. Alternatively, it is possible to consider external data provided by the user in the form of normalized performance curves. Then the HP power for SC and SH is represented by the variation of the COP and maximum thermal capacity as the outdoor air temperature changes, at the supply temperature set by the user in the inputs.

#### 2.4 Domestic Hot Water Demand

In addition to an HP to meet the space thermal requirement, ClustEnergy OpTool allows the user to include a DHW HP water heater with an integrated TES. As for buildings, the thermoelectric analogy is adopted to model the storage system (Fig. 3) and the energy dynamic is represented via state-space formulation. From Fig. 3, RC parameters useful for modeling can be computed from the technical characteristics (e.g., water volume, U-value, and envelope area (Table 1)) of a commercial system. The thermal demand due to hot water withdrawal (Qdraw) depends on the utilization profile (see Section 2.5) and the inlet water temperature set by the user (e.g., 10-15 °C). Loads for DHW production (e.g., Qtank), directly supplied to the thermal node of the water tank (e.g., Ttank), are calculated via LP problem. Accordingly, the problem formulation in Section 2.2 is modified as follows:

$$\min \sum_{t=1}^{n} Q_{tank,BL}(t) \tag{6}$$

Subject to the following constraints and bounds:

$\forall t: T_{tank,BL}(t) \le T_{set,tank}(t) + \Delta T_{up,tank}$	(7)
$\forall t: T_{tank,BL}(t) \geq T_{set,tank}(t) - \Delta T_{low,tank}$	(8)
$\forall t: 0 \le Q_{tank,BL}(t) \le Q_{tank,max}(t)$	(9)

Where  $T_{set,tank}$  represents the water temperature in the tank set by the user (e.g., 60 °C).  $\Delta T_{up,tank}$  and  $\Delta T_{low,tank}$  represent the upper and lower tolerances set by the user, respectively. While  $Q_{tank,max}$  represents the capacity of the HP water heater as the outdoor air temperature changes. The energy dynamics are represented by the constraints on temperature (i.e.,  $T_{tank,BL}$  in Eq. 7 and 8), and heat loads become a decision variable constrained to the capacity of the HP water heater (Eq. 9). Finally, the electricity demand for DHW production to be managed in the DR strategies is determined by considering the performance characteristics of a HP water heater (e.g., COP<sub>tank</sub>) provided by the user (Eq. 10).

$$P_{ele,tank,BL} = Q_{tank,BL}(t) / COP_{tank}(t)$$
(10)



Fig. 3 - RC network model of a heat pump water heater

Table 1 – Characteristics of a HP water heater for DHW production available in ClustEnergy OpTool library

U-value (Wm <sup>-2</sup> K <sup>-1</sup> )	Area (m²)	Volume (m³)	Capacity (kW)	СОР
0.23	3.40	178.00	1.30	3.10

#### 2.5 Utilization Patterns

In addition to different building types, differences in electricity consumption within a cluster are related to the occupancy behaviors of households. To capture utilization consumption patterns that help load diversity within the cluster, the user can change for each building (a) the occupancy profile and internal gains, (b) daily set-point temperature, and (c) the DHW draw profile. First, to consider (a) occupancy profiles and internal gains, the user can model their time trends through external tools such as richardsonpy (RWTH-EBC, 2017). Specifically, that tool provides stochastic occupancy profiles based on input parameters such as time step and number of occupants. These profiles distinguish between active and inactive occupancy states. From the occupancy models, utilization profiles of appliances and lighting are generated based on time-use data, allowing the calculation of electricity demand (Richardson et al., 2008) and related internal gains (RWTH-EBC, 2022). Meanwhile, (b) daily set-point temperatures are associated with each building. Selected temperature profiles for SH and SC are available in ClustEnergy OpTool database, otherwise they can be generated through probabilistic distribution, once main temperature and standard deviation are assigned. Alternatively, the user can set a fixed thermostat temperature for the entire simulation period. Finally, a (c) DHW draw profile can be considered for each building. For this purpose, water tapping profiles are available in the tool database. Otherwise, they can be defined according to occupancy and maximum daily water consumption (e.g., 200 l/day). During active occupation of the building, an amount of water to be consumed is randomly assigned, according to the probabilities determined from the profiles outlined in EN 15316-3-1 (UNI, 2008). These profiles allow each type of activity (e.g., handwashing, showering, housekeeping, etc.) to be paired with an amount of water based on the time required to perform the activity. To generate (b) daily set-point temperatures and (c) DHW draw profiles according to the methodologies described, useful modeling scripts are released together with ClustEnergy OpTool.

## 2.6 PV Generation and Price Signal

Through ClustEnergy Optool, aggregated electrical loads can be flexibly managed under the influence of (a) solar PV generation and (b) price signal. For this purpose, in addition to selecting the DR strategy to be applied (see Section 2.7 below) the user is required to set parameters to generate useful profiles for demand shifting. To consider solar PV generation, the user can specify the peak power (kWp) of the system for each individual archetype. To size the system, the user can decide whether to perform a calculation of the minimum required PV power under the Italian standard D.Lgs. 199/2021 (DL, 2021) via the tool. Specifically, the building area is multiplied by a K factor (0.05 for new buildings and 0.025 for existing buildings) to determine the minimum peak power (kWp) of the PV system to be installed. At this point, a (a) solar PV generation profile is created. Specifically, ClustEnergy OpTool simulate the performance of PV generation systems by using the Python library pylib (F. Holmgren et al., 2018) for the reference location. Finally, to shift the electricity demand in response to a (b) price signal, it is essential to establish electricity rates. Specifically, a bi-hourly Time Of Use (TOU) rate is being considered in ClustEnergy OpTool, which involves defining time intervals and corresponding electricity prices (e.g., Eur/kWh) within the parameters.

#### 2.7 Demand Response

Starting from the electrical demand (Pele,th,BL and Pele,tank,BL in Sections 2.3 and 2.4 respectively) of a baseline (BL) scenario, for each day of simulation, the peak time and magnitude of the aggregated electric consumption baseloads are identified. At this point, the user can estimate the energy demand in presence of different DR strategies available in the tool. These include peak-shaving, load-shifting based on PV generation, load-shifting based on price signal and loadshifting according to a price signal and centralized PV generation. In applying these DR strategies with the aim of limiting rebound effects, users might achieve a maximum peak load threshold through a limiting factor (flimit). To unlock energy flexibility, the thermostat flexibility is guaranteed. According to the objective function and thermal load considered (i.e., cooling or heating), during the DR event the set-point of indoor air temperature is allowed to increase or decrease in a pre-defined dead band. Optimal control is proposed to flexible manage the cluster. For this reason, the problem formulation in Section 2.2 is modified according to the strategy set by the user. The following is a brief description of the strategies available in the ClustEnergy Tool along with useful parameters for their execution.

#### 2.7.1 Peak-shaving

There is a minimization of electricity consumption. The LP-based control ensures that the aggregated electrical demand remains below a percentage of reduction ( $f_{red}$ ) during the period defined by the user (Ercoli et al., 2023).

#### 2.7.2 Load-shifting under PV generation

There is a minimization of grid-based electricity demand (i.e., maximization of individual or collective self-consumption). Two DR scenarios can be selected to evaluate a (a) distributed or (b) centralized PV generation (Ercoli et al., 2023). With distributed PV generation, each family has its own RES-based electricity source. However, with centralized PV generation, the energy source is shared by the cluster buildings. To apply this scenario, it is mandatory to size the PV generation system.

#### 2.7.3 Load-shifting based on price signal

The cost in grid-based electricity bills is minimized. Consequently, to apply this scenario it is mandatory to set the electricity rates (Section 2.5).

## 2.7.4 Load-shifting under price signal and centralized PV generation

The cost in grid-based electricity bill is minimized by considering the price signal and centralized PV production (sharing of the energy resource). Then, aggregate loads are constrained as follows:

 $\forall b: 0 \leq \sum_{b}^{N} Cost_{b} \leq (P_{ele,b} - u_{PV,b} \cdot P_{gen,PV}) \cdot C_{grid}(11)$ 

where N is the number of buildings composing the cluster and  $u_{PV}$  is the utilization factor of centralized PV generation. C<sub>grid</sub> is the bi-hourly electricity price set by the user (Section 2.5). Finally, centralized power demand is constrained to avoid exceeding the PV production as follow:

$$\forall b: \sum_{b}^{N} u_{PV,b} \leq 1 \tag{12}$$

#### 2.8 Performance Indicators

Once the necessary input parameters have been defined, simulations can be performed to calculate the power curves (i.e., thermal, electrical and PV consumption curves) for baseline and DR scenarios (both at the aggregate and individual building level). At this point, from the comparison of the results it is possible to evaluate the reserve of flexibility offered by the cluster of buildings. Several performance indicators can be evaluated, useful during energy resource allocation processes. Based on the selected DR strategy, it is possible to evaluate:

- Thermal and electrical demand for SC or SH, and DHW production during BL and all DR scenarios.
- Thermal and electrical power trends during BL and DR all scenarios.
- Collective or distributed PV self-consumption (DR scenarios described in Sections 2.7.2 and 2.7.4).
- Collective or distributed PV self-sufficiency (DR scenarios described in Sections 2.7.2 and 2.7.4).
- Distribution of PV electricity among buildings in case of shared energy resources (e.g., centralized PV generation).
- Cost of electricity bill (DR scenarios described in Sections 2.7.3 and 2.7.4).
- Indoor air temperature trends during BL scenario and all DR scenarios.

## 3. Example Of Application

To show the functionality of the tool, a simple cluster is evaluated for the scenario of cost reduction in grid-based electricity bill by considering the price signal and centralized PV production (Section 2.7.4). Given that summer is the period with more PV production, the case of aggregate electric loads for SC is analyzed. In addition, DHW production is considered. Accordingly, the inputs provided are:

- Location and simulation period: Turin (45° 04' N, 7° 40' E, Italy), 28 of July with a time-step of 15 mins.
- Cluster definition: 8 buildings (Table 2).
- HP for space cooling: sizes chosen from those available in the tool (table 4) with a supply temperature of 18 °C.
- Thermostat set point: random allocation according to normal distribution (mean temperature of 26 °C and standard deviation of 0.15 °C) (see Section 2.5).
- Baseline and DR thermostat tolerances: upper tolerance of 0.00 °C and lower tolerance of 1.50 °C. The same tolerances are considered during the application of the DR strategy.

- HP water heater for DHW production: considered with a tank temperature of 60 °C and inlet cold-water temperature of 15 °C. Characteristics of a HP water heater in Table 1.
- Occupancy profiles and related internal gains: calculated considering 4 inhabitants per building (see Section 2.5).
- Electricity price rates: day-price (from 8 am until 11 pm) of 0.0286 €/kWh, night-price (from 11 pm until 8 am) of 0.011 €/kWh (Enel, 2024).
- PV system: sized according to the standard considering 396 W monocrystalline panels (centralized system size of 23.76 kW).
- No limitation of rebound effects (high value of flimit).

Table 2 – Number of archetypes composing the reference cluster and related HP characteristics referring to an ambient temperature of 35  $^{\circ}$ C and a supply temperature of 18  $^{\circ}$ C

SFH class year	Buildings number	HP rated capacity (kW)	HP rated COP
1946–1960	4	14.22	3.43
1976–1990	2	14.22	3.43
1991–2005	1	11.50	2.94
2006–today	1	10.00	2.70

Table 3 - Aggregated demand for electricity (Pele), the PV collective self-consumption, PV collective self-sufficiency and the cost in electricity bill

	BL scenario	DR scenario
Electricity demand	170.35 kWh	389.24 kWh
Collective PV self-consumption	16.86%	64.25%
Collective PV self-sufficiency	57.28%	95.55%
Electricity bill	1.89 Eur	0.47 Eur

To reduce the influence of initial conditions on the results, the simulation is initialized on the previous day (i.e., July 27). Table 3 shows some results among those mentioned in Fig. 1 and Section 2.8 (e.g. aggregated electricity demand, PV collective self-

consumption, PV collective self-sufficiency and aggregated electricity bill). In addition, Fig. 4 shows (a) the trends of aggregate electricity during the BL and DR scenarios and (b) the allocation of PV electricity among cluster buildings during DR scenario. To achieve an electricity bill reduction of 74.99% during the DR scenario, there is an increase in collective PV consumption (Table 3), having a shift in aggregate loads toward RES production hours (Fig. 4a). Fig. 4b illustrates the distribution of PV electricity, that is influenced by the construction type (Section 2.1) and utilization patterns (Section 2.5).



Fig. 4 – (a) Aggregate electric power trends for SC and DHW production during baseline and DR scenarios and (b) distribution of PV electricity among cluster buildings during DR scenario

## 4. Conclusion

As part of the energy transition, flexible management of significant amounts of energy may involve moving to a building cluster level. However, deploying the flexible resources required for aggregate electrical management can be difficult. Therefore, this paper introduced ClustEnergy OpTool, an open simulation tool designed to evaluate the energy flexibility provided by a cluster of buildings. Based on a previous work, the released version of the tool includes a set of features aimed at representing a wide range of scenarios in which cluster energy flexibility is unlocked via demand management strategies. By defining the parameters of a representative cluster (e.g., building archetypes, thermostat settings, thermal emission systems, and DHW production evaluation) for a specific location, the user can assess the effects of the selected DR strategy (e.g., peak shaving or demand shifting). Proposing a control approach based on Linear Programming, the tool optimizes the distribution of energy resources between cluster buildings. In this sense, the tool can prove valuable in the decisionmaking processes of allocating energy resources and evaluating the rebound effects (such as energy shift and peak displacement) of DR strategies. Furthermore, the tool estimates photovoltaic self-consumption and reductions on the electricity bill, based on the selected DR strategy. Currently, the tool offers a wide heterogeneity through its database. However, as a flexible open-access tool, it can be modified according to specific needs of the user by following the proposed methodology. For more information on ClustEnergy OpTool, both tool and documentation are released on GitHub (Mugnini et al., 2024).

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# The Role of Dynamic Primary Energy Factors (PEFs) in Building Performance Assessment: A Case Study

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#### Abstract

The adoption of primary energy factors (PEFs) is very common in the building sector since primary energy is one of the main metrics for evaluating the energy performance of a building. The use of such factors is extensive in European and international legislative contexts to establish a regulatory framework for enhancing building energy efficiency policies. This study analyses how the use of dynamic PEFs, variable on an hourly basis, affects the assessment of building performance. The dynamic primary energy factor for electricity has been evaluated for the Italian scenario during the year 2022, applying the methodology outlined in the EN 17423:2020 standard with an hourly detail. The conversion factor was subsequently applied to the electricity demand of a reference building for residential use. The result obtained has been compared with the same evaluations carried out using the static conversion factors currently adopted by the legislation in force, showing that there is an urgent need for adjustment. The dynamically assessed total PEF stopped at an average value of 1.84, in contrast to the 2.42 used in current legislation. As a result, the total primary energy demand of a reference building decreases by 23.07%, also involving an alteration of the ratio of renewable to non-renewable share. The study concludes that the use of dynamic PEFs is essential for both the design of new buildings and the assessment of existing buildings, especially when time-dependent HVAC, renewable energy and control strategies are considered. It also allows for better energy flow management within buildings. Finally, the study emphasizes that up-to-date PEFs are crucial for improving the energy efficiency of buildings and guiding the future decarbonization of the building stock.

#### 1. Introduction

Primary energy represents a fundamental metric in the field of building performance, accounting for all energy inputs from the initial raw fuel sources to the final delivered energy services. This measure is of critical importance in evaluating the energy performance of buildings, understanding their environmental impact, and ensuring compliance with evolving energy policies. The assessment of primary energy consumption not only facilitates a comprehensive understanding of a building's energy demand but also aids in the comparative analysis of energy performance across different buildings. Within this topic, the significance of primary energy conversion factors (PEFs) is evident. These factors quantify the efficiency of converting primary energy sources into secondary energy carriers (Costantino et al., 2023). They play a double role: they provide a realistic measure of the energy performance of buildings and influence the perceived competitiveness of various energy technologies in the market. However, the use of primary energy factors (PEFs) has been the subject of debate, with numerous studies suggesting that they may obscure the true energy performance of buildings. This is because PEFs can vary significantly between regions and over time, reflecting the changing efficiency of energy conversion technologies and the political landscape (Bilardo et al., 2022; Baralas et al., 2023). Consequently, while PEFs are currently employed in energy performance calculations mandated by policies, there is a necessity to continue to explore their nature and their ongoing evolution, so that they can be more aligned with the objectives of reducing energy demand and promoting energy efficiency.

#### 1.1 Motivation of the Work

In recent decades, building performance assessment has transitioned from relying solely on static evaluations of energy supply and demand to accepting dynamic analysis. This shift is crucial not just for researchers but also for designers, as it enables a more accurate estimation of energy requirements of buildings that are highly interlinked with the energy networks and works as both producers and consumers of various forms of energy at different times (Bilardo et al., 2021). While dynamic building performance assessment has become widely accepted and practiced, a significant gap persists in its application to primary energy considerations.

Historically, the focus of dynamic analysis has been on final energy aspects, often overlooking the complexities associated with the energy supply and the primary energy. This oversight is evident in the prevalent use of static conversion factors to translate final energy into primary energy. To achieve a comprehensive understanding of building performance, it is essential to extend the dynamic approach, commonly applied to final energy, to primary energy requirements. This can be fulfilled by employing dynamic conversion factors (Noussan et al., 2018; Marrasso et al., 2019) that accurately reflect the energy flows utilized within buildings. By doing so, it is possible to enhance the precision and relevance of building performance assessments, providing the opportunity for the next generation of decisionmaking processes in future building design and operation.

Another crucial aspect of evaluating the performance of buildings in terms of primary energy is the electrification process, which is being supported by regulations, directives, and laws in many countries around the world. The transition towards an increasingly electrified building system is one of the primary solutions currently being pursued to mitigate fossil fuels and support decarbonization. The electric energy carrier, whose use in the construction sector is set to increase significantly in the coming years, is however highly variable, both in terms of generation and use. The strong penetration of renewable sources and the increase in variable electrical loads inside buildings (for example, electricitybased air conditioning systems) make this vector highly sensitive to the time factor. Therefore, the importance of dynamically evaluating coherent and reliable conversion factors of this specific vector takes on particular relevance in the performance assessment procedure.

Current advancements suggest that tools and methodologies for dynamic evaluation of primary energy conversion factors are readily accessible. Transmission System Operators (TSOs) and institutional databases, such as eGrid for the US and entso-e for the EU, provide public and frequent updates on electricity flows. Furthermore, regulatory initiatives, exemplified by the European standard EN 17423:2020 (CEN, 2020), emphasize the determination and reporting of Primary Energy Factors (PEF) and CO<sub>2</sub> emission coefficients through a defined framework that can be replicated in different contexts.

The motivations behind the development of this work can be summarized as follows:

- The use of static and dated conversion factors fails to align with the actual behavior of buildings and the significant efforts made towards a sustainable energy transition.
- The electric energy carrier, a key player in the decarbonization of the building sector, exhibits highly dynamic generation and use trends.
- To overcome the historical discrepancy between design and operation performance, and to optimize energy flows within buildings, it is imperative to consider the dynamics of the energy sources employed.

#### 1.2 Objectives and Paper Structure

The objective of this paper is to demonstrate the importance of dynamic primary energy conversion factors for the energy assessment of buildings. In order to achieve this, the following aspects will be addressed:

- Emphasizing the importance of utilizing dynamic primary energy conversion factors for accurate and relevant energy assessments of buildings.
- Conducting a comparative analysis between traditional evaluation methods, based on static conversion factors, and the proposed dynamic evaluation method, highlighting their respec-

tive advantages and limitations within the context of the Italian regulatory framework.

 Exploring detailed analysis on primary energy flows within buildings to inform future optimization and regulation strategies.

In order to achieve these objectives, Section 2 details the materials and methods utilized for the analysis. A dynamic primary energy assessment is conducted for a reference building in Italy that is fully electric, examining scenarios with and without on-site renewable energy generation. Section 3 presents the results of the study, offering a comparative analysis with traditional evaluation methods currently mandated by the Italian regulatory framework, which rely on static conversion factors (Section 3.1). Furthermore, the potential and adaptability of the proposed dynamic evaluation method are highlighted (Section 3.2). The insights derived from this analysis will support new guidelines and recommendations for future energy performance assessments of buildings, as discussed in Section 4.

## 2. Material and Methods

## 2.1 Methodological Framework for Dynamic Primary Energy Assessment

The methodological framework employed to assess the energy performance of the building utilizes the source energy balance as the principal assessment tool. The application of the source energy balance requires the identification of primary energy conversion factors, which are necessary for the calculation of numerical operations between different energy flows. Furthermore, the proposed method aims to guarantee a resolution of the balance on an hourly basis. This is achieved by evaluating the energy flows involved and the conversion factors in consistency with the chosen analysis timestep (Bilardo et al., 2024). Eq.1 provides a mathematical expression of the source energy balance that reflects all the elements involved in the assessment:

$$E_{bal,P}(t) = \sum_{i} E_{exp,i}(t) \cdot f_{P,i}(t) - \sum_{j} E_{imp,j}(t) \cdot f_{P,j}(t)$$
(1)

where:

- *E*<sub>exp,i</sub> and *E*<sub>imp,j</sub> represent the i-th and j-th exported and imported energy flows within the physical source boundary, respectively.
- $f_{P,i}$  and  $f_{P,j}$  represent the primary energy conversion factor of the i-th and the j-th energy flow.

The dynamic resolution of the balance will be carried out on an hourly basis for an entire year, identified by the time variable t = 1 to 8760.

The methodology employed in this study involves two key variables: energy flows and conversion factors. These variables can be sourced from various methods, including monitoring campaigns, numerical simulations, or standardized regulatory schemes. Regardless of their origin, it is crucial that both energy flows and conversion factors share a consistent analysis timeframe that aligns with the realistic dynamic evolution of the building entity.

Fig. 1 delineates the boundaries of the source energy flow, including both on-site renewable generation systems and conversion systems. As a convention adopted in this paper, the positive results of the energy balance represent an export from the building to the external grid. Conversely, a negative balance describes an energy import from the grid to the building.



Fig. 1 - Source energy balance boundary - generic

## 2.2 Case Study and Methodological Choices

The proposed methodology was applied to a specific Italian case study—a medium-sized, fully electric residential building situated in Bolzano province. The case study of an all-electric building with onsite renewable self-production systems is of particular interest for two reasons. Firstly, the electric-
ity carrier is very sensitive to variations in primary energy. Secondly, the decarbonization process required by the recent Energy Performance of Building Directive (EPBD) relies on a strong electrification of the building stock (European Parliament, 2024). This building features a maximum power meter of 6 kW and is equipped with a 9 kWp photovoltaic (PV) system installed on its roof.

The energy flows for this case study were determined using the following approaches:

- Total electricity demand was derived from statistical monitoring data provided by the Italian regulatory authority for energy networks and the environment (ARERA, 2023). Specifically, average hourly electricity consumption for a residential user accessing the free energy market in 2022 within the province of Bolzano was selected.
- The average hourly output of the PV system was simulated using the PVGIS tool. This simulation considered a 9 kWp system with a fixed slope angle of 40° facing south, also estimating system losses at 14%.

In terms of primary energy conversion factors, the following selections were made. The conversion factor applied to weigh the electricity exported to the grid utilized the avoided burden approach. This approach assumes that exported energy has an equivalent impact, in terms of primary energy, as imported energy, thus employing the same conversion factor for both flows. Furthermore, the conversion factor associated with energy exports is considered fully renewable. The conversion factor used to weigh the electricity imported from the grid was determined by applying the standard EN 17423:2020. This involved utilizing energy flow data related to the generation, import, and export of the Italian national electricity system, made available by the Italian Transmission System Operator (TSO) Terna (Terna, 2021). The application of this standard facilitated the derivation of the hourly dynamic trends for renewable and non-renewable shares of the conversion factor into primary energy for the electricity vector, as evaluated using Eq. 2 and 3.

$$f_{p,nren,el} = \frac{\sum_{j} (E_{in,el,j}) f_{p,nren,in,el,j} - \sum_{j} (E_{exp,el,j}) f_{p,nren,exp,el,j} + \sum_{j} (E_{pr,el,j}) f_{p,nren,pr,el,j}}{E_{delel}}$$
(2)

$$f_{p,ren,el} = \frac{\sum_{j} (E_{in,el,j}) f_{p,ren,in,el,j} - \sum_{j} (E_{exp,el,j}) f_{p,ren,exp,el,j} + \sum_{j} (E_{pr,el,j}) f_{p,ren,pr,el,j}}{E_{del,el}}$$
(3)

Detailed numerical procedures and the rationale behind the chosen calculations have been previously discussed in studies published by the authors (Bilardo et al., 2022, 2024). Fig. 2 provides a clear overview of how energy is managed within the context of the case study, offering insights into the various quantities involved in the source energy balance assessment. In order to better study the impact of the use of dynamic hourly conversion factors, this study also includes an initial comparison with static and outdated conversion factors.



Fig. 2 - Source energy balance boundary - case study application

These static factors are defined within Italian national legislation by the inter-ministerial decree dated 26 June 2015, commonly referred to as the Minimum Requirements Decree. According to this decree, conversion values of 1.95 are assigned to the renewable share and 0.47 to the non-renewable share when converting energy flows associated with the electric energy vector.

## 3. Results

This section presents the results of the proposed assessment methodology, focusing on the impact of dynamic primary energy conversion factors on building performance assessment. The methodology described earlier was applied to the case study introduced in the previous section.

The initial results belong not to the building itself but to the hourly trend of the adopted conversion factors, evaluated using the standardized methodology outlined in EN 17423:2020 (CEN, 2020) applied using data from year 2022. Fig. 3 illustrates the dynamic trends of the renewable (in green) and nonrenewable (in red) shares of the conversion factors associated with the electric energy carrier. The graph compares these dynamic values with the static quantities mandated by current Italian regulations, represented by the solid red and green lines. It is evident from the comparison that the static and outdated values, proposed in 2015, significantly exceed the calculated dynamic hourly values. Specifically, the average values for the non-renewable and renewable shares stop at 1.51 and 0.34, respectively. This discrepancy highlights the advancements in energy transition policies that have enhanced the efficiency of the national electricity system in recent years. The conversion factor values depicted in Fig. 3 are crucial variables for resolving the primary energy balance of the case study building in subsequent analyses.



Fig. 3 – Comparison of static and dynamic values of renewable and nonrenewable primary energy conversion factors during 2022

# 3.1 Static Vs Dynamic Primary Energy Assessment

Assessing the primary energy demand to meet the building's need is a key indicator used within the European Union for building evaluation and classification. In this section the annual absolute value of primary energy demand has been evaluated for the year 2022, taking into account the case study building capacity for self-consumption of electricity from a photovoltaic system. This allowed for the determination of the actual electrical energy required by the building to satisfy its load. The assessment, conducted on an hourly basis, revealed a significant mismatch between energy generation and consumption for the average reference building, resulting in an annual electricity demand of 10.10 MWh (final energy in Fig. 4).

By applying both static and dynamic conversion fac-

tors, the primary energy demand was assessed in terms of its non-renewable and renewable shares. Fig. 4 presents the results of this assessment, which align with earlier considerations.

Firstly, the application of dynamic conversion factors led to a reduction in the total primary energy demand, consistent with the previously discussed values (19.70 MWh (nren) + 4.75 MWh (ren) in the static evaluation compared to 15.70 MWh (nren) + 3.11 MWh (ren) in the dynamic evaluation). However, secondly, the percentage of primary energy demand covered by renewable energy decreased from 19.4% with static factors to 16.5% with dynamic ones. This reduction makes the use of updated dynamic factors less "advantageous" but more consistent with the effective energy use of the building. This outcome is attributed to the hourly resolution of the energy balance, which prevents the renewable share from compensating for the energy demand satisfied primarily by non-renewable sources. The proposed methodology, which aligns with the dynamic evolution of building energy flows, rewards consumption profiles that align with national renewable generation patterns. However, this was not observed in the analyzed case study, underscoring the need for further optimization to fully capitalize on renewable energy sources.



Fig. 4 – Renewable (green) and non-renewable (red) primary energy demand assessed over the course of a year on an hourly basis on the basis of final electricity demand (in grey)

# 3.2 Dynamic Trends for Primary Energy Flows

In order to better explore the potential and significance of a dynamic primary energy assessment, it is therefore necessary to shift the focus to a more detailed type of analysis that better visualizes the behavior of the building on an hourly basis. This section presents a specific focus on two days of the winter and summer season taken as a reference to better describe the previous yearly aggregate results.

In Fig. 5, two represented days of the winter season have been identified, showing the development of the hourly primary energy balance using both dynamic (left in Fig. 5) and static (right in Fig. 5) conversion factors. The balance was resolved in both its renewable and non-renewable portions. For greater understanding, the hourly trends of the conversion factors (bottom of Fig. 5) are also shown, as well as the value of final electrical energy (dashed black line) before undergoing the conversion process.

From the trend of the energy balance in Fig. 5, it can be seen that the ratio of renewable to non-renewable share varies during the hours of the day in the dynamic conversion condition, while it remains constant when using static factors.

The central hours of the day, characterized by a surplus in photovoltaic production, guarantee renewable primary energy export values (positive values in the graph).



Fig. 5 – Comparison between the application of dynamic (left) and static (right) conversion factors for the dynamic evaluation of the primary energy balance – application for two days during the winter season

As it is evident, during night hours the renewable share in the dynamic case decreases due to lower renewable inputs to the national electricity grid.

A slightly different scenario is depicted in Fig. 6, where the two-day trend of the summer season is shown. Even in this scenario, while the previous considerations remain valid, a greater variability of the renewable share can be observed, demonstrated by a dynamic conversion factor that is more sensitive to daily variation (probably due to the impact of photovoltaic systems on the national system).

From the trend shown in the Fig. 6, it can also be deduced that during the first day of the analysis, the building's needs could not be fully covered during the central hours of the day.

This situation, generated by a daily drop in onsite generation (due to the peculiar climatic conditions of the case study during those hours) demonstrates the effectiveness of the method in capturing possible performance variations, in line with the real behaviour of the building

#### Summer season (2 days)

12

10





with static factors

Fig. 6 – Comparison between the application of dynamic (left) and static (right) conversion factors for the dynamic evaluation of the primary energy balance – application for two days during the summer season

## 4. Discussion And Conclusions

This paper focused on assessing the primary energy demand for buildings, a widely recognized indicator used globally to evaluate and rank building performance. Specifically, it has explored how energy flow conversion factors into primary energy must align with the dynamic and realistic trends of energy generation and utilization within buildings. Utilizing static and outdated conversion factors fails to capture the complexity of building performance. To address this, a dynamic evaluation method based on the primary energy balance solution was proposed, combining variable PEFs with hourly energy flows. An Italian reference case study was selected to validate the reliability of this method.

The analysis of the dynamic primary energy balance revealed the indicator's sensitivity to conversion system variability, challenging the validity of current traditional methods and highlighting the need for more dynamic approaches to building performance assessment.

The results presented in this paper offer valuable insights into understanding building performance, but they represent just one aspect of the broader picture. Many of the considerations discussed here can also be applied to assess a building's environmental impact, specifically its emissions contribution.

Evaluating a building's emissions requires the use

of conversion factors, such as those for CO<sub>2</sub> or CO<sub>2,eq</sub> (Bilardo & Fabrizio, 2023). This process shares similarities with the considerations made in this study, particularly concerning the dynamic nature of emission factors. Findings of this study open the way for developing reliable, realistic, and detailed analyses of building energy performance. In this context, building performance simulation plays a key role in facilitating the adoption of dynamic PEFs. Simulation tools can easily integrate accurate and dynamic conversion factors to calculate the true energy and environmental demand of a building during a specific period of analysis. Building performance simulation also has the important responsibility of integrating a holistic evaluation process to correctly assess the optimization processes of renewable energy use, as well as more realistic advanced regulation and control systems. This is necessary in order to finally achieve an accurate process of predicting primary demand in real time.

#### 4.1 Future Developments

Future research starting from this work will explore related topics that necessitate further investigation, such as:

 Predicting and forecasting conversion factors to generate realistic values, facilitating more resilient design approaches adaptable to future changes.  Optimizing energy flows to minimize primary energy requirements not only during the design phase but also throughout the building's operational lifespan.

These research lines offer promising directions for advancing the field and enhancing the energy efficiency and sustainability of buildings through a more accurate evaluation of the energy exchanges of the building within the districts.

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## Nomenclature

## Symbols

EPBD	Energy Performance of Building
	Directive
PEF	Primary Energy Factor
$CO_2$	Carbon dioxide
Ε	Energy
f	Conversion factor
t	Time

## Subscripts/Superscripts

Р	Primary
eq	Equivalent
ren	Renewable
nren	Non-renewable
del	Delivered
el	Electricity
pr	Production
i	i-th energy flow

in	Input
j	j-th energy flow
imp	Imported quantity
exp	Exported quantity
bal	Balance quantity

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# Modeling a Dew Point Indirect Evaporative Cooling System for TRNSYS Building Simulations: Proposal and Validation

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#### Abstract

This paper aims to develop a mathematical model of a dew-point indirect evaporative cooler that can be easily implemented in a TRNSYS building simulation environment. The model is validated against experimental data from a tested mixed flow prototype. The results show that the model is consistent with the experiments with an error in the primary air temperature drop between 12% and 18%. Furthermore, a parametric analysis is performed to evaluate the effect of the size of the device. The temperature drop may double by increasing three times the height or the width of the device. In conclusion, this study reveals the importance of a proper calculation of the Nusselt Number, especially for the wet channel.

## 1. Introduction

In order to reduce the cooling energy consumption in buildings and the greenhouse emissions during the whole lifecycle of the cooling systems, efforts should be made to improve their effectiveness and reduce their environmental impact. In this direction, conventional cooling systems that are based on vapor compression cycles and use chemical refrigerants may not be the best solution in terms of energy-saving and carbon neutrality. Among the possible alternative cooling systems, evaporative coolers have gained interest in recent years due to the possibility of cooling down the ambient air by taking advantage of water evaporation: today, they mainly find application as a stand-alone system, but also in combination with other cooling devices.

A particular kind of evaporative cooler is called a "dew point indirect evaporative cooler" (DPIEC). Being an indirect evaporative cooler, it consists in a heat exchanger composed of two distinct and adjacent channels: the primary air stream flows in the dry channel, while the secondary air stream flows in the wet channel where it comes in contact with water. Differently from direct evaporative cooling systems - where water is sprayed directly in the primary air- this technology does not increase the humidity ratio of the supply air. Furthermore, a DPIEC has the advantage of providing high performance in terms of temperature drop between primary air inlet and outlet. In fact, in direct and conventional indirect evaporative coolers the temperature drop can approach the wet bulb depression; instead, in a DPIEC the primary air outlet temperature can ideally achieve the dew point temperature associated with the inlet conditions. This happens because in the DPIEC a portion of the primary air in the dry channel is diverted into the wet channel to form the secondary air flow, which allows secondary air to be pre-cooled.

Although dew point evaporative coolers were largely investigated at component level, few studies focused on the performance ensured by a building where the system is applied. This gap could probably be due to the absence of a component able to properly simulate a dew-point indirect evaporative cooler in the common building simulation tools, such as TRNSYS. Indeed, a similar component –Type 757 of the TESS libraries – can model a conventional indirect evaporative cooler by knowing its wet bulb effectiveness. However, this component is not suitable to model a dew point indirect evaporative cooler, especially when its effectiveness is not known *a priori*. Therefore, this work aims to develop a mathematical model of a dew-point indirect evaporative cooler that can be easily implemented in TRNSYS building simulation environment. The mathematical model is here described and validated against experimental data and allows predicting the outlet conditions of the supply air that can then be used as an input in the dynamic building simulations. Furthermore, based on the model, a parametric analysis is performed to evaluate the effect of the dimensions of the device.

#### 2. Methodology

The mathematical model presented in this study relies on the mass and energy balance equations and on the logarithmic mean temperature difference method (Jie & Chua, 2023). By knowing the heat transfer area (A) and the heat transfer coefficient (K) of the heat exchanger, the model can apply to other DPIECs with different configurations. The code is written in Python programming language, so that it can be easily called in TRNSYS Simulations Studio by Type 169 (TRNSYS 18). The model is validated against experimental data from a mixed-flow prototype.

## 2.1 Description of the Dew Point Indirect Evaporative Cooling System

The following figures show a schematic representation of the DPIEC modelled in this study (Fig. 1) and a detail of dry and wet channel (Fig. 2). The DPIEC consists of a heat exchanger with adjacent dry (primary) and wet (secondary) channels. Firstly, the inlet air enters the dry channels and is sensibly cooled down by the secondary air. After that, a portion ( $\eta$ ) of the primary air is diverted into the wet channels to form the secondary air, while the remaining portion  $(1 - \eta)$  of the primary air is blown to the indoor environment. Moreover, a water distributor irrigates the wet channels. In this way, the secondary air is evaporatively cooled down. The exceeding water falls in a tank where it is stored. At the end, a pump allows the water to re-circulate from the tank up to the distributor. Fig. 3 shows the primary air path (IN  $\rightarrow$  OUT-1) and the secondary air path (OUT-1  $\rightarrow$  OUT-2) in the psychometric chart; the inlet secondary air point corresponds to the outlet primary air conditions (OUT-1).





Fig. 1 - Schematic representation of DPIEC



Fig. 2 - Schematic representation of dry and wet channels



Fig. 3 – Psychometric chart from SICRO\_V2\_1\_3 (University of Valencia, Spain)

# 2.2 Mathematical Development

The mathematical model developed here requires the following input data:

- the inlet air hygrometric conditions, in particular dry bulb temperature, relative humidity, and pressure;
- the inlet air mass flow rate;
- the features of the device, i.e. working-tointake air ratio (η), heat transfer area, and heat transfer coefficient;
- the water inlet temperature.

Furthermore, the following assumptions hold:

- 1) steady-state conditions;
- 2) adiabatic heat exchanger;
- 3) saturation of the secondary air;
- no water losses between primary and secondary channel (primary process perfectly at constant humidity ratio);
- 5) water temperature is known and constant.

The energy balance applies to the control volume indicated in Fig. 1 and is given by Eq. 1:

$$\dot{m}h_{in} + \dot{m}_{w,in}h_w =$$

$$= (1 - \eta)\dot{m}h_{out1} + \eta\dot{m}h_{out2} + \dot{m}_{w,out}h_w (1)$$

Here,  $\dot{m}$  is the inlet air mass flow rate,  $\dot{m}_{w,in}$  is the inlet water mass flow,  $\dot{m}_{w,out}$  is the outlet water mass flow,  $\eta$  is the working-to-intake air ratio, and  $h_{in}$ ,  $h_{out1}$ ,  $h_{out2}$  are the specific enthalpy values of the inlet humid air, the outlet primary humid air, and the outlet secondary humid air respectively. Finally, $h_w$  is the specific enthalpy of the inlet and the outlet water that is considered constant, coherently with the steady-state hypothesis.

By introducing the mass balance in the secondary channel (Eq. 2), the energy balance can then be re-written as in Eq. 3:

$$\dot{m}_{w,in} - \dot{m}_{w,out} = \eta \dot{m} (x_{out} - x_{in}) = \eta \dot{m} \Delta x \quad (2)$$
$$h_{in} = (1 - \eta) h_{out1} + \eta (h_{out2} - \Delta x \cdot h_w) \quad (3)$$

With  $x_{in}$  inlet humidity ratio,  $x_{out}$  outlet humidity ratio and  $\Delta x = x_{out} - x_{in}$ . Therefore, the enthalpy of the primary outlet air is given by Eq. 4:

$$h_{out1} = \frac{h_{in} - \eta \cdot (h_{out2} - \Delta x \cdot h_w)}{(1 - \eta)}$$
(4)

This relation is not sufficient to solve the problem because the secondary outlet air conditions appearing in Eq. 4 are not known. The equation can be solved iteratively by supposing an outlet secondary air temperature  $T_{out,2}$  (which is sufficient to determine the associated enthalpy because of the hypothesis of saturation condition) and by finding a further equation to verify the exactness of this value. Such further equation can be derived by the logarithmic mean temperature difference method (Jie & Chua, 2023), in which the heat transfer rate between primary and secondary channel is given by Eq. 5:

$$\dot{q} = KA \cdot \Delta T_{lm} \tag{5}$$

Where K is the overall heat transfer coefficient and A is the heat transfer area. The logarithmic mean temperature difference  $\Delta T_{lm}$  in a DPIEC is defined as in Eq. 6:

$$\Delta T_{\rm lm} = \frac{\Delta T_1 - \Delta T_2}{\ln \frac{\Delta T_1}{\Delta T_2}} \tag{6}$$

With:

 $\Delta T_1 = T_{in1} - WBT_{out2} = T_{in} - T_{out2}$ (7)

$$\Delta T_2 = T_{in2} - WBT_{in2} = T_{out1} - WBT_{out1} \quad (8)$$

In Eq. 7, the wet bulb temperature of the outlet secondary air (WBT<sub>out2</sub>) is equal to its dry bulb temperature  $T_{out2}$  because of the assumption of saturated air in the secondary channel. Since the air conditions in the outlet of the primary channel are the same as the inlet of the secondary channel, in Eq. 8 the wet bulb temperature of the inlet secondary air WBT<sub>in2</sub> is replaced with the outlet primary wet bulb temperature WBT<sub>out1</sub>.

From the energy balance in the primary channel:

$$\dot{q} = \dot{m}(h_{out1} - h_{in}) = \dot{m}(c_a + x_{in}c_v)(T_{out1} - T_{in})$$
(9)

Where  $c_a$  and  $c_v$  are the specific heat of dry air and water vapor, respectively, and  $x_{in}$  is the humidity ratio of the inlet air that is the same as the outlet primary air because of assumption 4. Therefore:

$$\dot{m}(c_a + x_{in}c_v)(T_{out1} - T_{in}) = KA \cdot \Delta T_{lm} \qquad (10)$$

$$\Delta T_{lm} = \frac{\dot{m}(c_a + x_{in}c_v)}{KA} (T_{out1} - T_{in})$$
(11)

In this way the result of Eq. 11 is compared with Eq. 6 until convergence. The method used to iteratively solve the problem is reported in more detail in the next subsection.

#### 2.3 Mathematical Solution

The scheme in Fig. 4 shows the iterative method used to solve the above equations. A guess value for T<sub>out2</sub>– lower than the inlet air temperature T<sub>in</sub>–is assigned thus solving Eq. 4 and calculating h<sub>out1</sub>, hence T<sub>out1</sub>(inlet air has constant humidity ratio, corresponding to the inlet value). Then, two values of mean logarithmic difference temperature  $\Delta T_{lm1}$  and  $\Delta T_{lm2}$  are calculated by Eq. 6 and Eq. 11, respectively. The absolute value of their difference  $\Delta$  is compared to a small threshold value ( $\epsilon$ ). If  $\Delta \leq \epsilon$  the solution is found, otherwise the guess value of T<sub>out2</sub> is incremented by  $\delta$  and the scheme is repeated. In the following  $\epsilon = 0.0001$  and  $\delta = 0.005$  are adopted, respectively.



Fig. 4 - Step-by-step solution scheme

#### 2.4 Description of the Experiment

In order to experimentally validate the mathematical model, a real small-scale prototype was built and tested. The device is composed of overlapped modular elements made with polycarbonate sheets. Each modular element consists of 28 dry channels and a wet plate. In the dry channels, some air paths are blocked, and holes are drilled along the plate to drive part of the primary air through the wet plate. The wet plate is covered with cotton cloth on one side. The upper side is open, thus allowing air to flow out and the water to be supplied. The bottom side, instead, is closed by a rib that is perforated to drain the excess water. Once assembled, the prototype is composed of eight modular elements. The design specifications are summed up in Table 1.

Table 1 - Design characteristics of the tested heat exchanger

Parameters	
Heat exchanger volume	31 x 25 x 30.5 cm
Heat transfer area	1.00 m <sup>2</sup>
Flow configuration	Mixed flow
Dry channel length	30 cm
Dry channel width	9 mm
Dry channel height	9 mm
Number of dry channels	8
Wet channel length	30 cm
Wet channel height	30 cm
Wet channel gap	9 mm
Number of wet channels	8 x 28
Plate thickness	0.5 mm
Channel material	polycarbonate
Wicking material	cotton cloth

A water distributor is installed on the upper side and a water tank on the bottom side. A water pump allows the water to re-circulate from the tank to the distributor. Fig. 5 shows the test bench.



Fig. 5 - Test bench (the air handling unit is not visible)

The experiments are performed by connecting the prototype to an air handling unit that controls the inlet air conditions. Some sensors measure the temperature and relative humidity of the inlet primary air, the outlet primary air, and the outlet secondary air. Furthermore, the total air mass flowrate and the primary air mass flow-rate were measured indirectly by measuring the pressure drop between two orifice plates located respectively before and after the prototype. However, the secondary air mass flow is calculated through the difference between total and primary air mass flow-rate. The operative range and the accuracy of the sensors are reported in Table 2.

The tests are repeated three times, by setting the inlet air temperature at 30 °C, 35 °C, and 40 °C. The measures are taken after 20 minutes to enhance the steady state conditions. The inlet humidity ratio is  $13.2\pm0.8$  g/kg, the total air volume flow is  $6.25\pm0.27$  m<sup>3</sup>/min, the working-to-intake air ratio is about 0.42.

Table 2 - Operative range and accuracy of sensors

Sensor	Range	Accuracy
Static pressure	0/25 hPa	±0.02 hPa or ±1%
Dry bulb temperature	-20/+55°C	±0.4 °C
Air relative humidity	0/100%	±2% RHat +25 °C

# 2.5 Calculation of the overall heat transfer coefficient

The overall heat transfer coefficient K between wet and dry channels is calculated as in Eq. 12:

$$K = \frac{1}{\frac{1}{\alpha_{dry} + R_{wall} + \frac{1}{\alpha_{wet}}}}$$
(12)

Here,  $R_{wall}$  is the thermal resistance of the channel wall and is considered negligible due to the small thickness of both the polycarbonate plate and the cloth. Instead,  $\alpha_{dry}$  and  $\alpha_{wet}$  are the convective heat transfer coefficients in the dry and the wet side, respectively, determined as reported in Eq. 13.

$$\alpha = \frac{Nu}{Deq}\lambda \tag{13}$$

with  $\lambda$  thermal conductivity of the air,  $D_{eq} = 4S/P$  the equivalent diameter (being S the transversal section of the channel and P the corresponding perimeter). The equivalent diameter is 9 mm for the dry channel and 19 mm for the wet channel.

The Nusselt Number (Nu) is calculated by considering different sources (Jie & Chua, 2023; Deepak et al., 2022; Kashyap et al., 2020).

According to (Jie & Chua, 2023), the Nusselt Number in a dry channel Nudry is calculated from the following equations:

$$Nu_{dry} = \frac{\frac{Nu_0}{\tan h (2.264Gz^{-\frac{1}{3}} + 1.7Gz^{-\frac{2}{3}})} + 0.0499Gz \cdot \tanh (Gz^{-1})}{\tanh (2.432Pr^{1/6}Gz^{-\frac{1}{6}})} \quad (14)$$

$$Nu_0 = \frac{48}{11}$$
 (15)

$$Gz = \frac{D_{eq}}{L} RePr$$
(16)

Where Re and Pr are the Reynolds and Prandtl numbers respectively, while  $D_{eq}$  is the hydraulic diameter and L is the channel length.

The Nusselt Number inside the wet channel Nu<sub>wet</sub>, however, must be calculated as follows:

$$Nu_{wet} = 0.10 \left(\frac{L_w}{\delta}\right)^{0.12} Re_{Lw}^{0.8} Pr^{1/3}$$
(17)

$$Re_{Lw} = \frac{\rho v}{\mu} L_w \tag{18}$$

Where  $L_w$  is the thickness of the water film– that is not known and difficult to measure, thus its value is supposed as 0.5 mm –  $\delta$  is the total thickness including the water film and the channel wall, and  $\varrho$ , v, and  $\mu$  are respectively the density, velocity, and dynamic viscosity of the air in the wet channel.

However, (Jie & Chua, 2023) assumed a laminar flow regime, generalizing for all DPIECs because of the small section of the channels although a transition flow regime (Re between 2300 to 3500) is found out in the tested device for both wet and dry channels. Since the flow regime is very relevant in the description of the heat exchange (Gicquel, 2021), the model proposed by Jie and Chua might not be very accurate.

Even though the hypothesis of laminar flow is very common in the literature, (Deepak et al., 2022) found out a turbulent flow regime, thus calculating the Nusselt Number with the following equation:

$$Nu = \frac{(f/8)(Re-1000)Pr}{1+12.7(\frac{f}{8})^{\frac{1}{2}}(Pr^{\frac{2}{3}}-1)}$$
(19)

$$f = (0.790 \ln(Re) - 1.64)^{-2}$$
(20)

Nevertheless, the same equation is used in both dry and wet channels, which may also make this model unreliable.

Finally, a different approach is used by (Kashyap et al., 2020), who proposed to use the value of relative velocity of the air with respect to the water film to calculate the Reynolds number in wet channels. In this case the flow regime is laminar, and the Nusselt Number is calculated as follows:

$$Nu = 2 + 0.6 \cdot Re^{0.5} Pr^{0.33} \tag{21}$$

Since it is not possible to know *a priori* the mean temperature of the primary and secondary air flow, the convective heat transfer coefficient is estimated as a function of the temperature for all models. In particular, the Nusselt number is calculated for the temperature of 280, 290, 300, 310 K and a linear function is derived from these values. Even if the variation of the convective heat transfer coefficient which derives by varying the temperature is not very significant, the function is still implemented in the model, for the sake of accuracy. The convective heat transfer coefficient as a function of the mean temperature in primary channel  $T_{m1} = (T_{out1} - T_{in1})/2$  and in secondary channel $T_{m2} = (T_{out2} - T_{in2})/2$  is reported in table.

Table 3 – Calculated convective heat transfer coefficient as a function of the mean temperature in the channel

Model	Dry channel	Wet channel
Jie & Chua	$0.0174 \cdot T_{m1} + 27.034$	-0.0127·T <sub>m2</sub> + 5.9535
Deepak et al.	$-0.124 \cdot T_{m1} + 34.496$	- 0.0563·Tm2 + 12.92
Kashyap et al.	-0.0112·T <sub>m1</sub> +93.806	-0.0039·T <sub>m2</sub> + 39.549

## 3. Results and Discussion

#### 3.1 Model Validation

According to the results of this study, the proposed model to simulate the DPIEC is more consistent with the experimental data in terms of outlet temperature prediction if the Nusselt number is calculated according to (Kashyap et al., 2020).

As reported in Fig. 6, all models tend to overestimate the outlet primary air temperature and underestimate the outlet secondary air temperature. However, the outlet secondary air temperature predicted by the model looks not consistent with experimental data, independently on the Nusselt number calculation. Indeed, the energy balance in Eq. 1 is not closed even by considering the experimental results. This is probably due to inaccuracies in the measurement of the outlet air temperature: in fact, the temperature probe on the air stream is slightly detached from the outlet section (Fig. 5) to avoid any chance that the water spray might wet the sensor. In this way, the measure of the air temperature may be influenced by the air temperature of the laboratory that is warmer than the working air. This hypothesis will be verified in future experiments that will regard a larger and more realistic DPIEC model.



Fig. 6 – Model validation against experimental data. Outlet primary air temperature, outlet secondary air temperature, temperature drop

Looking at the temperature drop in the primary air – one of the most used parameters to evaluate the performance of DPIECs – the error in its prediction ranges between 12% and 18% with the model by (Kashyap et al., 2020). In the other cases, the error is unacceptable: indeed, it reaches 85% if the Nusselt Number is calculated according to (Jie & Chua, 2023), while it reaches 74% by referring to (Deepak et al., 2022). In other terms, the accuracy of the proposed model --in terms of temperature drop - is significantly influenced by the method used to calculate the heat transfer coefficient between air and the channel surfaces. While the dry channel could be considered in the same way as a conventional heat exchanger channel, this is not true for the wet channels: here, the heat exchange between air and wall is more complex due to the presence of water. The method used by (Jie & Chua, 2023) tried to model the effect of water, but this could be inconsistent with the reality. For example, the determination of the thickness of the water film may be very difficult in practice. In fact, the water might not be uniformly spread in the wall of the wet channel. However, the inconsistency of the model is demonstrated by the experiments. Also, the hypothesis of laminar flow, although acceptable in several cases, could not be suitable for all DPIECs.

Furthermore, the wide discrepancy between different methods to determine the Nusselt Number reported in the literature on DPIEC reveals the importance of delving on this issue.

## 3.2 Parametric Analysis

The temperature drop ensured by the prototype ranges between 3 °C and 5 °C. This result may improve significantly by increasing the heat exchange surface. For this reason, based on the developed model, a parametric analysis is performed by changing the size of the device. The inlet conditions are set as follows: air temperature 35 °C, relative humidity 50%, air mass flow rate 0.1 kg/s, working-to-intake air ratio 0.42.

With respect to the original size, each of the main dimensions (length, height, and width) are duplicated and triplicated. The results are shown in Fig. 7 by considering the same inlet air conditions, the temperature drop can increase from 2.2 °C to 4.9 °C by increasing three times the dimensions of the device. While the effect of enlarging the height or the width does not produce a significative difference, the augmentation of the length results in a minor temperature drop (4.2 °C against 4.9 °C).



Fig. 7 - Effect of a variation of length, height, and width of the device

# 4. Conclusion

This paper aims to develop a mathematical model of a dew-point indirect evaporative cooler to easily implement it in TRNSYS building simulations. The model is based on the mass and energy balance equations and on the logarithmic mean temperature difference method. The model refers to a mixed-flow prototype; however, it can be applied to other DPIECs with different configurations and design characteristics, by determining the heat transfer area and the heat transfer coefficient of the heat and mass exchanger.

The model has been written in Python programming language, so that it can be called in TRNSYS Simulations Studio by Type 169. The implementation of the Python code in TRNSYS and the building performance analysis will be evaluated in future studies. In this paper, the mathematical model is validated against experimental data: the results show that the model is sufficiently consistent with the experiments with an error in the primary air temperature drop between 12% and 18%. The relatively important discrepancy is most probably due to the inaccurate position of the temperature probe on the outlet air stream and is also influenced by the small size of the prototype.

However, the current study reveals the importance of a proper calculation for the Nusselt Number, especially in the wet channel where heat exchange is more complex than in conventional heat exchangers due to the presence of water: this suggests the need to better investigate the determination of the heat transfer coefficient in wet channels of DPIECs. In conclusion, a parametric study is performed to evaluate the effect of a variation of the length, the height, and the width of the device. With the same inlet air conditions, the temperature drop can increase from 2.2 °C to 4.9 °C by increasing three times the height or the width of the device. The increase in the length may be slightly less advantageous. However, the influence of the size should be evaluated carefully with respect to the technical possibility to ensure a uniform air distribution inside the channels, along with the necessity to create devices as compact as possible to save raw materials and make the installation easier.

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## Nomenclature

#### Symbols

А	Heat transfer area (m <sup>2</sup> )
c	Specific heat (J/kgK)
$D_{eq}$	Equivalent diameter (m)
DPIEC	Dew Point Indirect Evaporative Cooler
f	Friction factor (-)
h	Enthalpy (J/kg)
Κ	Heat transfer coefficient (W/m <sup>2</sup> K)
L	Channel length (m)
Lw	Thickness of the water film (m)
ṁ	Air mass flow-rate (kg/s)
Nu	Nusselt number (-)
Pr	Prandtl number (-)
R	Thermal resistance (m <sup>2</sup> K/W)
Re	Reynolds number (-)
Т	Temperature (°C)
х	Humidity ratio (kg/kg)
v	Air velocity (m/s)
α	Convective heat transfer coefficient (W/m <sup>2</sup> K)

δ	Channel thickness (m)
$\Delta T_{lm}$	Log mean temperature difference (°C)
η	Working to intake air ratio (-)
λ	Air thermal conductivity (W/mK)
μ	Air dynamic viscosity (kg/ms)
Q	Air density (kg/m³)

## Subscripts/Superscripts

a	air
in	inlet
m	mean
out	outlet
v	vapor
W	water
1	primary
2	secondary

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# Acoustic Correction of the Regional Theatre of Bejaia (Algeria)

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#### Abstract

Theatres must have an adequate reverberation time depending on their intended use. In this paper the acoustic characteristics of the regional theatre of Bejaia (Algeria) built in 1936 is discussed. The hall has a regular geometry with the shape of a shoebox, with a capacity of 420 seats. Measurements of the acoustic characteristics were carried out using the bursting of an air-inflated balloon. The room has an excessive reverberation time, which is not suitable for the performance of prose shows, and so it is necessary to carry out an adequate acoustic correction to reduce the reverberation time and increase the STI to improve speech understanding. The aim of this work is to analyze, using architectural acoustics software, the conditions for improving the acoustics of the room in order to reduce the reverberation time. The study uses numerical modeling to evaluate the effects of modifying the material of the stage tower or inserting surfaces with adequate acoustic absorption.

## 1. Introduction

In Algeria, the French colonists (1830-1962) started a series of works to gradually equip the territories with public buildings, including the construction of theatres. The aim of this work is to evaluate the acoustics of the Bejaia theatre, built in the 20th century. In this theatre, acoustic measurements were carried out in order to evaluate the average values of the acoustic characteristics measured. The measurements were carried out in accordance with the ISO 3382 standard (ISO, 2008). The acoustic measurements evaluate compliance with the acoustic parameters with respect to optimal conditions and to propose possible modifications. In order to improve the acoustics of the room, the study to evaluate the changes to be made was carried out with the aid of architectural acoustics software (Bevilacqua et al., 2023; Ciaburro et al., 2018). The most commonly used acoustic parameter is the reverberation time: a short reverberation time means few reflections of the sound inside the room and good speech understanding.

# 2. The Regional Theatre of Bejaia

The regional theatre of Bejaia was built in 1936 in Art Deco style, a modernist expression used in the first half of the 20th century. Fig. 1 shows the external view of the theatre.



Fig. 1 - External view of the theatre

The hall has a shoebox shape, with a capacity of 420 seats distributed between the stalls, the ground floor boxes, the two side galleries and the balcony. The dimensions of the main hall are 11 m x 21.3 m and the stage is 11 m x 7.6 m. The stage appears to be 1.2 m higher than the floor level of the hall. The walls are covered with plywood sheets, the floor with red carpet, while the ceiling is made of plaster in the peripheral part and a raised glass dome with a rectangular base. Fig. 2 shows the plant and the section of the theatre.



Fig. 2 – Plant and Section - The dimensions of the main hall: 11 m x 21.3 m

Furthermore Fig. 3 shows the interior views of the main hall of the Bejaia regional theatre.

# 3. Acoustic Measurements

The acoustic measurements were carried out inside the theatre and were carried out according to the requirements of the ISO 3382-1 standard (ISO, 2008), considered the international reference standard for objective acoustic parameters, used to better describe the perception of the sound field. Below is a brief definition of the main acoustic parameters analysed (Farina, 1995; Farina, 2007; Iannace et al., 2019; Merli et al., 2020).

The Early Decay Time (EDT) consists of the time it takes for the sound pressure level to decrease by 10 dB after the sound source is turned off. It is measured in seconds.

- Reverberation time (T30), similar to EDT and also defined in seconds, consists of the time required for the sound pressure level to decrease by 30 dB.
- Clarity Index (C80) is calculated on the basis of the energy that arrives within the first 80 ms

expressed in decibels and is used to evaluate good musical performance.

- The Definition (D50) is calculated based on the energy arriving within the first 50 ms and is used to evaluate the speech understanding.



Fig. 3 - Interior views of the theatre

The acoustic measurements were performed in unoccupied conditions. The sound source was placed on the stage at a height of 1.6 m, in the actor's position, and the receivers were uniformly distributed on one side of the stalls, the balconies and the gallery thanks to the axial symmetry of the rooms, to a height of 1.2 m from the arrival floor, simulating the ears of seated spectators. Fig. 4 shows the location of the sound source and receivers. The following equipment was used: balloon bursts; audio recorder (type Zoom H4n) (Merli et al. 2021; Iannace et al., 2020). Plastic balloons inflated with air were used. The explosion of the balloons provides a good S/N ratio and allows us to obtain a good value of the impulse response. This type of sound source, characteristic for its ease of use, had been used by the authors in previous measurement campaigns in other closed places with success.

Fig. 5 shows the average measured values of acoustic parameters initial decay time EDT; Fig. 6 shows the average measured values of acoustic parameters T30 reverberation time; Fig. 7 shows the average measured values of acoustic parameters Clarity Index C80; while Fig. 8 shows the average measured values of acoustic parameters D50 Definition.



Fig. 4 - Positions of sound sources and receivers



Fig. 5 - Average measured values of EDT



Fig. 6 – Average measured values of T30

The graph relating to the EDT shows the average values of 3.0 s, so if we compare them with the optimal values defined by Jordan, which vary be-

tween 1.8 and 2.6 s, we observe that the optimal values are not reached in theatre (Bevilacqua et al., 2022; Jordan, 1981; Fearn, 1975). The trend of the T30 line seems stable at medium-low frequencies, with values fluctuating around 2.5 s. While in musical terms, the Clarity C80 values remain below the range limit (-2 < C80 < 2 dB). D50, Definition, results remain below 50% in all frequency bands. For the definition, where the value the highest of 0.4 (40%) from Bejaia's theatre at 4 kHz. While average values STI = 0.35, is poor.



Fig. 7 - Average measured values of C80



Fig. 8 - Average measured values of D50

Fig. 5–8 show the acoustic characteristics of the values of the standard deviations measured. At low frequencies it is possible to notice the greater difference in the standard deviations of the measured values. This means that at low frequencies the greatest differences between the measured values of the acoustic characteristics are present.

#### 4. Theatre Acoustic Correction

For the measured characteristics of the theatre, some corrections should be made to improve the acoustic quality, reducing the reverberation time through the introduction of absorbent materials applied to the walls. Therefore, the use of acoustic simulation makes it possible to evaluate these corrections. A simplified geometric model was created by simplifying the surfaces of the room with flat surfaces. The software uses the sound ray tracing model, straight lines that simulate the sound rays are sent from the source point (Tronchin et al., 2020; Sukaj et at., 2021). When the lines meet the boundary surfaces, these are reflected with an angle equal and opposite to that of incidence in accordance with Snell's law. The energy of the sound beam is reduced by a rate equal to the sound absorption coefficient of the wall. The calculation is performed as a function of the frequency since the value of the absorption coefficient is a function of the frequency in the octave bands from 125 Hz to 4000 Hz. The calibration is considered completed and correct when the difference between the value of the measured T30 and the calculated one is less than 5%. Fig. 9 shows the virtual model used by Ramsete software (Bevilacqua et al., 2023; Ciaburro et al., 2020; Farina et al., 2022; Giron et al., 2017).



Fig. 9 - Virtual model used by Ramsete software

Fig. 10 shows the spatial distribution of T30 after the calibration procedures at the frequency of 1000 Hz.



Fig. 10 – Spatial distribution of T30

The room presents an almost uniform value of the spatial average distribution. The average value is around 2.5 s which gives the room poor acoustic characteristics for understanding speech. Fig. 11 shows the spatial distribution of STI after the calibration procedures.



Fig. 11 – Spatial distribution of STI

The acoustic characteristics of the theatre in its current state highlight an excessive sound tail which does not allow the theatre to have good acoustics both for understanding speech and for listening to music. Generally, this type of theatre is used for prose performances, therefore understanding speech should be given priority. To evaluate possible interventions for acoustic correction so as not to distort the aesthetic appearance, covering the walls with a sound-absorbing material fabric can be considered. In this way, using the Ramsete software, by replacing the absorption coefficient of the walls in their current state, it is possible to evaluate the new acoustic characteristics. After acoustic simulation, Fig. 12 shows the spatial distribution of T30 after the acoustic correction at the frequency of 1000 Hz. In this way, the room presents a uniform value of the spatial average distribution. The average value is around 1.5 s which gives the room good acoustic characteristics for understanding speech. Fig. 13 shows the spatial distribution of STI after the acoustic correction. The average value is around 0.7 which gives the room good acoustic characteristics for understanding speech.



Fig. 12 – Spatial distribution of T30



Fig. 13 - Spatial distribution of STI

## 5. Conclusion

In this work, the acoustic characteristics of the Bejaia regional theatre in Algeria were analysed. The hall has a regular geometry with the shape of a shoebox, with a capacity of 420 seats distributed between the stalls, the ground floor boxes and the two side galleries and the balcony. The theatre was built in the last century. The acoustic measurements carried out with the balloon bursting technique gave a T30 value at a frequency of 1000 Hz of approximately 2.5 s. The theatre does not have good characteristics for understanding speech. To evaluate possible acoustic corrections to improve speech understanding using architectural acoustics software, the possibility of covering the walls with a sound-absorbing sheet was evaluated. The simulations formed a reduction in reverberation time, and an increase in STL

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# From Theatre to Cinema to Theatre Again: The Acoustic History of the Vittorio Emanuele II Theatre of Benevento Through Simulations

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#### Abstract

The Vittorio Emanuele II Theatre of Benevento was designed with a horse-shoe shaped plan, following the architectural trend 1860. The project, originally designed by architect Francesconi, was modified after World War II due to the development of cinema, which replaced traditional theatrical performances. To accommodate this shift, the room volume was reduced, as the screen was installed at the fire curtain level, effectively eliminating the fly tower. Additionally, the wooden balustrade was replaced with glass to provide a clearer view of the screen.

Acoustic measurements were carried out inside the theatre according to ISO 3382-1. The main acoustic parameters were evaluated and compared with the theatre's original function as a performance venue. The measured and simulated results indicate that the acoustic response is well-suited for an amplified audio system, though it is perceived as drier compared to its historical function.

## 1. Introduction

Benevento is a city located in southern Italy, historically known as a centre of sound, first with the presence of the Witch Valley, later with the Roman Theatre, which served as a cultural hub during the Roman Empire, and finally with the construction of the Vittorio Emanuele II Theatre, one of the opera houses dating back to the 19<sup>th</sup> century. Throughout its history, this theatre has undergone different renovation works, not only to comply with safety regulations but also to accommodate the evolving needs of the local community for new types of events.

# 2. Historical Background

In 1850 a commission composed of representatives from the City Council and the Vatican was established to select the architect, contractor, and location for a new opera house.

The design project was awarded to architect P. Francesconi during a period when the entire city was undergoing to urban transformations approved by Pope Pius IX. Francesconi designed a horseshoe-shaped layout featuring three levels of balconies and a top gallery (*loggione*), as shown in Fig 1.



Fig. 1 – Internal view of the Vittorio Emanuele II theatre of Benevento

A distinctive feature of this opera house is the presence of a resonance box beneath the stalls floor, 1.28 m deep, a construction technique also used in other opera theatres to improve low frequencies.

The completion of the works was delayed from 1854 to 1862, with a final quality check conducted in 1866, the same year as its official opening.

Throughout the following century, different restoration projects took place, including the addition of two doors on the stage, the transition from candlelight to electric lighting, and the renovation of the roof above the stalls.

# 3. Architectural Characteristics

The main hall features a horseshoe-shaped plan (Tronchin et al., 2022; Merli et al., 2020; Bevilacqua et al., 2022), and measures 11.3 m along the main axis, with a maximum width of 13.8 m. The audience is composed of 43 boxes distributed across four orders of balconies, with walls completely covered in fabric. The total seating capacity is 400 seats, including the stalls. Table 1 reports the geometric data of the volumes.

Table 1 – Main acoustic features

Stage	Proscennium	Main Hall (Stalls & Boxes)
Surface 200 m <sup>2</sup>	Surface 19 m <sup>2</sup>	Surface 140 m <sup>2</sup>
Height 16.8 m	Height 10.6 m	Height 12.9 m
Volume 3350 m <sup>3</sup>	Volume 200 m <sup>3</sup>	Volume 1799 m <sup>3</sup>

# 4. Acoustic Measurements

Acoustic measurements were performed inside the Benevento Theatre at selected positions across the sitting area. Fig. 2 illustrates the equipment positions during the survey. The instrumentation used for the survey was the following:

- Omnidirectional sound source;
- Microphone (Brahma);

An exponential sound sweep (ESS) signal with a duration of 15 s, covering a frequency range from 40 Hz to 20 kHz, was used to generate the impulse response (IR).



Fig. 2 – Equipment location during the acoustic survey inside the Vittorio Emanuele II theatre of Benevento

The acoustic measurements were performed in line with the standard requirements outlined by ISO 3382 (ISO, 2008).

## 5. Calibration of Digital Model

The measured impulse responses were processed using the Aurora plugin suitable for Audition 3.0 (Farina, 1995; Farina, 2007; Farina, et al., 2022). Before running any simulations, the measured values were used to calibrate the digital model. The main acoustic parameter considered for this operation was the reverberation time (T30) across the spectrum from 125 Hz to 4 kHz, averaged over all source-receiver position under unoccupied conditions. Table 2 shows the absorption coefficients used for calibration, while Fig. 3 shows the model calibration based on the reverberation time T30 (Bevilacqua et al., 2023a; Bevilacqua et al., 2023b). The theoretical study will be carried out using the architectural acoustics software Ramsete, which is based on sound ray tracing. Ramsete operates according to Snell's law: when a sound ray strikes a flat surface, it is reflected at an angle equal to the angle of incident. The reflected sound energy is reduced by a percentage corresponding to the absorption coefficient assigned to the surface. In raytracing-based acoustics simulations, sound reflection is evaluated in terms of energy, meaning that the reflected sound energy is decreased in proportion to the absorption coefficient.

Table 2 – Absorptior	coefficients	used for	the c	alibration	process
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Material	125	250	500	1k	2k	4k
Floor - Stalls	0.15	0.25	0.35	0.43	0.45	0.45
Perimeter Walls	0.18	0.25	0.27	0.28	0.30	0.28
Balustrades	0.63	0.70	0.74	0.75	0.75	0.75
Box Partitions	0.63	0.70	0.74	0.75	0.75	0.75
Stage Floor	0.55	0.50	0.40	0.30	0.30	0.27
Fly tower walls	0.28	0.28	0.26	0.27	0.25	0.26
Seats	0.64	0.75	0.80	0.82	0.83	0.83



Fig. 3 – Calibration of simulated results with measured values of T30  $\,$ 

The calibration was performed on the reverberation time, as this acoustic parameter is independent of the measurement position within the seating areas. In contrast, other parameters are highly sensitive to the distance between the source and receiver, leading to a significant increase in potential error.

# Acoustic Simulations Reproducing the Condition of the Theatre Transformed Into a Cinema

After World War II, the opera theatre in Benevento was transformed into a cinema (Dolci et al., 2021). The architectural changes included replacing the wooden balustrades with glass, adding more seats allocated to the stalls, and installing a white synthetic fabric screen in place of the heavy dark red curtain. This change was made to improve movie projection clarity without any color distortion.

The acoustic simulations presented in this paper reflect the condition of a cinema set up inside the theatre. As such, the results shown in the following graphs compare two scenarios:

- The measured data mirroring the current state of the theatre, which is quite similar to its condition in 1860, and
- The simulated data representing the theatre's transformation into a cinema.

The main acoustic parameters are analyzed in the frequency band between 125 Hz and 4 kHz, averaged for the stalls and balconies, under unoccupied conditions.



Fig. 4 - Values of early decay time (EDT)

Fig. 4 shows that the current EDT values are around 1.0 s in the stalls and 0.7 s in the boxes at medium frequencies, with a downward trend for the measured values in the boxes. These results fall below the minimum threshold of the optimal range established for opera theatres (Ciaburro et al., 2020; Fearn, 1975). The simulated EDT values show little difference between stalls and balconies, at around 0.6 s and 0.55 s, respectively. This means that the cinema configuration produces a drier acoustic response compared to the existing condition.



Fig. 5 – Values of reverberation time (T30)

Fig. 5 shows that the T30 values from the cinema simulation are around 0.6 s. This consistent difference, compared to the measured values, is primarily due to the reduction in room volume, as the simulation does not account for the volume of the fly tower behind the screen. A secondary factor influencing this reduction in reverberation is the addition of seats with light upholstery. The reverberation time in the current state is suitable for both music and prose, while the results for the cinema setup are also appropriate for an amplified audio system (Jordan, 1981; Merli et al., 2021; Sukaj et al., 2021; Berardi et al., 2022).



Fig. 6 - Values of clarity index (C80)

Fig. 6 indicates that the averaged values of C80 are above the upper limit of the optimal range estab-

lished for good clarity (+2 dB), meaning that the energy content of early reflection predominates over the reverberant tail.



Fig. 7 – Values of definition (D50)

Fig. 7 shows the D50 values fluctuate around 0.7 (70%), with a small difference between measured and simulated values. Overall, the results indicate that the definition is slightly more suitable for speech. This outcome should be compared with the sound transmission index (STI) values, which are found to be 0.84 for male voice, placing it in the "excellent" category for speech comfort, in accordance with the intelligibility rating defined by ISO 9921 (Giron et al., 2017; Iannace et al., 2019; Iannace et al., 2020).

## 7. Discussion

The acoustic simulations carried out for the adaptation of the theatre into a cinema screen show that the acoustic response is suitable for the new function of the space, especially because the cinema is equipped with an amplified audio system, which requires a drier environment than what existed before. This was achieved by reducing the volume of the fly tower, which had significantly contributed to increasing the reverberation in the space. Given the upholstery of the seats, it is assumed that there would not be much difference between unoccupied conditions, as measured and simulated, and full occupancy by spectators.

# 8. Conclusions

The long story of the Vittorio Emanuele II Theatre in Benevento has been analyzed with the aid of acoustic simulations, which were based on a campaign of acoustic measurements. After calibrating the model, representing the existing condition, with the measured data, the model was used to simulate the theatre's condition when it was transformed into a cinema. This transformation involved the removal of the fly tower, leading to a significant reduction in room volume, replacing the wooden balustrade with glass for increased transparency and better sightlines to the screen, and adding more seats to the stalls to expand the overall capacity.

Regarding the acoustic response for an amplified audio system, the simulated values were found to be suitable for the new function that occurred after World War II. However, the drier environment was intentionally created. In addition, this study provided an analysis of the measured acoustic data, which were found to be lower than the limit in terms of EDT, aligning with speech understanding in terms of reverberation and definition, and with clarity values found to be above the upper limit established in the literature.

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# Economic and Environmental Optimization of Retrofitting Options for a Community Building: A Case Study from Förslöv-Grevie Parish, Sweden

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#### Abstract

The research evaluated retrofitting options for a threestory church community building in Grevie, Sweden, assessing the impacts on energy efficiency, life cycle cost, and environmental concerns. An energy model was generated in IDA ICE to simulate the building performance. Various improvements were tested in two separate retrofit package scenarios. They had the following measures in common: the addition of insulation to the walls and roof, the addition of sealant and secondary glazing, the installation of a heat pump with a better seasonal coefficient of performance (SCOP) on the ground floor, and the installation of a photovoltaic (PV) system. In the first scenario, modifying the controllers of electric radiators was considered while leaving other preexisting systems untouched. In the second scenario, all systems were replaced by two heat pumps, one for the ground floor and the second for the first floor, with improved SCOP. In the study, 1,620 different energy improvement cases with simultaneous 3,000 simulation combinations of PV systems were examined, using scripted and parametric optimization. Results suggest that adjusting controllers and adding PVs could yield significant energy savings and cost reductions. Notably, cases with an additional air-to-air heat pump on the first floor showed the best energy consumption reduction, though not the highest profitability. The research highlights the importance of combining passive and active measures and their impact on energy efficiency, life cycle costs, and environmental factors. It also shows that the most energy-efficient options may not always be the most cost-effective or environmentally friendly during a building's lifetime.

#### 1. Introduction

Aligned with the EU's and Sweden's shared energy reduction goals for 2050, there is a focus on improving existing building energy efficiency. Targets include a 20% reduction by 2020 and 50% by 2050. The growing building sector emphasizes the need to upgrade older structures (Communication from the Commission to the European Parliament, 2023). Heat pump systems play a crucial role in boosting efficiency and cutting emissions. EU heat pump sales data show a steady annual market growth of over 10% in recent years (Monica & Fredrik, 2005). There is also rising interest in combining heat pumps with solar systems for both single-family and multi-family buildings. This aims to increase the renewable portion of the system's heat source by enhancing PV power selfconsumption and reducing grid-supplied energy (Isoleringsskiva Lambda 37 Isover, 2023). The study explores retrofitting active and passive measures for economic viability, energy savings, and environmental impact reduction.

## 2. Methodology

#### 2.1 Overview

The study comprised four stages. Initially, the current building condition was evaluated through a site visit and energy usage data provided by the owners. Building geometry was then created in Revit and exported to IDA ICE 4.8for energy simulation, validated against actual energy use. In the second stage, two scenario groups were suggested

to involve active and passive measures. In scenario one, all combinations of the passive parameters combine with two active parameters: adjustment of the controller type on the electrical radiators (PI and thermostat) and whether to keep the current ground floor air-to-air heat pump (A2A HP) or replace it with a more efficient one (seasonal coefficient of performance (SCOP) of 4.5, 5.0), resulting in 684 cases. In two, the same set of passive parameters was taken into account while also adding two active parameters: keeping the current ground floor A2A HP or replacing it with a more efficient one (SCOP of 4.5, 5.0), and adding a second A2A HP on the first floor (SCOP of 3.9, 4.5, and 5.0) to replace the hydronic radiators, resulting in 972 cases. Parametric simulation was performed for all 1,620 cases (annual energy, a software limitation in parametric study). The life cycle cost (LCC) analysis for the 1,620 cases was performed using Visual Basic Application (VBA) in two economic situations (see LCC section), considering each case's net present value (NPV). In the third stage, hourly energy simulation results were used to assess the PV system's performance combined with the 42 improved cases, accounting for the variation in production and consumption. Conducting hourly energy simulations was considered too timeconsuming for 1,620 cases. To avoid bias and data loss during the selection process of retrofitting cases, a semi-random selection was introduced to cover a wider distribution of parametric input rather than only using the four identified cases. If only the cases with the most significant energy savings were kept for further analysis, there would have been a risk of excluding less optimized cases with a different energy use pattern than those with the most significant energy savings. This method includes one of the passive or active represented measures to a fixed value, while other parameters were chosen randomly. For example, a wall's insulation thickness of 45 mm could be a fixed control element, and other variables (e.g., glazing U-value, SCOP of heat pump, etc.) were chosen randomly by VBA script from the parameter mentioned above in each scenario the selection process scripted the way to avoid the repetition of the 37 cases. The 4 cases with the most significant energy savings and 37 semi-random cases were selected for integration with photovoltaic (PV) systems on an hourly energy basis. These less optimized cases could potentially better match the PV electricity production. Finally, the optimal cases and PVs were chosen for LCA evaluation and postprocessing.

#### 2.2 Energy Measures

In this study, passive and active measures were applied to comply with Swedish building regulations (BBR 29 by the Swedish National Board of Housing, Building, and Planning – Boverket). In Table 1 and Table 2, the inputs used for the base case are listed.

Table 1– Base case simulation inputs

	Basement	Floor 0	Floor 1
Area/ m <sup>2</sup>	134.3	144.9	102.0
Lighting load/ W/m <sup>2</sup>	0.1	2.291	0.163
Equipment load / W/m <sup>2</sup>	4.4	6.694	-
Domestic hot water	0.5	0.5	0.5
Infiltration rate / ACH50	1.3	1.3	1.3
Heating set point/ °C	17	23	17
Cooling set point / °C	-	_	-

Table 2- Base case U-values of various building elements

	Roof	Ext. wall	Window	Ground slab
<i>U</i> -value / W/(m²⋅K)	0.250	0.202	0.950	3.170

#### 2.2.1 Passive measures

On-site measurements revealed CO<sub>2</sub> concentrations exceeding 1,000 ppm during occupancy. Therefore, natural ventilation was implemented in all improved cases by opening up to eight ground-floor windows from 12:00 to 13:30, and from 14:30 to 15:00 (at the beginning and the end of the occupancy schedule), reducing CO<sub>2</sub> levels to 800 ppm during operational hours. Thermal insulation was added to the exterior side of the wall to mitigate heat loss, with options of 45 mm and 95 mm thickness of Isover glass wool ( $\lambda = 0.037$  W/(m·K)),

guaranteed to contain at least 70% recycled glass (Isoleringsskiva Lambda 37 Isover, 2023). Retrofit measures can reduce infiltration rates by up to 77%, contributing to decreased energy demand and costs (Johnston et al., 2023). By enhancing the building's air-tightness, the infiltration rate can be lowered from 1.3 ACH at 50 Pa to the proposed values of 1.1, 0.9, and 0.7 ACH at 50 Pa. Windows contribute to heat transmission five times more than the other envelope components (Bülow-Hübe, 2001). However, secondary glazing can reduce this effect by enhancing the thermal performance of existing single/double-glazed windows, without removing the original glazing. It is achieved by adding a second glass pane, low emissivity coating, or plastic film, thereby reducing the U-value by up to 50% (Madushika et al., 2023; Harjunowibowo et al., 2019). The current window with a Uvalue of 0.95 W/(m<sup>2</sup>·K) and two new windows with U-values of 0.85 and 0.65 W/(m<sup>2</sup>·K) were used in the parametric simulation.

#### 2.2.2 Active measures

The proposed retrofit involves adding a new A2A HP, either as a replacement on the ground floor or adding a new A2A HP with a different SCOP while removing the current hydronic radiators on the first floor. Three sizes of A2A HPs with SCOP values of 3.9, 4.5, and 5.0 were considered. Two different temperature control systems were assessed: the existing PI controller and an improved thermostat. Mechanical ventilation was excluded due to the perceived inefficiency of ducting in lowinfrequent building ceilinged floors and occupancy. Passive and active measure parameters created two scenarios aimed at reducing energy demand and electricity consumption (see Table 3 and Table 4). The scenarios were then simulated in IDA ICE, resulting in 648 cases for scenario one and 972 cases for scenario two.

Table 3 – Parameters of passive retrofitting measures

Measure	Scenarios 1 and 2
Wall and Roof insulation / mm	0, 45, 95
Infiltration / ACH50 Pa	0.7, 0.9, 1.1, 1.3
Window <i>U</i> -value / W/(m²·K)	0.65, 0.85, 0.95
Natural ventilation	Scheduled in all cases

Table 4 Descriptions of a still a structure fitting a second	
Table 4 – Parameters of active retrotitting me	asures

Measure	Scenario 1	Scenario 2
Controller type	PI, thermostat	-
SCOP Floor 0	3.9, 4.5, 5.0	3.9, 4.5, 5.0
SCOPFloor 1	-	3.9, 4.5, 5.0

## 2.2.3 PV system

In the System Advisor Model software (v. 2022.11.21), 3,000 annual simulations were performed parametrically, with variations in modules per string (5–16), number of parallel strings (1–10), tilt (25°–45° in steps of 5°), and number of inverters (1-5). The azimuth was fixed at 180°. Uniform module (Molin, n.d.) and inverter ("Sunny Tripower Mit SMA Smart Connected 8.0 / 10.0," n.d.) types commonly available in the Swedish market were used: a monocrystalline module with 48 cells, maximum power of around 550 W<sub>p</sub>, and a nominal efficiency of 22.1%; the inverter of maximum DC power of around 12,200 Wp. The linear decline in energy output capacity over the module's 30-year lifespan was disregarded for simplicity. No shading or self-shading was considered in the analysis, supported by the analysis of the site geometry and neighboring objects. Typical irradiance losses, and DC and AC losses were also assumed.

## 2.3 Life Cycle Cost

The life cycle cost for all 1,620 cases in scenarios one and two were calculated using the VBA script to seek profitability for each case. Two scripts were developed to calculate LCC for each scenario. These scripts identify the parameters used in each case, allocating each parameter's initial cost, labor cost, operation cost, and all costs for replacement

and repair during the study lifespan (Wikells, 2023; Svensson 2017). A 50-year building occupancy period was examined, and an NPV geometric gradient equation (Eq. 1) was used for cost calculation. The windows and ground floor A2A HP repairs were excluded from the calculation due to the consistency of these costs in the base case and improvement cases. For the sensitivity analysis, an interest rate of 3.5% (Statistics, 2023), an inflation rate of 2% (The Inflation Target, 2023), and 7.5% (The Inflation Rate According to the CPI, 2023) were used. This resulted in economic scenarios one and two, respectively. The life span of the thermostat is 15 years so three replacements were considered at years 15, 30, and 45. For the A2A HP, the yearly maintenance over 50 years was applied in the calculation.

NPV<sub>energy</sub> =  $A_I \cdot [(1 - (1+g)^N \cdot (1+i)^{-N})/(i-g)]$  (1)

- *A*<sub>1</sub> annual savings in the first year
- *g* nominal rate of price change
- *i* nominal interest rate
- *N* number of years

Building consumption and PV production vary at each time of day, so to analyze the performance of PV systems with improved cases, hourly energy results of improved cases were compared with the PV production on an hourly basis. Considering the hourly price of the electricity for buying to and selling from the grid, the NPV was calculated, evaluating the profitability of each case. As described below, a limited number of diverse cases were selected for this evaluation. Based on the highest NPV and the highest reduction in energy demand (the Pareto optimum), four optimal cases were selected among all improved cases. Additionally, by semi-random selection, 37 cases were selected, aiming to encompass more results from the entire parametric field and, consequently, minimize the likelihood of focusing solely on a local maximum. A VBA script was devised for this selection. As depicted in Fig.1, the selection principle is configured to ensure the inclusion of each variable at least once, with other parameters being assigned randomly. In scenario one, 18 cases were selected, whereas in scenario two, 19 such cases were chosen.

Case	Controller	Insulation wall	Insulation roof	Window	Infiltration	A2A HP SCOP
1	PI	random	random	random	random	random
2	Thermostat	random	random	random	random	random
3	random	00	random	random	random	random
4	random	45	random	random	random	random
5	random	95	random	random	random	random
6	random	random	00	random	random	random
7	random	random	45	random	random	random
8	random	random	95	random	random	random
9	random	random	random	0.95	random	random
10	random	random	random	0.80	random	random
11	random	random	random	0.65	random	random
12	random	random	random	random	0.7	random
13	random	random	random	random	0.9	random
14	random	random	random	random	1.1	random
15	random	random	random	random	1.3	random
16	random	random	random	random	random	3.9
17	random	random	random	random	random	4.5
18	random	random	random	random	random	5.0

 $\mbox{Fig.1}$  – Schematic representation of the semi-random selection principle for the first scenario

Additionally, to assess the PV system's performance with improved cases, the hourly energy simulation results were used, accounting for the variation of production and consumption throughout the day. Considering hourly electricity price for grid transactions (Day-Ahead Prices on SE4 -Malmö, 2023), with economic situation 1 (real interest rate at 3.5%, inflation rate at 2%, and price growth of 4%) the NPV uses the same equation mentioned above, evaluating the profitability of each case. In PV systems, replacement of the inverters was also assumed every 15 years, thereby considerably increasing the PV system costs, as seen in Table 5.

Table 5 –	Costs of PV	systems
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PV system	Inverter replacement
10.9SEK/W <sub>p</sub>	228,596SEK/inverter

#### 2.4 PV System Selection

To come up with a manageable number of hourly simulations to run manually in SAM, some of the 3,000 results had to be filtered out, as graphically depicted below Fig. 2, firstly based on the high AC and DC inverter clipping losses. After, due to simulation-proved inferior energy output, all cases with the oversized inverters were eliminated. In the following step, options characterized by an excessive number of inverters, which result in energy production achievable with a smaller number of inverters, were also disregarded. From the remaining options, suboptimal tilt options were excluded (45° is in the vast majority of cases the best). Additionally, suboptimal combinations of parallel strings and the number of modules per string were filtered, (e. g.  $8 \times 3$  or  $12 \times 2$  would have the same amount of PV panels, but different energy production). In the end, 81 cases remained, from which only 16 representative cases were selected in steps of approximately 5,000 kWh of energy production to ensure diverse output options were investigated, but also that the too-similar results would not be redundantly analyzed.



Fig. 2 – Visual representation of the filtering process for the PV cases selection

## 2.5 Life Cycle Assessment

LCA is performed in two parts: firstly, calculating the environmental impact of the building's operational energy using Open LCA 2.0. In the second part, the focus is on evaluating the environmental impact of the newly introduced materials in each case. These evaluations were done using EPDs ("EPD International," n.d.) and VBA scripts. For normalization and weighting, the shadow cost method (Javed, 2023) was used. The LCA included cases with the best performance with the PV system (five cases-all with the thermostat as the controller), the four best cases (with the highest NPV and the highest reduction in energy), and the base case. Additionally, the LCA of a random PV system (production of 55 500 kWh annually) is calculated. In the next step, LCA results were integrated with the LCC results. The integration sensitivity analysis was calculated considering 30%-70%, 50%-50%, and 70%-30% of environmental and economic impact ratios, respectively. In the assessment, a period of 50 years, and cycle stages A1-A3 and B6 were taken into consideration, with a unit of the heated floor area with sustained thermal comfort (m<sup>2</sup>) as the functional unit. When looking at typical impact categories applied to the buildings' LCA, the most frequently examined ones included global warming potential (GWP), ozone depletion potential (ODP), acidification potential (AP), and eutrophication potential (EP), as these factors were consistently addressed (Scheuer, Keoleian, and Reppe, 2003; Buyle, Braet, and Audenaert, 2013). Therefore, these four categories were chosen to evaluate the environmental effects of the presented cases.

# 3. Results and Discussion

## 3.1 Energy Measures

The building energy consumption during occupied six hours per week (base case) is 28,981 kWh. In scenario 1, the energy reduction with only passive measures ranges from 0.05% to 17.3%. By changing the controllers of electric radiators, higher energy reduction is achieved, ranging from 46.5% to 60.2%. After proposing a second A2A HP for the first floor in scenario 2, energy consumption is significantly reduced, and the reduction of energy ranges from 69% to 77%. The best cases have passive measures and thermostat controllers and a reduction range of 57% to 62.2%, and random cases have various reductions and are distributed among all cases.

# 3.2 Life Cycle Cost

NPV results for all 1,620 cases on an annual energy basis and electricity price indicate that only cases with passive measures and thermostat controllers in economic scenario one is profitable, as shown in Fig. 3. The savings from energy reduction surpass the investment in thermostat controllers, rendering these cases profitable.



Fig. 3 – The net present value of all cases with the energy savings relative to the base case

The remaining cases are not profitable in either economic scenario. Introducing a new A2A HP yields diminishing returns, with increased energy savings failing to justify high initial and maintenance costs. Among the 16 PV systems evaluated, only six are profitable, ranging from around 40 kWp to 90 kWp, or 50,000 kWh to around 100,000 kWh annual production, as seen in Fig. 4. Cases with thermostats demonstrate the highest NPV when combined with PVs. Only five cases out of 42 selected ones are profitable (red dots in Fig. 4) with all six PV systems starting from PV11 to PV16. These cases share existing windows and thermostat controllers, while other parameter values vary. It is worth noting that the study's limitation lies in not simulating all potential cases hourly, as the semirandom selection method does not guarantee identifying the ultimate best solution.

#### 3.3 PV Systems

For PVs, the energy production of the final 16 PV cases is directly correlated with the size of the system or the total module area. This shows that there is no option that is inherently more energy-efficient, and therefore the determination of which case merits investment should be based on an economic or environmental standpoint.

#### 3.4 Life Cycle Assessment

The results depicted in Fig. 5 show that the lowest LCA belongs to cases "best 1" and "best 4", which have the existing windows, leakage of 0.7 ACH<sub>50 Pa</sub>, a new A2A HP with SCOP of 5, and additional wall and roof insulation thickness of 95 mm. Random case 16 has the highest environmental impact, including existing windows, leakage of 0.7 ACH50 Pa, A2A HP with SCOP of 4.5, and additional wall and roof insulation thickness of 95 mm. The majority of cases have a higher environmental impact than the base case. Most of the difference between the cases is seen in the GWP, which stems from the more efficient A2A HP for the ground floor and additional insulation thickness implemented in the wall and roof, and the airtightness of the building in random cases 7 and 16, "best 2", and "best 3".



Fig. 4 - NPV of the integrated PV systems and selected energy cases. PV11 is the PV system selected for further life cycle analysis



Fig. 5 - Integrated LCA of the base case and 9 selected cases



Fig. 6 - Sensitivity analysis weighting LCA and LCC

The significant difference between LCA and LCC resulted in the same trend in the three integrated weighting scenarios. As shown in Fig. 6, when LCA has more weight, the shadow cost of cases and cases including the PV goes down, due to the reduction of the energy impact. Three cases show more promising results in all three domains. One of these cases originated from the initially best cases that were chosen from a pool of 1,620 cases, while two others were selected from random cases that have the lowest LCA. This highlights the fact that the most economical scenarios may not necessarily be the most favorable ones when it comes to either LCA or integration with PVs.



Fig. 7 – Relationship between LCA, energy use, and LCC of the base case and 9 selected cases

## 4. Conclusion

The study assessed energy improvements and life cycle costs across various scenarios. Passive measures alone resulted in modest energy consumption reductions (0.05% to 17.3%). However, adding thermostat controllers for electric radiators substantially increased energy reduction (46.5% to 60.2%). Introducing a second heat pump on the first floor led to significant energy consumption reductions (69% to 77%). Profitability analysis indicated that only cases with passive measures and thermostat controllers were profitable. While an additional A2A HP saved more energy, higher initial and maintenance costs offset the savings. Among PV systems, only six cases showed profitability, with annual production ranging from 50,000 to 100,000 kWh. However, combining a second heat pump with PV systems was not profitable in any scenario. Assessing energy consumption, life cycle cost, and PV system evaluations identified only five profitable retrofit cases when combined with selected PV systems. These cases differed from the initially selected four best cases based solely on NPV and energy reduction. GWP was the highest environmental impact category, mainly from the new heat pump and increased wall insulation thickness. Integrated LCA underscored the need for balanced decision-making in energy systems, as achieving lower costs, reduced energy use and lower environmental impact simultaneously may be challenging or unattainable.

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# Installation of Reflecting Panels in the Main Church of Aversa

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#### Abstract

The lack of performance art spaces in Italy led the local authority to convert some abandoned religious buildings for live musical shows. The church of Aversa has been digitally rebuilt and used for acoustic simulations that focus on two scenarios: the existing conditions and the installation of some acoustic panels that help to direct the sound towards the seating area. The validation of the simulations is based on the acoustic measurements carried out inside the church that have been used to calibrate the 3D model. The results show that the acoustic parameters for music are highly improved, resulting within the optimal range as established by the criteria. To improve the acoustic characteristics of the church, the effects of inserting panels to be placed on the audience area were studied using numerical simulation. The procedure was performed with dedicated software for architectural acoustics.

## 1. Introduction

The lack of buildings dedicated to holding shows of different kinds has led to the conversion of some abandoned religious buildings into buildings to host musical performances. The acoustics inside churches have been the subject of numerous studies. One of the acoustic problems is due to excessive height which causes late reflections. Furthermore, finishing materials such as plaster, stucco and marble contribute to building the sound and creating excess reverberation. The complexity of church acoustics also lies in the multiple locations of the sound source, which could be on the altar (closer to the public), or in the choir of the apse. The church of Aversa was restored to host music concerts. The church was digitally reconstructed and used for acoustic simulations that deal with two scenarios: the existing conditions and the installation of some acoustic panels that help direct the sound towards the listeners. The validation of the simulations is based on the acoustic measurements carried out inside the church which served to calibrate the 3D model. The results show that the acoustic parameters for music improve (Iannace et al., 2019; Iannace et al., 2020; Merli et al., 2021; Tronchin et al., 2020). To improve the acoustic characteristics of the church, the effects of inserting panels to be placed on the audience area were studied using numerical simulation. The procedure was performed with dedicated software for architectural acoustics.

## 2. Historical Background

The church was built during the 17th century. The earthquake of 1732 damaged the convent, leading the nuns to collect some donations to fund the restoration works that involved the construction of a lightweight wattle vault above the nave of the church, the consolidation of the front elevation and the decoration of the floor with majolica. When the order of Poor Clares was suppressed in 1866, the church became part of the clergy and abandoned until 1961. In fact, after the abandonment, the church did not have any maintenance work. Over the years the roof has fallen, and vegetation has invaded the interior of the church. Fig. 1 and Fig. 2 show the church before the restauration works. Recently the church is under restoration works which consist of rebuilding the roof and it being
converted into a concert hall for temporary venues besides the sacred functions. The works are to be completed in summer 2022 and this paper deals with the acoustic analysis of the church in relation to the configuration at the end of the works (Fearn, 1975; Giron at al., 2017). Because the church has excessive reverberation, panels suspended from the ceiling were designed to reduce reverberation time and make the environment more comfortable and responsive to the needs of good acoustics for listening to music (Merli et al., 2020; Sukaj et al., 2020; Ciaburro et al., 2018; Ciaburro et al., 2020).



Fig. 1 - Church without ceiling, before the restauration works



Fig. 2 – Internal view before the restauration works

# 3. Architectural Characteristics

The church is architecturally composed of a single nave having dimensions of 22 m and 7.2 m (L, W), for a total volume of 2000 m<sup>3</sup>. Fig. 3 shows the plan of the church.



Fig. 3 - Plant of the church

The work consists of the construction of vault and arches with light wood boards, representing a delicate intervention that leaves the spectator to be imaging how the original structure could be. This solution is considered also beneficial under an acoustic perspective because the new skin is not opaque to create a detrimental excess of reverberation, but linear and purified by all frames typical of the Baroque style. Furthermore, the planks are narrow, in line with the concept of transparency that leave a free view of the double-sloped roof, as shown in Fig. 4.



Fig. 4 - Roof of the church after the restauration works

Fig. 5 shows the interior of the church. Note the floor with restored majolica tiles. Furthermore, in the church the plaster of the walls has been rebuilt with white as was originally intended.



Fig. 5 - Inside the church after the restauration works

### 4. Acoustic Measurements

Acoustic measurements were carried out inside the church before the restoration works by using firecrackers as an impulsive sound source. Firecrackers have the advantage of being very small, but the exposure provides excellent impact with a high S/N ratio. Firecrackers have been used by the authors in many acoustic situations, especially for large environments and in the absence of the electric current signal used to power traditional sound sources. The Brahma microphone was used as a receiver. The acoustic measurements were performed in accordance with the standard requirements outlined by ISO 3382-1. The firecrackers were ignited at a height of 1.5 m above the ground, while the microphone was placed at different positions at a height of 1.6 m. Measurements were made during the daytime, with a temperature of 13-15 °C. The sound source was placed on the altar and closer to the apse, while the microphone was moved across the nave by following a regular grid. The results of the main acoustic parameters were assessed in accordance with ISO 3382-1. Fig. 6-9 indicate the measured values of EDT, T30, C80, C50 and D50 in the octave bands comprised between 125 Hz and 4 kHz (Jordan, 1981). The acoustic parameters were assessed against the criteria for both a good speech understanding and classic music. EDT and T30 inside the church differ from the acoustic parameters desired. This is due to the excess of reverberation. This outcome is considered higher than the optimal value as shown should be 2.5 s based on the room volume of the church. Fig. 8 indicates the response of the clarity index, that

shall be between -2 dB and +2 dB. The C80 values in St Spirit's church were found to be within the criteria from 1 kHz onwards, while at low frequencies the results fluctuated up to 2 dB below the lower range limit. The Speech Transmission Index (STI) parameter is a value for the definition of the intelligibility of speech in room, so it is a parameter for the evaluation of good comprehension of speech. The STI index aims to objectively quantify the comprehensibility of speech in a specific position in a room. The acoustic analysis is the starting point on which to carry out an evaluation for a study to improve the acoustics of the room. The acoustics of the church can be improved by inserting a special shell in the area where the musicians will be placed, i.e. in the altar area (Berardi et al., 2022; Bevilacqua & Iannace, 2023).



Fig. 6 - Values of early decay time (EDT)



Fig. 7 – Values reverberation time (T30)



Fig. 8 – Values of Clarity (C80)



Fig. 9 - Measured values of definition (D50)

The study for the acoustic improvements will be carried out using the architectural acoustics software (Ramsete). Ramsete software for acoustic simulations is based on sound ray tracing and geometric acoustics. The sound ray tracking algorithm is able to solve sound propagation problems within environments, following the assumptions of geometric acoustics. The specular and diffuse reflections on the boundary surfaces of the environment under study are analysed. The principle is based on Snell's law for the light ray incident on a flat surface, the incident ray is reflected from the surface at an equal and opposite angle, and the energy of the reflected ray is reduced by a percentage according to the sound absorption coefficient assigned to the surface. Ray-tracing-based architectural acoustics software evaluates sound reflection in energy terms, the reflected sound is decreased by an amount equal to the absorption coefficient. Fig. 10 shows the virtual model for the Ramsete software for the church in the current state (Bevilacqua et al., 2023; Farina, 1995; Farina, 2007; Farina et al., 2022).



Fig. 10 - Virtual model in Ramsete software

# 5. Calibration of Digital Model

The measured impulse responses were elaborated with the plugin Aurora suitable for Audition 3.0. Before any simulations, the measured values were used to calibrate the digital model. The main acoustic parameter taken in consideration for this operation is the reverberation time T30 in the spectrum between 125 Hz and 4 kHz, to be considered the average of all source-receiver positions, in unoccupied conditions. Table 1 shows the absorption coefficients used for the calibration.

Table 1 - Absorption coefficients used for the calibration process

Material	125	250	500	1k	2k	4k
Floor	0.01	0.01	0.01	0.01	0.01	0.01
Shell	0.15	0. 15	0.15	0.15	0. 15	0.15
Ceiling	0.20	0.10	0.10	0.10	0.10	0.10
Walls	0.01	0.05	0.05	0.05	0.05	0.05

For example, for the ceiling, the alpha value depends on the fact that the wooden panels that make up the ceiling can be assimilated to vibrating panels that absorb low frequencies. The calibration was done on the reverberation time as this is an acoustic parameter that is independent of the position taken in the seating areas. All the other parameters are very sensitive to the distance between source and receiver, meaning that the percentage of mistake increases considerably. The calibration procedure is performed on the T30 value. The alpha values are changed so that the calculated T30 approximates the measured T30. The procedure stops when the difference between the measured T30 and the calculated T30 is less than 5%.

# 6. Acoustic Simulations

The acoustic parameters are analysed in the frequency band comprised between 125 Hz and 4 kHz in unoccupied conditions. Fig. 11 indicates that the averaged values of C80 are under the limits of the optimal range established for good clarity (-2 dB), for the high value of reverberation time. Fig. 12 shows the STI values are all fluctuating around 0.5, with a small difference between measured and simulated values. Overall, the results indicate that the definition is slightly more suitable for speech. The room needs acoustic correction, but the designers consider it unpleasant to install soundabsorbing panels on the side walls. To improve acoustics, the possibility of installing removable plasterboard panels on the audience is being evaluated.

# 7. Acoustic Correction

Because the reverberation is excessive and the acoustic conditions are far from those recommended for good music listening, it is necessary to intervene with an adequate acoustic correction. Many projects are available to improve the acoustics of rooms by inserting sound-absorbing panels or inserting sheets with sound absorption characteristics. In this specific case we intervened with an arrangement of diffusing panels in the area where people sit. In this way the sound is concentrated in the area where the spectators sit, the sound spreads evenly, allowing for good conditions for listening to music. In the proposed study the panels are made of diffusing material and have a low absorption coefficient, and they can be made with polymer-glass or plasterboard panels. Fig. 13 shows the virtual model of the new room with the diffusion panels under the audience area. Fig. 14 shows the virtual model of the new room with the panels on the audience area.



Fig. 11 - Values of clarity index (C80)

The acoustic parameters are analysed in the frequency band comprised between 125 Hz and 4 kHz in unoccupied conditions. Fig. 15 indicates that the averaged values of C80 the limits of the optimal range for good clarity is 2 dB. The numerical simulation is without an audience.



Fig. 12 - STI values



Fig. 13 - Virtual model for the Ramsete software



Fig. 14 – Virtual model for the Ramsete software with the panels on the audience area

Fig. 16 shows the STI values are all fluctuating around 0.6. Overall, the results indicate that the definition is more suitable for speech. The insertion of the panels makes the room have better acoustics. The sound is concentrated on the audience area, and the sound is spread evenly. The choice to insert the panels means the walls do not have to be covered with sound-absorbing panels. From an aesthetic point of view, sound-absorbing panels are not widely accepted by designers and new aesthetically acceptable but also innovative solutions are being sought. The church should become a cultural centre for listening to music and having an innovative interior design can make the hall sought after for holding concerts.



Fig. 15 - Values of clarity index (C80)



Fig. 16 – Values of STI

# 8. Conclusions

This paper deals with the analysis of the main acoustic parameters measured inside the St Spirit's church of Aversa. The survey was carried out before construction work began to realize a doublesloped roof and the barrelled vault of the nave, constructed with narrow wooden planks in accordance with the concept of transparency. The results indicate that the acoustic conditions of the church before the works were slightly far to be suitable for an auditorium. As such, the authors have proposed a design project that focused mainly to close the damaged roof of the church so that it would be able to host temporary musical events. It has been predicted that with the addition of the roof, the reflecting surface area will increase the values of reverberation time. Therefore, additional absorbing panels shall be calculated to be in place and to balance the values of the main acoustic parameters, which will be measured after completion of the construction works.

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# Building Information Modeling (BIM) and Building Energy Modeling (BEM): Interoperability and Interactive Data Representation for the Energy Management of the Existing Buildings

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#### Abstract

The text discusses the potential for energy efficiency improvements in existing buildings, emphasizing the importance of digital modeling and Building Performance Simulation (BPS) methods to achieve Net Zero Energy Building (NZEB) standards. The integration of Building Information Modeling (BIM) and Building Energy Modeling (BEM) approaches is highlighted as crucial for enhancing energy efficiency. The proposed workflow involves four steps: i) collection of building data through documental analysis and on-site surveys; ii) the construction of a BIM model and its production in Industry Foundation Classes (IFC) standards, including thermo-physical parameters; iii) the developing the BEM model; iv) the creation of a Virtual Reality (VR) interactive environment. The methodology is tested on an office building at the University of Rome Tor Vergata, built in the 1980s. Key outcomes include verifying data interoperability, optimizing energy simulation processes, and enabling interactive exploration of energy data through VR techniques. This integrated approach reduces errors, time, and costs, while also serving as a decision-making support tool for building managers and an educational tool for energy design awareness. The study presents a scalable workflow for energy building management and lays the groundwork for innovative digital twin development for buildings and structure.

# 1. Introduction

In Europe, the 20<sup>th</sup> Century existing building stock, constructed using industrial-derived techniques

and materials, needs to undertake massive assessment of its energetic performances. Looking to Italy, 75% of residential sector building stock was constructed before 2000, avoiding detailed consideration about energy consumptions, and only 2% was built after 2010, according to recent environmental criteria (Gevorgian et. al, 2021). The enhancement of the energy performance of this building stock – achieving Net Zero Energy Building (NZEB) standards (European Commission, 2020) – can significantly contribute to global efforts to mitigate climate change (Arenas, 2024).

This pursuit represents a significant research endeavor and requires a multidisciplinary approach and a continuous updating of research tools.

In particular, the process benefits from the combination of a solid knowledge base of the building, obtained through documental analysis and on-site surveys, with advanced digital modelling, to organize information, to support Building Performance Simulation (BPS), and to facilitate the visualization of data. In this field, one promising approach is the integration of Building Information Modeling (BIM) and Building Energy Modeling (BEM) methodologies (Spiridigliozzi, 2019). By combining these approaches, we can leverage the wealth of building technology data provided by BIM with the detailed energy simulation capabilities of BEM. This integration allows for a holistic assessment of a building's energy performance and facilitates informed decision-making throughout the design, construction,

and operation phases. However, despite the significant advancements and widespread application of both BIM and BEM in recent years, challenges remain in establishing an efficient workflow that enables seamless interoperability and interactive visualization of energy data. In this framework the interoperability workflows support the integration of sensors-acquisition data, to be exploited for both the calibration and validation of the BEM model and the active monitoring of the building.

Leveraging Virtual Reality (VR) techniques presents an exciting opportunity to enhance the representation and understanding of energy-related information (Pan, 2023). By immersing stakeholders in virtual environments, VR enables more intuitive exploration and analysis of complex energy data. However, developing effective VR-based tools for energy analysis and decision-making requires interdisciplinary collaboration and innovative approaches (Panya, 2023).

# 2. Methods

The proposed workflow consists of five steps: i) construction of a philological BIM model based on the original project documentation and photogrammetric surveys of the actual state of the building; ii) production of the geometric model exploiting IFC standards; iii) informative enrichment of the IFC databases embedding the thermo-physical parameters of the building elements; iv) development of the BEM model based on the IFCs; v) development of a VR interactive environment including geometries, graphical elements and data panels, based on the IFC (Elagiry, 2020).

The workflow is based on combining different software platforms and codes. In particular, Autodesk Revit 2023 is used for the BIM's first development while the informative customization of the model, in terms of thermophysical parameters, is performed by exploiting the 'IfcOpenShell Phyton' open-source Toolkit. On the basis of the customized IFC, the energy simulation is developed exploiting the IDA-ICE environment (Sahlin, 2004), while the VR interactive environment, embedding the energy data – concerning thermophysical parameters of the building elements and main results of the analyses – is built using the Unity platform with the Unity XR Interaction Toolkit by Unity Technologies (San Francisco, CA, US) and then tested using different head-mounted displays (HTC Vive Pro, HTC XR Elite and Meta Quest Pro).



Fig. 1 – Workflow diagram

#### 3. Results

The proposed methodology is tested on the case study of an office building of the University of Rome Tor Vergata, considered a sample of the late 20th century existing building stock featuring a complex building system composed of a steel load-bearing frame, reinforced concrete slabs, and precast concrete panels for the envelope. A single room of the building, with two windows, was considered as a sample to test the interoperability procedure within the VR data visualization.

#### 3.1 From Building Data to IFC

For the collection of building data intended for integration into a Building Information Modeling (BIM) system, the principal source considered is the repository of building execution design documents preserved within the University's technical archive. These documents contain significant building data relating to geometry, detailed building elements, and construction materials. Specifically, the execution drawings include precise specifications regarding the composition of the building envelope, encompassing the layering of façade panels and the classification of window frames.

To ensure the accuracy and comprehensiveness of the data, information extracted from the original design drawings undergoes cross-validation with onsite survey data. This process facilitates the precise characterization of the "as-built" condition of the structure. The amalgamation of data derived from building execution design and on-site surveys serves as the foundational input for subsequent BIM processes. Within the BIM Authoring platform, Revit 2023, a conventional modeling approach is adopted, making use of the platform's standard native functionalities. For instance, geometric modeling of the building envelope relies on the "architectural wall" system library, while structural components are represented using standard steel component libraries. Concurrently, the informative modeling phase follows a highly customized procedure tailored to project-specific requirements. This involves extensive utilization of Revit's native take-off sheet function and the enrichment of the Industry Foundation Classes (IFC4) open standard. The IFC enrichment entails associating specific Property set data with building elements, encompassing thermal and physical properties of materials. The considered thermal and physical parameters are specific heat capacity, thermal conductivity, and mass density. They are associated to the IFC4 Ifc Materials category with specific names presented in Table 1.

Table 1 – IFC4 names of the thermal-physical parameters

Parameter name	Ifc name
Specific Heat Capacity	IfcSpecificHeatCapacityMeasure
Thermal Conductivity	IfcThermalConductivityMeasure
Mass Density	IfcMassDensityMeasure

In particular, the native take-off sheet function was used for the labelling of the building areas depending on their intended use, numbering, level and exposure to map the results of IDA-ICE energy simulation to each thermal zone. The native take-off sheet function was further used to prepare the IFC for the VR. In this case the sample, composed of a room with two windows, was considered. The takeoff sheet elaboration focuses on the association of building properties, such as geometric features and thermal parameters to the single building component.

#### 3.2 From IFC to BEM

The enrichment of IFC with Building Energy Modeling (BEM)-oriented Property Sets, which include thermal and physical properties of materials, significantly reduces data loss during the interoperability process. This enrichment is achieved through the utilization of a Python script that leverages the IFC Open Shell library. The script is designed to automatically parse a simple text file containing thermal and physical properties of materials and populate specific BEM-oriented Property Sets of each material, embedding the corresponding values of these parameters. The script considers the association between thermal and physical parameters and the categories of the ICFx4 open standard, presented in Table 1. Fig. 2 illustrates the main step of the script.



Fig. 2 – The algorithm to generate Property Set of thermal and physical parameters of the building materials in IFC4

The IFC file also contained informative data regarding the labeling of building areas and all geometric features of the building. Fig. 3 displays an image of the IFC model embedding the thermal and physical parameters, while Table 2 provides a concise overview of the parameters that can be read by the BEM.

Table 2 - Interoperability check

BIM data	IFC4	IDA-ICE 4.8
Geometry	х	х
Envelope stratigraphy	x	x
Wall	x	х
Windows	x	х
Thermal Zone	x	x
Thermal Properties	х	-



Fig. 3 - The algorithm to generate Property Set of therma
and physical parameters of the building materials in IFC4

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All the geometric and informative data contained in the IFC file were correctly read by the IDA-ICE model: Fig. 4 shows two examples of mapping to imported IFC resources in the IDA-ICE model: first, the external wall and then of the thermal zones. To associate thermal properties of each material embedded in the envelope stratigraphy, a manual mapping is required by the actual version of the software IDA-ICE 5.0.

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# 3.3 From IFC to VR

With the aim of making the geometric model of the building usable, navigable, and interactively interrogable, a methodology for the integration of the BIM model in a generic virtual reality environment has been designed and implemented. The environment was built using the Unity platform by Unity Technologies, which represents the state of the art

ThermalConductivity

for the development of virtual and augmented reality environments. Version 2023.1 has been used. The main challenge in the integration is the ability to manage the correct importing of the model within a scene, including the transfer of the VR Property Set of the various geometrical objects (walls, windows, floors, etc.). In fact, commonly used import systems limit the transfer to geometrical features and texture properties only. Other properties, such as structural or energy variables or even simulation results, may be of interest for a comprehensive exploration of the building. They can be recalled, queried, and inspected by the user in the virtual scene. For this purpose, a C# script has been implemented and attached as a Component to an empty Game Object in Unity. The script allows for the reading of a generic IFC4 format file, extracts the names and values of the variables of the VR Property Set, and associates them with their respective bodies as additional userdefined variables. By assigning these variables as global, it is possible to recall them at any time during the acts of interaction and navigation. The reading of the file, parsing of strings and matching for names are performed using Microsoft Regex class methods for extended compatibility. After the importing, it is possible to make an object of the model interactable, providing that a user selection corresponds to the popup of an informative panel summarizing the specific properties. This is made possible thanks to the use of the XR Interaction Toolkit, which is a third-party library fully integrated into the Unity environment. It allows the simplified management of user tracking, including the interaction with virtual objects using gestures and controllers. It has been successfully used in many engineering applications for both virtual and augmented reality (Cellupica et al., 2024; Cirelli et al., 2024).

Fig. 5 summarizes the algorithm implemented in the VR Property Set import script.

Fig. 6, on the other hand, shows an image of the immersive navigation experience in which the user is inside the BIM geometric model and interacts by selecting one of the walls, obtaining the appearance of a panel summarizing the remarkable properties.



Fig. 5 – The algorithm for importing VR Property Set into Unity



Fig. 6 – The implemented virtual reality environment for testing the proposed procedure. The user is wearing a HTC Vive Pro 2 helmet

The complete navigation and interaction methodology has been tested in the Joint Laboratory of Virtual and Augmented Reality using the most popular virtual reality systems: HTC Vive Pro, HTC XR Elite, Meta Quest Pro and Meta Quest 3. Navigation and interaction using the HTC Vive Pro system have proven to be the most stable and accurate. However, the resolution performance is comparable between the four headsets. Meta Quest Pro has proven to be the most comfortable to wear, considering both the helmet and the controllers.

# 4. Conclusions

Among the main results of the work, the analyzed case study presents: i) the verification of data interoperability between the BIM and BEM models, taking advantage of the customization of the IFC open standards; ii) the optimization of the energy simulation process, in terms of modeling time and cost, fully fruiting the organization of the database, in both geometric and informative terms, of the BIM model and minimizing data loss; iii) the effectiveness of the interactive exploration and interrogation of the energy data, exploiting the VR techniques, for both the knowledge and the energy management of the existing buildings.

In this sense, as a further step, the workflows will enclose even the sensors-acquisition data for microclimatic measurements – already deployed in the considered case study – to be exploited for the both the calibration and validation the BEM model, and to the potentiality of the VR representation.

From a broad perspective, the present paper remarks that the use of a unified BIM-BEM database limits the possibility of error caused by the development of different simulation models and, as a result, reduces costs and time; on the other hand, the integration with interactive visualization enabled by VR expands the scope of application of integrated BIM and BEM models as building management support tools dedicated to multiple levels of users, without specific modeling skills.

At the operational level, the proposed workflow can be adopted as a tool for the energy management of the existing building stock, enabling at the same the fruition of organized building data and the results of the BEM, supporting the planning of maintenance and energy retrofit solutions.

In this sense, the development of VR visualizations of the energy data allows, on the one hand, access to rapid preliminary energetic analyses of the buildings, providing a practical "decision-making" support tool for building managers and, on the other hand, a robust dissemination and educational tool to raise awareness of the importance of the energy design process.

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# Modelling of Aquifer Thermal Energy Storage Connected to Hospital Buildings: A Case Study in Denmark

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#### Abstract

Aquifer thermal energy storage (ATES) is a type of underground seasonal thermal energy storage which uses underground water as the storage medium. Different modeling and simulation tools have been used to model ATES coupled with building and district energy systems. However, most of these methods use co-simulation techniques, which are computationally expensive, time consuming and complex to set up and debug. This paper illustrates a simplified cooling-mode operation of an ATES-based system model developed entirely using the Modelica language. Results indicate that Modelica is an appropriate tool for developing energy system models consisting of ATES to assess their performance. For the case study analyzed in this paper, we controlled the aquifer circulation pumps to supply a constant water temperature of 12 °C to the buildings. Furthermore, the model allowed us to predict the aquifer temperatures in the warm well over time at different distances.

# 1. Introduction

Buildings account for about 32% of the total energy demand in the EU. According to the International Energy Agency (IEA), to meet the EU's goal of net carbon neutrality by 2050 ("Buildings - Energy System", 2023); important measures must be taken in the building and district energy sector to include a higher share of renewable energy in the supply mix. To increase the share of renewable energy in district energy systems, researchers have explored ways to utilize geothermal energy as a source of heating and cooling in district energy networks. Since geothermal energy is a readily available source, it is used to meet the demands of consumers for space heating, space cooling and domestic hot water. In recent years, research into geothermal energy as a renewable source for district heating and cooling networks has gained increasing interest.

Utilizing geothermal energy storage technologies can enhance the integration of renewable energy sources into the energy supply mix. Seasonal energy storage systems can effectively provide heating and cooling solutions during peak demand hours. Aquifer thermal energy storages (ATES) are one type of seasonal thermal energy storages which have been utilized for decades to provide heating and cooling to buildings by use of groundwater (Fleuchaus et al., 2018). An ATES system typically functions in two modes as shown in Fig. 1. During winter, the ATES system extracts water from the warm wells of the aquifer, which is then directed to a heat pump. The heat pump transfers heat from the warm water to the building's heating system, increasing the water temperature for effective heating. The cooled water is then redirected to the cold well of the aquifer for storage. In cooling mode, the water from the cold wells is used to provide space cooling. In some cases, a third regeneration mode is used to maintain a thermal balance in the wells (Vanhoudt et al., 2011), or to store excess heat when electricity is cheap from renewable sources such as wind and solar.



Fig. 1 – ATES operation during summer and winter months

In recent years, there have been significant advances in the research on optimizing the performance of ATES systems. For example, Ribas Tugores et al. (2015) and Todorov et al. (2020) have utilized modeling and numerical simulations to analyze the operational dynamics of ATES systems.

Modeling of ATES systems has been done using different modeling tools (Lee, 2010). Different parameters are considered when evaluating the performance of an ATES system. Based on the requirement of the ATES system, research based on derived KPI's was performed by (Abuasbeh et al., 2021). The thermal efficiency, recovery ratio and hydraulic balance were considered for long term performance of the aquifer. Over a four-year period, the temperature in the cold side of the aquifer increased by 2 °C indicating thermal breakthrough. Further studies in ATES efficiency were conducted by Beernink et.al (2022). Optimal well placements were explored to improve the efficiency and reduce the overall GHG emissions of the ATES coupled energy system. The study concluded that densely placed wells lead to lower electricity consumption from heat pumps and at the same time reduce GHG emissions from other sources of heat such as gas or electric boilers. A method to optimize the DH grid using large-scale thermal energy storages was explored by (Tosatto, Dahash, & Ochs, 2023) where the system performance was evaluated based on the energy and exergy analysis of the TES.

System integration of ATES with district energy systems was recently explored by Bozkaya et al. (2018) where a co-simulation approach was utilized to simulate the operation of the ATES connected to buildings. TRNSYS was used to develop the building model, while COMSOL was utilized to model the aquifer storage. Typically, to analyze the performance of coupled sub-surface and abovesurface components of ATES systems, sophisticated and computationally expensive co-simulation techniques are used. This is mainly due to the lack of sub-surface ATES models that can be seamlessly integrated into building and district energy simulators. Recently, Maccarini et al. (2023) developed a low-order sub-surface ATES model using the Modelica language. The accuracy of the model was verified against other simulators, confirming its suitability to be used in the development of integrated system models based on ATES technology.

This paper aims to demonstrate the application of such a sub-surface model for a case study involving an ATES system connected to hospital buildings. This work focuses on the analysis of the cooling-mode operation of the system during the summer months.



Fig. 2 – Modelica diagram of the ATES system. (The dashed lines represent the control sequence, and the solid lines represent the component connections)

# 2. Methodology

# 2.1 Pilot Site Description

The ATES case study is located in Copenhagen, Denmark and it consists of 12 wells (6 hot wells and 6 cold wells). During winter months, heat pumps are used to heat the water from the warm wells to meet the heat demand. During summer months, cooling is provided by the groundwater ATES system to the hospital. Domestic hot water is supplied by the district heating network in the region. The heat pumps are not in operation during the summer months. As previously mentioned, this paper focuses only on modeling the cooling-mode operation of the cooling system that provides the hospital buildings with cold water during the summer months. The information on the installed cooling system inside the hospital substations is unavailable to the authors.

# 3. Modelling approach

The model of the ATES system was developed using the Modelica language, and it describes the thermal and hydraulic dynamics of the system, together with the control logic. Modelica is a freely available, object-oriented, and equation-based language for modeling physical systems and controls (Mattsson, Elmqvist, & Otter, 1998). Component models from the Modelica Buildings Library version 11.0.0 (Wetter et al., 2014) were used in this work. Simulations were run using Dymola 2024 on Windows with the DASSL solver and a tolerance of 1E-6. Fig. 2 illustrates the Modelica diagram view of the ATES system.

The system model includes the following main component models:

- Sub-Surface aquifer storage.
- Heat exchanger connecting aquifer and building hydraulic circuits.

- Circulation pump for the building hydraulic circuit.
- Control logic

The sub-surface aquifer storage component is modeled based on the partial differential equation (PDE) for 1D conductive-convective transient radial heat transport in porous media. In the Modelica implementation, the domain is assumed to be spatially discretized along the radial direction. The heat transfer process within the aquifer is represented by a series of thermal capacitances and resistances. The fluid flow between the wells through the subsurface was modeled by adding a series of fluid volumes, which are connected to the thermal capacitances via heat ports. Circulation pumps are included in the model and can be controlled using a dedicated connector. The aquifer model was developed with the following assumptions,

- The computational domain is homogenous.
- Movement of water in the aquifer is only in the radial direction.
- No vertical heat transfer and the flow of groundwater is neglected.

More details can be found in (Maccarini et al., 2023). The number of well doublets in the model can be adjusted using the parameter, *nPai*, which represents the number of paired wells.

The heat exchanger component models the heat transfer between the fluids using an effectiveness coefficient of 0.8.

The circulation pump in the building hydraulic circuit was modeled to be capable of providing the

required mass flow rate at any time by overcoming the corresponding pressure loss. The required mass flow rate was calculated from the cooling loads as

$$m=Q/(C_{p}*delta T)$$
(1)

where  $C_P$  is the water specific heat capacity and delta T = 4 K is the water temperature difference between supply and return. The cooling load of the hospital buildings is shown in Fig. 3 for the period between 1st April–30th November, 2023. The cooling load was obtained from the operational data gathered from the buildings during the period. Table 1 shows the main input parameters used to model the sub-surface aquifer, which is made of

Table 1 – Simulation parameters for the ATES model

limestone.

Aquifer properties	Values
Undisturbed aquifer temperature	10 °C
Number of well pairs	6
Aquifer thickness	70 m
Domain radius	250 m
Thermal conductivity of limestone	1.7 W/(m K)
Density of limestone	2800 kg/m <sup>3</sup>
Specific heat capacity of limestone	840 J/(kg K)



Fig. 3 - Cooling demand of the hospital buildings (period between 1st April-30th November)

# 3.1 Control Strategy

To guarantee that the system effectively meets the required cooling demands, we implemented control logic based on the operational strategy implemented in the installed ATES system. The goal is to track a supply water temperature setpoint of 12 °C in the building cooling circuit. This is achieved by using a PI controller that modulates the water flow extracted from the cold well. The proportional and integral gain of the PI controller was initially set to default values recommended in the building library for similar system topologies. Minor adjustments were then made to enhance the system's response such that the supply temperature was stable. A switch block is employed to ensure that during periods of no cooling demand in the building, there is no flow from the aquifer wells. This prevents recirculation in the aquifer wells through the heat exchanger.

# 4. Results and Discussion

Fig. 4 shows the water temperature supplied to the hospital buildings. The figure shows that the control logic can maintain the water temperature at approximately 12 °C over the entire cooling period. The small oscillations around the set-point value are due to the tuning parameters chosen for the PI controller.



Fig. 4 - Supply water temperature to hospital buildings

The temperature in the aquifer was analyzed as a function of distance and time. Fig. 5 shows the temperatures in the aquifer at different distances from the warm well over the simulated period. The results indicate that the aquifer temperature is influenced by the injected water up to approximately 20 meters from the center of the well. As expected, the closer the analyzed location is to the well, the more rapidly the aquifer temperature approaches the injected temperature (around 15 °C).

The increased temperatures observed in the warm well during summer months suggest that the accumulated heat can be utilized during winter to enhance the performance of heat pumps.



Fig. 5 - Temperature in the warm well of the aquifer at different distances

# 5. Conclusion

In this paper, we developed an ATES model which simulates the cooling operation of an energy system connected to hospital buildings. The system model resembles an installed ATES system located in Denmark. Results indicate that the model can be used to effectively analyze the operation of ATES systems including sub-surface and above-surface components connected to each other. To regulate the system, the authors implemented a simplified control strategy with the objective of stabilizing the supply water temperature at 12 °C.

For future studies, the authors plan to advance their model by developing a comprehensive full plant simulation. This upgraded model will integrate more sophisticated control strategies aimed at accurately predicting the operation of the ATES system across both heating and cooling seasons. The overall goal is to enhance the system's efficiency and performance.

In addition to its current applications, future uses of the model may involve power-to-heat applications, allowing excess heat to be stored in aquifers during periods of affordable and clean electricity from wind and PV.

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#### Nomenclature

#### Symbols

m	Volumetric flow rate (m <sup>3</sup> /s)
Q	Heat flow (W)
c <sub>p</sub>	Specific heat capacity (J/(kg K))
Т	Temperature (°C)

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# Analysis of Energy Consumption Scenarios of the Italian Residential Building Stock

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#### Abstract

Building stock energy models have been receiving increasing attention in the last years as powerful tools to forecast energy policies at national levels. This work contributes to the existing discussion on this topic by presenting a bottom-up physic-based model of the Italian residential stock that can calculate national energy consumption using data collected by ISTAT from a 2013 survey. Such a model exploits electric appliance data and dynamic building energy simulations to analyse the current state of Italian houses' energy consumption, and by presenting possible scenarios for 2050. The analysis of the current state focuses on the energy vectors employed, primary energy, and validation with respect to external sources. Results show good accuracy with respect to national energy balance and with respect to regional data for heating and domestic hot water. The presented future scenarios are based on expected changes in climatic condition, technology replacement, and retrofits of buildings. Considering current renovation rates, envelope insulation and heat pump installation could produce a reduction of 12% of the final energy.

# 1. Introduction

In 2019, the European Commission presented the Green Deal, a package of proposals to reduce net greenhouse gas emissions by 55% by 2030 compared to 1990 levels (European Commission, 2020). In this perspective, Italy has outlined the first phase of the plan's implementation for the period 2021-2030 in the "Piano Nazionale Integrato per l'Energia e il Clima" (PNIEC), which is now extended with new REPowerEU investments. The residential sector accounts for approximately 30%

of the final energy consumption in Italy, and a significant share of it is covered by natural gas, emphasizing the importance of focusing on its decarbonization.

National building stock energy modeling represents a great opportunity for stakeholders and policy makers in the process of fostering energy efficiency and European carbon emission targets. Several international sources report the great inefficiencies connected to the European building stock (Economidou et al., 2011), which is mainly due to a great percentage of buildings built before the first energy efficiency directives, as the EPBD ("Energy Performance **Buildings** of Directive, (2018/844/EU)", 2018). In this context, developing new tools to analyze the national energy consumption of buildings, disaggregate it, and predict future trends is a crucial step. The most used methodology in analyzing country-wide building stock typically uses top-down approaches. In this case, demographic and economic reports at the national level are combined with purely statistical methods to calculate specific indicators for the building stock energy consumption, (Summerfield et al., 2009). Despite this methodology being fast and easy to implement, it often does not give a wide and disaggregated representation. On the contrary, the bottom-up approach, based on the physic simulation of representative buildings whose results are then scaled up to the stock level, allows more detailed analysis and permits the evaluation of future scenarios.

This paper presents a nationwide bottom-up model of the Italian residential building stock, built on top of the data provided by the Italian Statistical Institute survey on households' energy consumption, dated 2013 (ISTAT, 2016). The model exploits the survey responses to build dynamic Building Energy Simulations for each entry, providing great granularity and detail on the energy consumption of the whole stock. First, the paper includes a brief description of the data in the survey, then the model and methodology are detailed. Finally, the results section shows the calculation reliability with respect to well-known benchmarks and the model's potential in analyzing future scenarios.

# 2. Material and Methods

After the description of the data included in the survey, this section provides the details of the performed calculation.

# 2.1 ISTAT Survey Outline

The model's core strongly depends on the dataset describing the building stock. For this purpose, the 2013 Italian survey of household energy consumption was chosen (ISTAT, 2016), as it provides the answers of 20 000 different house owners to more than 350 queries on their building and energy consumption spread around the country. In particular, the questions are subdivided in the following categories:

- Occupancy: information about the occupants, including gender, number, and age.
- *Dwelling characteristics*: typology (single family house, apartment, ...), floor plan, construction period, footprint area, windows, materials, orientation. The location of the dwelling is provided only as a region.
- *Space heating*: type, number, layout, energy vector, and emission system.
- Domestic Hot Water (DHW): similar to heating.
- *Space cooling*: type, number of rooms cooled, average usage during summer.
- *Biomass consumption*: system type, yearly consumption, rough costs.
- *Lighting*: number of light bulbs, divided by type, traditional bulbs or energy-saving bulbs, typical usage.
- *Appliances*: presence, number, size, frequency of use, for every type of appliance, including

refrigerators and freezers, washing machines, dryers, dishwashers, cooking tops and ovens, screens and computers, and others.

- *Energy expenses*: generic yearly costs for each energy vector.

In addition to these data, each survey entry is assigned to a national refactor coefficient, i.e., the number of houses at the nation level represented by that specific entry. This number is calculated by ISTAT using literature methods, and it produces a statistically relevant representation of the whole national building stock, starting from the 20 000 entries of the dataset. Fig. 1 shows, as an example, the percentage of type of dwelling split by region.



Fig. 1 – Distribution of dwelling types across Italian regions

# 2.2 Model Description

The model presented in this work, i.e., MODENA (MODello Energetico Abitazioni, housing energy model), was developed as part of a collaboration between the University of Padova and the Italian Research on Energy System company (RSE, Ricerca sul Sistema Energetico). The input of this model consists of the microdata matrix collected in the previously described survey. The application, written in Python, uses the survey to build a dynamic building energy simulation of all households, calculating the consumption of appliances, heating, and cooling. The model structure is divided into four phases, i.e. input loading, appliances and domestic hot water consumption calculation, space heating and cooling consumption, output processing, and national scaling of results. Apart from the first section, which only loads the dataset, each phase is outlined in the following sections.

# 2.2.1 Lights, electric appliances and DHW consumption

Results from previous work have been applied to electric appliances (Besagni et al., 2020). Once the necessary data for individual devices are obtained, each respondent's electrical and gas consumption (for cooking uses) is calculated by combining the ISTAT survey responses with the unit consumption of the devices. For example, the annual consumption for lighting is calculated by multiplying the number of light bulbs, the average power consumption of each bulb, the number of daily hours of use, and the annual number of days in use. The assumed power consumption is 15.36 W for energy-saving bulbs and 40.19 W for traditional bulbs, and three daily usage patterns are also assumed: 3 hours, 7 hours, and 14 hours. For the sake of brevity, the calculation for other appliances is not detailed. However, the method is similar and always consists of multiplying the typical consumption of a type of appliance (from external sources, Growth for Knowledge, 2021) by the estimated yearly usage. The reader can find the detailed calculation in Besagni et al., 2020, and the report from Ricerca Sistema Energetico 2022.

The domestic hot water energy need, D<sub>dhw</sub>, is calculated using UNI/TS 11300-2 Standard (Ente Italiano di Normazione, 2014), which calculates the DHW consumed daily volume, V, with respect to the floor area of the dwelling, A<sub>floor</sub>.

$V = a \cdot A_{floor} + b$	(1)
$D_{dhw} = \varrho \cdot c_p \cdot V \cdot 365 \cdot \Delta T_{av}$	(2)

Where coefficients a and b are provided in the standard depending on the size of the building.

#### 2.2.2 Heating and cooling consumption

Concerning heating and cooling consumption, the EUReCA building energy model was used for the simulation (Prataviera et al., 2021). The latter is a Python package that implements physic-based simplified lumped parameter models to run the hourly dynamic simulation of the building. In particular, the BES model is developed considering the following assumptions.

Climatic data are taken for each region from the dataset of Comitato Termotecnico Italiano, n.d.,

considering the most representative city. The geometry of each dwelling is created by considering its type (single-family house, multi-family house, or apartment), footprint area, prevailing orientation of external walls, and the number of windows reported in the ISTAT survey responses. A square footprint is assumed for each case, while the number of floors and boundary conditions are assumed depending on the other data. An archetypical envelope representation is selected based on the age class (Carnieletto et al., 2021) and subsequently corrected by the possible presence of an insulation retrofit. These assumptions allow the construction of the RC equivalent network to calculate the heating/cooling demand (Prataviera et al., 2021).

Concerning the usage, systems operation is assumed based on the responses from the survey, which allows a first estimation of the number of hours the heating and cooling systems are operated. Instead, heating/cooling system efficiency is calculated using the well-known method of subsystem efficiencies and following the UNI-EN 15316 Standard (CEN, 2017). In particular, the emission, distribution, control, and generation efficiency are assumed for each dwelling considering the type of emitters, the system layout, the age declared in the responses. The only exception to this method is represented by heat pumps, whose efficiency is calculated dynamically using the correlation proposed by Staffell et al., 2012.

 $\begin{aligned} & \text{COP}_{ashp} = 6.81 - 0.121 \cdot \Delta T + 0.000630 \cdot \Delta T^2 \quad (3) \\ & \text{COP}_{gshp} = 8.77 - 0.150 \cdot \Delta T + 0.000734 \cdot \Delta T^2 \quad (4) \end{aligned}$ 

Where  $\Delta T$  represents the temperature difference between the outdoor air (or ground) and the heating loop water (considered 35 °C for radiant panels, 45 °C for fan coils, and 60 °C for radiators). With geometry, envelope, and systems assumptions, EUReCA simulation is set, and consumption is calculated accordingly.

#### 2.2.3 Post processing

After the calculation from the previous steps, energy consumption for each final use is combined to obtain the yearly consumption for each energy vector, including electricity, gas, biomass, LPG, and others. Such a calculation allows for granular analysis of the different end-uses and the regional distribution of consumptions. Ultimately, it is possible to multiply each dwelling's consumption by the national refactor coefficient, moving to regional and national consumption.

#### 2.3 Methodology

The analyses proposed in this work are mainly two. First, the model is validated using national energy consumption from TERNA 2013 and International Energy Agency, n.d. Space heating and DHW final energy is also compared GSE data at the regional level (Gestore Sistema Energetico, 2021).

After the validation process, the model is exploited to run future scenario analyses. Three cases are considered:

- 1. Future scenario with 2050 climate without any retrofit of the building stock;
- 2. 2050 future scenario with envelope insulation and condensing boilers;
- 3. 2050 future scenario with envelope insulation and heat pump substitution.

Concerning weather conditions, 2050 climatic data obtained using CCWorldWeatherGen were (Jentsch et al., 2008), developed by the University of Southampton. This tool converts standard epw weather files into climate-changed epw files. The second-to-last most critical scenario for 2050 was chosen for this simulation, i.e., scenario A2. Moreover, it is worth mentioning that 2050 weather conditions are calculated starting from the historical Test Reference Year datasets (available at the EnergyPlus website, "Weather Data | EnergyPlus," n.d.), whereas the starting simulation has been carried out considering the real weather condition from 2013, allowing validation. Simulations 2 and 3 account for the advancements expected in energy efficiency in building envelopes by 2050. On these, the former considers the retrofit of building envelopes (opaque and glazed considering current criteria) of a portion of the residential building stock and the replacement of traditional boilers with natural gas condensing boilers, while the latter considers both these measures and the replacement of boilers with heat pumps. The estimated fraction of renovated buildings has been assumed to be 21.8% by 2050 (Ministero dello Sviluppo Economico, 2020), and renovated buildings were chosen randomly within the dataset.

# 3. Results

#### 3.1 Standard Simulation

First, the results from the standard simulation, referring to the 2012 building stock, are presented. To start, Fig. 2 shows the specific final energy of the households, split by fuel type and area. The energy mix is mostly consistent for the North-East, North-West, central, and southern regions, while it is very different for mountainous areas and islands. The latter, including Valle D'Aosta and Trentino Alto Adige, exhibit high specific consumption values that exceed 275 kWh/m<sup>2</sup>; they rely heavily on biomass and partly on gasoline due to difficulties in extending the gas network to the more elevated zones and the greater availability of biomass from nearby woods. North-East, North-West, and central regions present similar energy mixes, with natural gas being the main energy vector. Their specific consumption ranges from approximately 135 kWh/m<sup>2</sup> in the central area to 250 kWh/m<sup>2</sup> in the North-East. Natural gas consumption on the islands is quite limited as Sardinia is not connected to the natural gas network, resulting in a higher share of LPG and electric energy.



Fig. 2 – Specific final energy consumption divided by energy vector

Concerning primary energy, the estimated national total primary energy consumption is equal to 39.4

Mtoe. Of this total value, 35.9 Mtoe is nonrenewable primary energy (91%) and 3.5 Mtoe is renewable primary energy (9%). The primary energy consumption, related to the different energy vectors, is reported in Table 1. Natural gas covers almost half (48%) of the primary energy consumption, followed by electric energy (31%) and biomass (14%). The use of LPG and gasoline is limited (4% and 2%), and the use of oil and coke is negligible (less than 1%).

Table 1 – Primary energy	consumption by	energy vectors
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Energy vector	Primary energy [ktoe]
Electric energy	12266 (31%)
Natural gas	19100 (48%)
Biomass	5552 (14%)
LPG	1591 (4%)
Gasoline	884 (2%)
Oil	16 (<1%)
Coke	0 (<1%)
Total	39428

Table 2 presents the energy consumption by energy vector obtained by simulating the model, compared with the data provided by TERNA and IEA for 2013 (TERNA 2013; International Energy Agency, n.d). From these values, it is possible to observe how the model can estimate the consumption of natural gas and electricity with good accuracy. Concerning national references, natural gas and electricity consumption have an error of about 0.6% and -4%, respectively. Such an error increases when other fuel types, such as wood and pellets, are considered. This larger error is mainly due to a larger uncertainty in the modeling process (stove/biomass boiler efficiency is not precisely modeled) and due to the wood self-production and consumption, which is not easily predictable with the available information. However, such fuels are less spread nationwide, keeping the overall model error below 9%.

Table 2 – Italian final energy consumption compared with data from TERNA and IEA

Energy vector	Model results	Reference	Error
Natural gas [ktoe/y]	18190	18073	0.6%
Electric energy [GWh/y]	58948	61379	-4.0%
Biomass [ktoe/y]	5552	6633	-16.3%
LPG [ktoe/y]	1515	1193	27.0%
Gasoline [ktoe/y]	826	1511	-45.3%
Total [ktoe/y]	31166	34230	-9%

To move further with the validation, a deeper comparison is presented concerning data obtained from a top-down method by GSE (Gestore Sistema Energetico, 2021). GSE data refer to 2018, while the model's values refer to weather conditions of 2013. For this reason, a correction of the results using Heating Degree Days (HDD) of each weather file for 2013 and 2018 has been applied before comparing them. It can be observed that the model can simulate with good accuracy the energy consumption for most of the regions, in particular Piemonte, Lombardy, Friuli-Venezia Giulia, Valle d'Aosta, and Abruzzo. However, the values reported in the graph below are underestimated for other regions such as Lazio, the islands, and the southern regions. Such errors occur in areas where the difference in HDD between 2013 and 2018 is higher. The error in this case can therefore be associated with the uncertainty linked to weather conditions of the two different sources, as data from the same source was not available.

Fig. 4 compares the regional final consumption for DHW with the values provided by GSE. It can be observed that the model accurately estimates these consumption values, providing a total of 4293 ktoe/y. In comparison, GSE's estimation is 3943 ktoe/y, resulting in an error of 9%.



Fig. 3 – Validation of the final energy consumption for space heating with GSE data



Fig. 4 – Validation of the final energy consumption for domestic hot water with GSE data

#### 3.2 Future Scenarios

Moving to the future scenarios results, the average difference between 2050 average temperatures and 2013 average temperatures is 1.39 °C, leading to an increase of cooling consumption. Fig. 5 provides an overview of the final energy consumption for space cooling in each region, allowing for a comparison between the values from 2050 and those from 2013. Notably, all regions either experience an increase or show no significant variation in space cooling consumption. Among them, Veneto, Emilia-Romagna, and, to a lesser extent, Sicily demonstrate the most prominent increases. Veneto exhibits a substantial 71% increase in space cooling consumption compared to 2013, rising from 189 ktoe to 323 ktoe. Similarly, Emilia-Romagna experiences an even higher increase of 125%, with consumption rising from 141 ktoe to 319 ktoe. Sicily also sees a significant increase of 24%, going from 241 ktoe to 310 ktoe. Even though such increases might look overestimated, it is worth noting that the final energy for space cooling is still a minor fraction of the total electric consumption of the residential sector. Besides some increases, a few regions, such as Lombardy and Calabria, present a reduction in cooling consumption. This behavior is due to an average temperature for 2013 (CTI data) higher than the projected 2050 average temperature. These inconsistencies and uncertainties lead to lower cooling consumption, which is particularly problematic for the Lombardy case, as it represents 20% of the national energy consumption in the residential sector.



Fig. 5 – Comparison of space cooling final energy consumption between 2013 and 2050  $\,$ 

Moving to the building stock retrofit, national results from all future scenarios are reported in Table 3. From the simulation results considering only the retrofit of building envelopes, S2, a reduction in natural gas consumption of 7% is observed compared to the simulation with 2050 climatic data, equivalent to 1407 ktoe. Electric consumption remains relatively unchanged due to its marginal use for space heating. Overall, there is an 8% reduction in total final consumption. Compared to the simulation that considers only 2050 climatic conditions, the simulation that considers both retrofitting of building envelopes and installing heat pump systems, with a renovation rate of 21.8%, exhibits a reduction in natural gas consumption by 18%, equivalent to 3340 ktoe. This reduction is primarily attributed to replacing traditional boilers with condensing gas boilers and heat pumps. Additionally, there is a 20% increase in final electric energy consumption, equivalent to 11765 GWh. The final energy consumption shows a decrease of 12%, equivalent to 3605 ktoe, providing a better solution compared to the previous case (no PV selfconsumption is considered, resulting in a conservative analysis).

Table 3 – Final energy consumption provided by the four model simulations, for the different energy vectors

	2013	S1	S2	<b>S</b> 3
Natural gas	18190	18309	16983	14969
[ktoe/y]		(0%)	(-7%)	(-18%)
Electric energy	58948	59314	59202	71079
[GWh/y]		(0%)	(0%)	(+20%)
Total	31297	31197	28667	27592
[ktoe/y]		(0%)	(-8%)	(-12%)

#### 4. Conclusion

Using a bottom-up model based on simplified dynamic energy simulation, this work has explored consumption patterns within the Italian residential sector, specifically focusing on heating, as it is the major contributor to households' consumption. The utilized model has demonstrated good accuracy in calculating natural gas and electric consumption with respect to national benchmark data, with deviations of +0.6% and -4%, respectively. The total consumption error stands at -9% due to the difficulty in tracking the annually consumed quantity of biomass and other fuels, which are marginally used. Besides the current state, possible future scenarios involving envelope insulation and heating system subtitution are analyzed based on current national renovation rates. Considering that 21.8% of the building stock will be renovated by 2050, natural gas consumption reduction is forecasted to be around 18%. These scenarios show that despite a relatively high rate of renovation, driven by recent incentivization measures, achieving complete decarbonization by that date, and therefore accomplishing the goal set by the European Union, will require significant efforts.

#### Nomenclature

#### Acronyms

DHW BES	Domestic Hot Water Building Energy Simulation	
Symbols		
А	Area (m²)	
COP	Coefficient Of Performance (-)	
c <sub>p</sub>	Specific heat (kJ kg <sup>-1</sup> K <sup>-1</sup> )	
D	Demand (kWh)	
$\Delta T$	Temperature difference (K)	
6	Density (kg m <sup>-3</sup> )	

# V Volume (m<sup>3</sup>)

#### Subscripts/Superscripts

ashp	Air Source Heat Pump		
av	Average		
floor	Net floor area		
gshp	Ground Source Heat Pump		

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# Automating Solar Shading Control in Residential Buildings Located in a Temperate Climate: A Household-Specific Decision

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#### Abstract

The implementation of movable solar shading is strongly encouraged in order to reduce the overheating of residential buildings. However, their efficacy is, amongst other factors, determined by the control system employed. Building occupants are often relatively passive in manually operating their shading, leading to suboptimal use, whereas automated control reacts consistently to changes in outdoor and indoor conditions. This study evaluates the impact of automated shading control on annual heating and artificial lighting energy consumption, and thermal comfort compared to manual operation in residential buildings without cooling installations. Building performance simulations are conducted for three building designs in the temperate climate of Belgium using EnergyPlus. Multiple variations are investigated to analyse the sensitivity of the impact of automated control to boundary conditions such as the orientation, reflectance of the solar shading, household composition and manual operation strategy. The results demonstrate that the implementation of automated shading control has the potential to substantially reduce thermal discomfort while exerting a minimal impact on the energy consumption. However, the relative differences in overheating show considerable variation, primarily influenced by the building design and occupant behaviour. These findings emphasise the necessity of considering co-benefits (e.g. thermal comfort) and boundary conditions when evaluating shading control strategies.

### 1. Introduction

There is an increasing demand for cooling in residential buildings in temperate maritime climates. From a technical perspective, this is driven by the enforced improvements in thermal resistance of the building envelope, combined with a decrease in the thermal mass in many new dwellings. In addition, this is reinforced by the building occupants, who are tightening their (thermal) comfort requirements. Moreover, the occurrence and severity of heat waves associated with climate change are also contributing factors. Many design guidelines recommend prioritising passive measures, such as the installation of solar shading, to reduce indoor overheating risks (Ozarisoy, 2022). However, their impact is highly dependent on the type of solar shading installed and its characteristics, as well as on the effectiveness of the control system (Tzempelikos & Athienitis, 2007).

The implementation of movable solar shades can enhance the thermal and visual comfort of the residents, while simultaneously reducing the energy demand in the case of active cooling (Yao, 2014). Nevertheless, the use of improper control strategies may lead to an increase in the total building energy consumption (Grynning et al., 2014). In this regard, the effects of shading on the artificial lighting energy consumption are often overlooked (Van Thillo et al., 2022).

The control of the position of solar shades should ideally reflect the prevailing and anticipated indoor and outdoor environmental conditions. Conventional manually operated shadings require the intervention of the building occupants, who typically show a rather passive attitude towards adapting the solar shading. Frequently, the closure of the shades is only initiated following a prolonged period of discomfort sensations. Furthermore, control actions are often associated with other activities, such as entering or leaving a specific room, particularly for opening actions (Correia da Silva et al., 2015; O'Brien et al., 2013). This results in a hysteresis phenomenon between raising and lowering actions (Sutter et al., 2006; O'Brien & Gunay 2015). Consequently, manual operation leads to suboptimal control of the shading in residential buildings, particularly given that the residents are often absent during the hours of high solar penetration.

The automation of control allows the solar shading to act upon changes in the indoor and outdoor conditions. The efficacy of this system depends on the control approach selected, with scenarios designed to minimise overheating risks and daylight penetration potentially increasing the energy demand of artificial lighting. The configuration of control triggers, sensor positions and threshold setpoints therefore plays a pivotal role in determining the system's performances (Tabadkani et al., 2021).

In temperate climates, there is an increase in the risk of overheating, while many houses are not (yet) equipped with cooling installations. In these houses, the investment costs for automating the installation are not outweighed by reductions in cooling energy savings. Therefore, it is essential to consider the non-economic benefits in order to make informed design decisions.

It is generally assumed that well-tuned automatic control is more energy-efficient than its manually operated counterpart. The standard EN ISO 52120-1 proposes the BAC factor method to facilitate the estimation of this impact on the building energy demand (European Committee for Standardization (CEN), 2022). The corresponding BAC factor defines the cooling energy savings due to automated control at 20% compared to manually operated shading. Nevertheless, the impact of automated control on the heating and cooling consumption can differ by as much as 11% depending on the sensors employed, with solar radiation-based controls proving superior (Yao, Wang, et al., 2016). Furthermore, the actual impact on the energy consumption is also influenced by features related to the building and shading devices design (Van Thillo et al., 2022).

Similarly, the impact of automated shading on thermal comfort appears to be influenced by the building and its context. The efficacy of different automated control systems in reducing the operative temperature is, for example, affected by building design features such as the window-to-wall ratio (WWR) and orientation. In addition, the effectiveness of upgrading the control in improving the indoor environment is greater in climates with high seasonal variations (Tabadkani et al., 2021).

The building occupants themselves also exert a major influence, as they are directly responsible for the manual operation of the system (Littlefair et al. 2010). The effectiveness of their interactions will determine the level of thermal comfort and energy consumption of the baseline scenario (Yao, Chow, et al., 2016). Additionally, households have distinct habits related to the presence and production of internal heat gains. These interfamilial differences can have a substantial impact on the thermal comfort of houses.

Residential buildings differ in this way from office buildings with the latter typically exhibiting more regular occupancy patterns, which coincide with times of high solar gains. The majority of the studies related to shading control have focused on office buildings, as solar shading is likely to provide the most direct benefits in this type of building. In contrast, automated shadings are far less common in residential houses; although they could also provide significant benefits, especially considering that occupants will often not be in their home at times when solar gains are high and hence control actions would be appropriate.

This paper aims to determine the impact of automated shading control on annual heating and lighting energy consumption and overheating risk compared to manual operation in residential buildings without cooling installation. It is assumed that these performances are influenced by boundary conditions. Variations in occupancy behaviour (i.e. presence and manual operation) are therefore combined with diversity in the building and shading characteristics.

# 2. Building Performance Simulations

The energy and thermal comfort performance of residential buildings with manually operated and automatically controlled shading is contrasted through the use of building energy performance simulations. The annual heating and lighting energy consumption and indoor operative temperatures of all variants are simulated in EnergyPlus (version 9.6) with a simulation time step of 2 minutes.

# 2.1 Case Studies

The impact of shading control is evaluated for three different building designs of which the characteristics correspond to a recent detached, semi-detached and terraced building (Cyx et al., 2011). Each building comprises a living room with an open kitchen, three bedrooms, a bathroom, two toilets, a storage area, a corridor and an attic. The detached building also has a garage. All rooms are modelled as separate thermal zones.

The houses are situated in Uccle (Belgium), within a temperate maritime climate zone. The climate data utilised for Uccle is adopted from the International Weather for Energy Calculations (IWEC). Moreover, the set of simulations for each house is repeated four times, with each iteration representing a different orientation and corresponding variation in the solar heat gains per thermal zone.

Table 1 – WWR per orientation

Facade	Detached	Semi-detached	Terraced
Front	18.70%	7.18%	17.9%
Right side	27.52%	7.44%	-
Rear	15.02%	29.62%	39.2%
Left side	9.76%	-	-

The external walls of the houses consist of windows for 17.71%, 13.00% and 28.56%, respectively for the detached, semi-detached and terraced building, distributed over the different facades (Table 1). The entire building envelope is well insulated with a thermal transmittance of 0.1 W/(m<sup>2</sup>K) for the opaque constructions and 0.6 W/(m<sup>2</sup>K) for the windows and doors. The windows are further characterised by a solar heat gain coefficient of 0.5. Moreover, a timber frame construction, characterised by a low thermal mass, was chosen, resulting in a high potential for overheating. During the winter months, the houses are heated continuously at 20 °C in the living room, kitchen, bedrooms and bathroom, while the corridor and storage room are kept at 16 °C. In contrast, there is no active cooling during summer months, but the building is equipped with external textile screens with an openness factor of 5%. Two types of screens are investigated, with reflectance values of 0.6 and 0.1 respectively.

The presence of occupants and the produced internal heat gains are generated probabilistically based on the Belgian Time Use Surveys of 2013 (Verbruggen, 2021). The associated lighting requirements are met by controlling the lighting installation automatically (Van Thillo et al., 2023). The performance of the case study dwellings is evaluated for 18 different households, ranging from one to six persons. For each number of inhabitants, three household routines are evaluated. From the ten generated patterns, the families with the minimum, average and maximum occupancy were selected to capture the variability between families.

# 2.2 Shading Control

The effects of automated shading control are compared to those of manual operation. Therefore, two manual operation strategies are considered in the simulations: in the first scenario the occupants tend to adjust the screens passively, while in the second scenario they interact more frequently. Although many occupants interact with their shading for reasons other than preventing solar gains (e.g. to darken their bedrooms), only the actions related to overheating are included here.

# 2.2.1 Passive manual operation

The majority of the building occupants exhibit a passive attitude towards the opening and closing of their shading in order to prevent overheating. It is anticipated that the occupants will close their shading when they are experiencing discomfort in their living room/kitchen or offices. For this scenario, the threshold is set to 26 °C for closing the shading on the condition that an occupant is present in the room (European Committee for Standardization (CEN), 2019). Conversely, the shading will be reopened upon the first entry into the room after the indoor operative temperature has dropped below 24 °C.

#### 2.2.2 Active manual operation

Some occupants are more concerned about their thermal comfort perception and are therefore more proactive in operating their screens to anticipate on future overheating risks. Consequently, they will close the solar shading in their living room/kitchen and bedrooms as soon as they notice that the indoor operative temperature in one of these rooms exceeds 24.5 °C. In addition, they maximise daylight entrance by only closing the screens in the orientations where the solar radiation on the façade exceeds 150 W/m<sup>2</sup>. Similarly, the occupants reopen them when the indoor operative temperature has dropped below 22.5 °C or the sun intensity on the window is less than 50 W/m<sup>2</sup>. However, the family members show a more passive attitude towards opening actions, only opening the shades when entering a room.

#### 2.2.3 Automated shading control

In this scenario, the solar shading is switched when sensor readings exceed predefined thresholds. A combination of an indoor temperature sensor and an outdoor solar radiation sensor are here implemented to control the position of the screens. They will close when the solar radiation exceeds 79 W/m<sup>2</sup> and the indoor air temperature simultaneously reaches 21 °C during the cooling season. During the heating season, this temperature is set to 24.5 °C to maximise the heat gains. Once a trigger has fallen below the threshold for a period of 20 minutes, the solar shading will reopen. In this scenario, all windows are equipped with solar shades and are controlled separately.

#### 2.3 Impact Assessment

This study examines the impact of solar shading on thermal comfort and energy consumption. The energy performance is divided into two categories: space heating demand and artificial lighting energy. The thermal comfort performance, and more specifically overheating, is evaluated based on the indoor operative temperatures and room occupancy. In residential buildings, the comfort requirements depend on the function of the room. The rooms with short and irregular occupancy patterns (i.e. the corridor, toilets, storage and attic) are not included in this analysis. The remaining rooms can be classified into three groups with different requirements: (i) the bathroom, (ii) the bedrooms and (iii) other rooms (i.e. the living room and kitchen and home offices). Furthermore, the perception of indoor temperatures as acceptable is found to be strongly dependent on the recent outdoor temperatures. Therefore, the maximum comfortable temperature for each room type is determined as a function of the outdoor conditions (Peeters et al., 2009). For each time step and each room, the operative indoor temperature ( $\theta_i$ ) is compared to the corresponding maximum temperature by 10% PPD ( $\theta_{max}$ ) to identify any overheating risk. However, this is only included in the key performance indicator if there are actually occupants present at that moment. The degree of discomfort per time step is expressed as a function of the time step (t), the number of occupants (N) and the extent to which the comfort temperature is exceeded. Finally, the annual thermal discomfort of the family is calculated as the sum of the discomfort experienced in the different rooms and over all time steps using equation (1).

discomfort =  $\Sigma\Sigma t * N * (\theta_i - \theta_{max})$  for  $\theta_i > \theta_{max}$  (1)

### 3. Results and Discussion

# 3.1 Impact of Automated Shading Control



Fig. 1 – Impact of automated shading control

The simulation results indicate that the implementation of automated solar shading control can significantly reduce thermal discomfort for occupants, in comparison to manual operation. As presented in Fig. 1, the experienced overheating decreases by a median of 52.74% following the introduction of the automated control. In contrast, the median increase in heating energy and artificial lighting consumption is relatively small, with differences of 1.18% and 2.14%, respectively.

Fig. 1 indicates that there is a considerable variation in the improvements in thermal discomfort among the investigated combinations, with values ranging from a slight increase in the discomfort of 1.74% to a reduction of 99.36%, whereas the relative differences in the annual heating and artificial lighting energy are rather limited. However, it appears that the annual heating and lighting energy can both increase and decrease when automated shading control is implemented. In general, the relative differences in annual heating energy consumption range between an increase of 3.66% and a decrease of 5.89%. Although the annual heating energy increases on average, in 35% of the investigated variants the heating demand is slightly reduced as a result of automated shading control. In the case of artificial lighting energy, only in a very small minority of the cases (i.e. 4%) the energy demand decreases by automating the shading devices. These reductions are relatively small, with a maximum of 0.46% of the annual artificial lighting energy, while the increases reach up to 17.26%.

# 3.2 Influence of boundary conditions

A sensitivity analysis was carried out, varying the following parameters: building type, orientation of the building, reflectance of the solar shades, number of occupants, household routines, and manual shading control. A Wilcoxon signed-rank test with a 5% confidence interval was used to explore their influence on the differences in relative impact. The results indicate that each of the properties affects the relative differences to a greater or lesser extent.

As pointed out in Table 2, the impact of automated shading control on overheating is most significantly influenced by the differences in the building designs and the behaviour of the occupants. Of the latter, the number of inhabitants appears to have a more pronounced impact than their habits regarding shading control. In contrast, the reflectance of the screens seems to have negligible effects on the thermal comfort impact of shading control. Furthermore, the sensitivity of the impact of automated shading control on the annual heating and artificial lighting energy to the investigated boundary conditions is rather limited, except for the influence of the manual control behaviour on the heating energy consumption.

Table 2 – Median differences in relative impact of automated	
control for the investigated variations in the sensitivity analysis	\$

Variation	Discomfort	Heating	Lighting
Building type	23.27%	1.20%	1.61%
Orientation	15.51%	0.93%	0.67%
Reflectance	1.94%	0.06%	0.07%
Number of occu- pants	28.59%	1.15%	1.21%
Household routines	3.44%	0.35%	0.25%
Manual control	19.21%	3.06%	0.06%



Fig. 2 – Linear regression of the impact of automated shading control on the thermal discomfort per building design

The investigated building types, namely detached, semi-detached, and terraced buildings, and their respective designs appear to have a major impact on the relative improvement in thermal discomfort when comparing automated control and manual operation of shading devices. A linear regression analysis, as presented in Fig. 2, indicates that higher reductions in the thermal discomfort are observed for the detached case study, followed by the semi-detached and terraced building. The results reflect the differences in window area between the case studies: automated control appears to be more effective in reducing the overheating risk in dwellings with a high glazed area.
#### 3.3 Influence of Occupant Behaviour

The sensitivity analysis addresses various aspects of the occupant behaviour: the number of inhabitants, their routines regarding presence, and their habits for manually operating the screens.

#### 3.3.1 Household composition

The composition of the family has a significant influence on the absolute discomfort experienced. The number of occupants is included in the calculation of the discomfort indicator, which means that higher occupation rates directly affect the absolute values. By normalising these results in relation to the total occupied hours, the differences are smoothed out. However, Fig. 3 shows that a lower number of inhabitants generally results in overheating during a smaller share of occupation or in a less extreme feeling of discomfort. The reduced risk of overheating is a consequence of the decreased internal heat gains that are associated with smaller households. Nevertheless, this trend is also subject to differences in family routines.



Fig. 3 – Impact of automated shading control normalised for the period of occupation

When considering the relative impact of automating the shading control, it is observed that the household size has a major impact, while their routines only have a limited influence. As presented in Fig. 4, the relative impact varies considerably according to the number of occupants due to differences in family composition and associated routines, as well as they are influenced by the other boundary conditions. Despite these variations, it appears that the relative improvements diminish with an increasing number of inhabitants, which may be attributed to changes in the ratio of external to internal heat gains, as well as differences in the degree of absolute discomfort.



Fig. 4 – Relative improvements in thermal comfort per number of occupants

#### 3.3.2 Manual operating behaviour

The interaction of occupants with the solar shading is identified as one of the most significant influences on the potential for automated control. Two distinct scenarios have been simulated: occupants with a more passive and more active attitude, thus representing two extremes in the range of manual control. The distribution of the results shows that this reference behaviour has a significant impact on the effectiveness of manual operation in reducing thermal discomfort, especially for increased occupancy. While the differences in heating demand are less pronounced, the automation of solar shading generally results in an increase in the annual heating energy consumption compared to a passive operation strategy. Conversely, there is a decrease in this consumption as the users interact more actively with their screens (Fig. 5).



Fig. 5 – Influence of manual shading operation strategies on annual heating energy consumption



Fig. 6 – Influence of manual shading operation strategies on thermal discomfort

As illustrated in Fig. 6, the potential for reducing thermal discomfort by automating control is greater when occupants passively engage in manual shading operation than when they actively open and close their solar screens. More specifically, the median percentage reduction in discomfort when occupants interact with their shading in a passive manner (63.25%) is 1.59 times greater than when they are more actively involved in shading control operations (39.86%). The associated absolute differences are relatively limited for households with low absolute thermal discomfort, as the interactions are constrained by the presence of occupants, but gradually increase as the absolute values increase.

## 4. Conclusions

The implementation of automated shading control in a highly insulated residential building without cooling, located in a temperate maritime climate, can reduce the thermal discomfort by a median value of 52.74% compared to manual operation, with a relatively small impact on the annual heating and lighting energy consumption (i.e. a median increase of 1.18% and 2.14%, respectively). The relative differences in overheating exhibit significant variations, primarily driven by the number of inhabitants, the building type and the definition of the reference manual control behaviour, while they are to a lesser extent influenced by respectively, the orientation, household routines and shading reflectance. However, the absolute reduction in thermal discomfort is strongly related to the hours of occupation and the number of inhabitants.

The main impact of shading control is observed in

the field of (thermal) comfort, particularly in dwellings without cooling, which is common in temperate maritime climates. Tools such as the BAC factor method of EN ISO 52120-1, however, focus on energy performance, whereas these impacts (i.e. on the annual heating and artificial lighting energy consumption) are limited for the investigated case studies. Moreover, they assume that automating the solar shading reduces the cooling demand by 20% compared to manually operated shades. This results in a reduction of the total energy consumption as the impacts on the heating energy demand and artificial lighting energy are not considered. However, the results of this study indicate that, on average, a small increase in energy consumption can be expected in houses without cooling, which leaves the economic investment unbalanced. Co-benefits as the reduction of thermal discomfort should be taken into account to support decisions, as well as boundary conditions. For the investigated cases, the susceptibility of the house to overheating and occupant behaviour affect the impact, while the presence rate and tolerance to thermal discomfort co-determine the benefits for a family. In future research, the set of influential parameters will be further extended to cover a broader range of buildings and contexts.

## Nomenclature

#### Symbols

t	time (h)
N	number of occupants
θ	temperature (°C)

#### Subscripts/Superscripts

i	indoor operative
max	upper limit for 10% PPD

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# Simulating the Microclimate of a Pilot Greenhouse for the EU Project REGACE on Innovative Agri-Voltaic Technology

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#### Abstract

Agri-Photovoltaics (Agri-PV) integrated in greenhouses optimize land use by combining solar energy production with crop cultivation, promoting sustainable agriculture. The REGACE project, funded by Horizon Europe, aims to develop innovative technology for PV in greenhouses to ensure uninterrupted food production. This paper introduces the initial steps of REGACE's vision by creating a dynamic model using Dynamic Building Simulation (DBS) software to understand the relationship between plant growth, energy use, and microclimate conditions in a pilot greenhouse at the University of Thessaly, Greece. The study uses the Penman-Monteith evapotranspiration model to simulate the greenhouse's thermal dynamics, identifying discrepancies between model predictions and actual temperature and humidity levels. The paper discusses these issues, attributing them to model simplifications and the need for more precise data on shading curtains and cooling systems.

#### 1. Introduction

In the face of escalating global challenges such as climate change, resource depletion, and increasing population demand, there is an urgent need to develop innovative and sustainable solutions in agriculture. One promising avenue is Agri-Photovoltaics (Agri-PV) which has emerged as a viable approach to optimize land use by combining solar energy harvesting with agricultural activities (Dinesh & Pearce, 2016; Schweiger & Pataczek, 2023). Greenhouses (GHs) provides a controlled environment for optimizing crop growth, extending growing seasons, and protecting plants from adverse weather conditions. The integration of photovoltaic (PV) technology within greenhouse structures represents a progressive step toward achieving sustainability and energy efficiency in agricultural practices. In this framework, the project REGACE (www.regaceproject.com), funded by Horizon Europe will develop and validate a disruptive innovative technology to generate renewable electricity in greenhouses in all seasons of the year to enable the constant production of food without energy limitations.

In the last 20 years, several studies have focused on different aspects of energy optimization in greenhouse production (Rodríguez et al., 2015). Either the focus has been on the introduction of new technologies, e.g., infrastructure (glass and screen types), light-emitting diodes, or other types of equipment. Various projects have focused on the development of various IT and decision support systems for improved climate control that balances optimal photosynthesis and plant growth (or transpiration) with energy consumption and cost (Zhang et al., 2020). However, there is a lack of correlation between morphological plant development, optimization of energy consumption, and production. In greenhouses, energy optimization, product flow, and artificial climate are currently operated as three separate systems. In practice, these systems are undoubtedly interconnected in greenhouse production. The RE-GACE approach aims to create a Digital Twin (DT) ecosystem, REGACE DT that integrates crop production, PV production and microclimate modelling with the final objective of integrating these aspects using Artificial Intelligence techniques.

The main goal of the work presented here is to build a dynamic model of the greenhouse using an advanced software for Dynamic Building Simulation (DBS) taking into account the plant interaction with the environment. DBS is a powerful means of estimating trends in indoor environmental variables and energy demand as climatic conditions change and as a function of the building envelope characteristics. The greenhouse, being an enclosed space, can be assimilated to a building and as such can be simulated in dynamic conditions using the tools that are commonly used for building simulation. The thermal field inside the greenhouse, however, is also affected by a number of physical processes such as plant growth and water use that must be properly considered within the dynamic model (Baglivo et al., 2020; Ouazzani Chahidi et al., 2021). In the current discourse of greenhouse optimization, various researchers have dedicated efforts to study structural configurations, ventilation systems, and the implications of evapotranspiration on environmental parameters such as temperature and humidity. Stanciu et al. (2016) provide insight into the thermal dynamics within a polyethylene greenhouse, analysing the effects of different orientations and ventilation regimes in Bucharest's seasonal extremes, emphasizing the role of evapotranspiration. Similarly, Abdel-Ghany and Kozai (2006) evaluate a small glass greenhouse in Tokyo, focusing on temperature and humidity fluctuations during a short summer period, highlighting evapotranspiration's significant impact.

In contrast, Mobtaker et al. (2019) prioritize the study of thermal transmittance through different glass roof shapes and orientations in Tabriz, without considering evapotranspiration or ventilation systems. Singh et al. (2018) advance this approach by modeling a large greenhouse in Punjab with a double gothic arch structure, integrating natural ventilation and a thorough analysis of evapotranspiration's comprehensive impact using Matlab-Simulink.

Fitz-Rodríguez et al. (2010) have developed a variable model applicable to various U.S. locations, considering different heights and roof shapes of

greenhouses, including the effects of material selection, evapotranspiration, and integrated heating/cooling systems.

Innovation in greenhouse energy sustainability is represented by Ouazzani Chahidi et al. (2021)), who simulate a glass-covered greenhouse integrated with photovoltaic panels and a geothermal pump in Albenga, focusing on internal temperature regulation, energy efficiency, and solar energy utilization.

Baglivo et al. (2020) employ TRNSYS software for a detailed simulation of a greenhouse in Crotone, taking into account plant evapotranspiration, natural ventilation, and temperature control systems, presenting data over varying time scales. This software's versatility is further echoed in the studies of Opeyemi Ogunlowo et al. (2023) and Brækken et al. (2023), who employ TRNSYS and IDA ICE for dynamic greenhouse modelling, examining the influence of structural designs, climatic conditions, and operational systems on vearly temperature, humidity, and energy patterns. In our approach we wanted to improve the capability of the software IDA ICE to simulate the microclimate inside a greenhouse by implementing the evapotranspiration equations directly into the energy balance of the thermal zone of the tool. In this way we have created a new custom zone that could take into account the hygrothermal interaction of the plants with the greenhouse's microclimate. The findings of our work will be used to better understand the physics behind the greenhouse system and, together with data gathered in the pilot, will contribute to the development of a reliable DT of the system.

## 2. Simulation and Experiment

## 2.1 Pilot Greenhouse Description

The approach consists in the construction of a DBS model in the IDA ICE 4.8 (Sahlin et al., 2003) environment of one of the 5 pilot greenhouses of the REGACE project. The objective is to reproduce the indoor microclimate also considering the evapotranspiration process due to the presence of crops. Evapotranspiration is a combined mechanism that comprises the loss of water from the soil both by evaporation from the soil surface and by transpiration from the leaves of the plants through their stomas.

In order to take into account this mechanism in the greenhouse simulation, the regular thermal zone model implemented in the software has been modified integrating the heat and moisture balance equations with the evapotranspiration model of Penman-Monteith (Monteith, 1965).



Fig. 1 – Aerial and front view of the pilot greenhouses from Google Maps

The simulations were performed for a six-span N-S oriented gothic arch greenhouse, located at the University of Thessaly near Volos (Latitude 39.22', Longitude 22.44, Altitude 85 m), on the coastal area of Eastern Greece. According to the Köppen-Geiger classification, the prevailing climate in this region is categorized as Csa (Hot-summer Mediterranean climate).

The side walls of the greenhouse are covered by polycarbonate sheets (thickness of 1 cm) while the roof is covered by polyethylene films (thickness of 180  $\mu$ m, light transmission of 93%). Polycarbonate sheets are also used to cover the internal side walls between the six spans forming in this way six independent compartments with dimensions of 9.6 m (width) and 25 m (length) each. The greenhouse has a gutter height of 5.0 m and ridge height of 7.35 m. Each greenhouse compartment is equipped with: (a) a continuous roof vent opened whenever the greenhouse air temperature exceeded 21 °C during

the day or 18 °C during the night, or whenever the greenhouse air relative humidity exceeded 95% during the night or 87% during the day (max vent opening for dehumidification of 10%) (b) a pad (15 cm thick, 9.6 m width and 2.0 m height) and fan (capacity of 35 000 m<sup>3</sup> h<sup>-1</sup>, 1.1 kW) system operating whenever the air temperature exceeded 25 °C, (c) a pipe rail heating system (12 pipes of 5.1 cm diameter) operating to maintain a greenhouse air temperature of 18 °C during the day and 14 °C during the night (max pipe temperature set at 60 °C), (d) a thermal/shading screen with light transmission of about 50% and energy saving of 60% used during the night reducing mainly thermal radiation heat transfer, whenever the outside air temperature was 2 °C lower than the heating temperature set point or during the day whenever the outside solar radiation exceeded 750 W m<sup>-2</sup>. Each greenhouse compartment is equipped with six hydroponic gutters of 20 m each located 0.5 m above the ground at a distance of 1.6 m between each other, holding 19 perlite slabs of 35 L each (average substrate water content of 25-30%) the substrates used for rooting/cultivation of the crop. A drip irrigation system was used for the crop fertigation needs with 5 drippers per slab.

External environmental data were obtained through on-site measurements (referred to year 2020). These data include parameters such as temperature, humidity, radiation, wind speed and direction, and rainfall. Internal measurements of temperature and humidity within the six zones at ground level were also recorded. Table 1 shows type of main sensors, accuracy ad scan rate.

Table 1 – Characteristics of the sensors installed outside and inside the greenhouses in Volos

Variable	Type	Accuracy	Scan rate
Temperature	PT100	0.1 °C	15 min
Relative Humidity	Capacity	±3%	15 min
Solar irradiance	Thermopile	$\pm 10 \text{ W/m}^2$	15 min

A critical aspect of this study involved decomposing measured global solar irradiance into the direct and diffuse components as requested by the IDA ICE local climate file ingested by the model. We used the decomposition model by Erbs implemented in PVLib (Jensen et al. 2023) collaborative platform for PV simulation to calculate direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) based on global horizontal irradiance (GHI), zenith angle, and day of the year.

## 2.2 IDA-ICE Modelling of the Greenhouse

The GH geometry and materials together with the evaporative cooling system have been implemented in IDA ICE 4.8 (Fig. 2) and the regular thermal zone has been replaced with a new custom zone that considers the evapotranspiration mechanism. Table 1 shows the main thermal properties of the GH cover (polycarbonate for the side walls and polyethylene for the roof).

IDA ICE provides direct and indirect evaporative cooling system in its environment. Suitable modifications have been applied to the components to fit the specifications of the real fan-pad (only direct evaporative cooling).

This component was developed to closely mimic the system's functionality. Observations from the simulation revealed that the air exiting the pad was cooler compared to the incoming air, particularly during periods of high summer temperatures.

	Table 2 – Therm	al properties	of the GH	envelope
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ТҮРЕ	g	Tsol	Tvis	Uw (W/m²K)
Polycarbonate Corrugated	0.773	0.631	0.636	2.527
Polyethylene	0.830	0.771	0.884	5.299

Additionally, the trends in absolute humidity showed an increase when there was a divergence in temperatures, indicating the effective operation of the fan and pad setup.

Furthermore, in the testing greenhouse, a Natural Ventilation and Temperature Control system was implemented. Natural ventilation was facilitated by opening windows located on the roof of each zone. As a first attempt the temperature setpoint for window opening has been set at 20 °C.

In the simulation of shading, an integrated window

shading approach was adopted for all the roof windows. The control of the shading curtains was based on the measurements of global radiation components, specifically DNI and DHI.



Fig. 2 - IDA ICE greenhouse representation

#### 2.3 Evapotranspiration Due to Plants

In order to take into account the plants' evapotranspiration in the greenhouses we have developed a tool within IDA-ICE 4.8. To do that, we have designed a custom zone within the DBS software that considers the crop evapotranspiration process. This is modelled as proposed in Katsoulas and Stanghellini (2019). In particular, the Penman-Monteith equation is used to compute the evapotranspiration mass flow,  $\dot{m}_{ET_0}($ in  $kg \ s^{-1})$ (Monteith, 1965):

$$\dot{m}_{ET_0} = A_c \frac{\Delta R_n + \rho C_p D_i g_a}{\lambda \left[ \Delta + \gamma \left( 1 + \frac{g_a}{g_c} \right) \right]}$$
(1)

where  $R_n$  is the net radiation intercepted by the crop  $(Wm^{-2})$ ,  $D_i$  is the vapor deficit of the air (kPa),  $g_a$  and  $g_c$  are the crop aerodynamic and stomatal conductances  $(ms^{-1})$ ,  $\Delta$  is the slope of the saturation vapor pressure-temperature relationship  $(kPa K^{-1})$ ,  $\gamma$  is the psychrometric constant  $(kPa K^{-1})$ ,  $A_c$  is the crop area  $(m^2)$ , and  $\rho$ ,  $C_p$ ,  $\lambda$  are the air density  $(kgm^{-3})$ , specific heat capacity  $(J kg^{-1}K^{-1})$  and latent heat of vaporization  $(J Kg^{-1})$ . In the zonal model, the aerodynamic and stomatal conductances  $(g_a, g_c)$  are assumed to be constant and must be provided by the user. On the other hand,  $\Delta$  is computed as:

$$\Delta = \frac{4098P_{v,sat}}{\left(T + 237.3\right)^2}$$
(2)

with *T* and  $P_{v,sat}$  being the air temperature and the saturation vapor pressure (*kPa*).

Following Katsoulas and Stanghellini (2019), the intercepted net radiation is modelled as:

$$R_n = a \left( 1 - e^{-k_s LAI} \right) R_s \tag{3}$$

where  $R_s$  is the solar radiation per unit area ( $Wm^{-2}$ ), a is an empirical constant (indicating the fraction of net radiation absorbed by the crops),  $k_s$  is the extinction coefficient for shortwave radiation, and *LAI* is the leaf area index. In the zonal model, the coefficients a and  $k_s$  are set to 0.86 and 0.7. In addition, the solar radiation  $R_s$  is calculated as the shortwave radiation reaching the floor divided by its area (since the crops are assumed to be at the ground level). Moreover, the leaf area index is multiplied by a "schedule factor" in IDA ICE, since *LAI* is not constant throughout the year.

Finally, the latent power related to the evapotranspiration mass flow is calculated as in (Baglivo et al., 2020):

$$P_{ET} = \dot{m}_{ET_0} \left( \lambda + C_{p,v} T \right) \tag{4}$$

 $(C_{p,v}$  is the specific heat capacity of the vapor,  $J kg^{-1}K^{-1}$ ).

In the zonal model, the evapotranspiration mass flow is added to the humidity balance equation:

$$\rho V \frac{dW}{dt} = F_{occ} + F_{eqp} + F_{lks} + F_{trm} + F_{lu} + \dot{m}_{ET_0}$$
(5)

where *W* is the vapor fraction, *V* is the zone volume,  $F_{occ}$  is the vapor flow due to occupants,  $F_{eqp}$  and  $F_{lu}$ are the vapor flows due to equipment and local units,  $F_{lks}$  and  $F_{trm}$  are the vapor flows through leaks and air terminals.

On the other hand, the latent evapotranspiration power is included as a sink term in the energy balance equation:

$$\rho V \left( C_p + W C_{p,v} \right) \frac{dT}{dt} + \rho V \lambda \frac{dW}{dt} = \dot{Q}_{occ} + + \dot{Q}_{eqp} + \dot{Q}_{lu} + \dot{Q}_{cv,srf} + \dot{Q}_{cv,lt} + \dot{Q}_{dv} + \dot{Q}_{lks} + + \dot{Q}_{trm} + \dot{Q}_{Loss} - P_{ET}$$
(6)

where  $\dot{Q}_{occ}$ ,  $\dot{Q}_{eqp}$  and  $\dot{Q}_{lu}$  are the heat flows from occupants, equipment, and local units (both convective and latent contributions),  $\dot{Q}_{cv,lt}$  and  $\dot{Q}_{dv}$ are the convective heat flows due to lights and convective devices,  $\dot{Q}_{lks}$  and  $\dot{Q}_{trm}$  are the heat flows due to leaks and terminals,  $\dot{Q}_{cv,srf}$  are the convective heat flows at the surfaces, and  $\dot{Q}_{Loss}$  are the heat losses to the zone. In this study the simulation was carried out for the most critical summer season with a variable simulation time step with maximal time step of 1.5 hours and an output time step of 1 hour.

## 3. Results

The GH model has been built and the first tests on the model functionality have been carried out. A first preliminary validation with available microclimate data is presented in this paper. We focused on the first greenhouse (GH1) cultivated with tomatoes.

## 3.1 Annual Trends of Temperature and Relative Humidity as Affected by Different Cooling Systems

This section presents the outcomes of year-long simulations conducted on the greenhouse model, focusing on GH1 zone while exploring different cooling system configurations. GH1 By sequentially implementing various cooling systems, the aim is to illustrate how temperature and relative humidity align with measured values as the complexity of the cooling systems increases. The simulation sequences are as follows:

- Initial simulation without any cooling system.
- Simulation with ventilation and window opening control set at 20 °C.
- Simulation adding shading to the ventilation setup.
- Simulation incorporating evaporative cooling alongside ventilation and shading.
- Simulation involving ventilation, shading, evaporative cooling, and integrating evapotranspiration theory with minimal crop size.
- Further simulation with ventilation, shading, evaporative cooling, and evapotranspiration theory applied with maximal crop size.

This systematic approach in introducing cooling systems in the simulations provides a deep insight into the impact of each addition on the internal greenhouse climate.

Starting from a scenario where no active or passive cooling was utilized, the initial simulations were based on the climatic data from the Volos climate file and the greenhouse's geometric model. The temperatures remained below 40 °C during the coldest months, but a notable increase was observed from late March to early October, attributed to the substantial incident radiation on the greenhouse covering, leading to an intensified greenhouse

effect. Notably, temperatures exceeding 60 °C were frequent during the summer months, which severely impacts crop viability.

Although the introduction of a controlled shading system, which affects both direct and diffused radiation, results in a reduction in temperature, this change is not immediately evident from the temporal temperature trend. Furthermore, with the addition of evaporative cooling, an additional 2–5 °C reduction in temperature is achieved.

The evaporative cooling system operates continuously throughout the day. The relatively minor variations in temperature and relative humidity can be attributed to changes within the evaporative cooling system. These observations confirm the operation of the evaporative cooling system, although it should be noted that the use of default values and the incremental approach detailed in this study may limit the results to some extent.

Additionally, the subsequent implementation of evapotranspiration into the model introduces the physical presence of crops within the greenhouse system, thereby fundamentally altering the interactions among various internal thermal flows. In the absence of crops, the thermal power reaching the ground is partly exchanged through conduction to deeper layers and partly transmitted through convection towards the internal air and radiation, resulting in increased sensible heat and subsequent temperature rise. However, with the presence of crops, a portion of the available sensible heat is utilized as latent heat for water vapor formation, released into the internal air from the plants and soil. Consequently, the internal air temperature is expected to decrease while humidity rises, with variations largely dependent on the size of the plants. Initially, a model representing the plants during their early growth stage, where their impact on internal temperature and relative humidity variation is minimal, was implemented (LAI = 1).

As a final step, we added the evapotranspiration model into the simulation dynamics, focusing on how this influences internal air conditions such as temperature and relative humidity. Analysis of internal temperature trends during hot summer months (Fig. 3) revealed a decrease in temperature up to 20-35 °C accompanied by increasing humidity

levels (exceeding 50%) as plants grow (LAI = 4). These fluctuations align with the maximum and minimum evapotranspiration rates. Monthly average analyses revealed temperature decreases from non-cooled to maximum evapotranspiration cases in warmer months, while relative humidity showed an opposite trend, increasing with cooling system complexity during hot periods.



Fig. 3 – Carpet plot for yearly values of greenhouse internal temperature and relative humidity with ventilation, shading, evaporative cooling and maximum evapotranspiration (LAI = 4)

## 3.2 Daily Trends of Temperature and Relative Humidity Inside the Greenhouse

Results from the daily variability shows that the most substantial deviations in measured values typically occurred during the months of July and August, between 3:00 PM and 7:00 PM or 8:00 PM on the same day, with deviations averaging up to 6 °C for temperature and 20% for relative humidity. Fig. 4 shows the first ten days of June where, on the contrary, the agreement with the measured values is fairly good. In this case maximum

evapotranspiration (LAI = 4) was considered. Despite the abovementioned variations, the introduction of cooling systems brought about significant daily enhancements in both thermal conditions and humidity levels compared to scenarios with no cooling in place. Among the systems analysed, natural ventilation, shading, and the natural variability in crop size through evapotranspiration emerged as key contributors to the improvement of the internal greenhouse climate.



Fig. 4 – First 10 days of comparison in June between simulated internal temperature of the greenhouse with ventilation, shading, evaporative cooling and maximum evapotranspiration (LAI = 4) and the measured temperature

While natural ventilation exhibited high efficiency, it showed limitations in maintaining optimal relative humidity levels between 11:00 AM and 3:00 PM, prompting evaporative cooling and other complementary systems to become notably effective during this period, establishing an optimal synergy among multiple subsystems.

# 3.3 Comparison Between GH1 and the Area Without Crops

In the study, comparisons were made between greenhouse conditions featuring different cooling systems in the presence of crops (GH1) and an area without plants (Zone 1). The analysis aimed to emphasize the role of evapotranspiration in greenhouses and its impact on overall cooling effectiveness. Initially, a scenario was considered where all cooling systems were active but with minimal evapotranspiration (LAI = 1). It was observed that in winter, the temperature deviation between Zone 1 and GH1 was minor, but this difference became more pronounced in the warmer months due to increased radiation and enhanced evapotranspiration effects.

Subsequent simulations with maximum evapotranspiration (LAI = 4) revealed significant deviations in temperatures during the summer, with GH1 showing up to a 10  $^{\circ}$ C advantage due to the cooling effect of evapotranspiration.

Further comparisons of measured and simulated temperature and humidity trends for all greenhouse zones, particularly in July, highlighted the influence of shading effects on different zones relative to the sun's position.

## 4. Conclusion

In this study, we develop a dynamic greenhouse simulation model using the IDA ICE software, to simulate a greenhouse situated near Volos, Greece. The findings from our simulations revealed differences between the model-predicted internal temperatures and humidity levels and those recorded in the actual greenhouse. These discrepancies became more pronounced as external temperatures increased. Despite these discrepancies, the installed cooling systems were effective significantly mitigating in these differences. For instance, in the absence of cooling measures, internal temperatures could reach up to 70 °C, which were reduced to approximately 30-35 °C with cooling interventions. Similarly, the minimum relative humidity levels were observed to increase from 10% to a range of 50-60% due to the cooling systems.

A notable challenge encountered in the model pertained to accurately simulating conditions between 3:00 and 7-8:00 pm during summer days. This issue was primarily attributed to the assumptions made regarding the physical properties and placement of shading curtains. These curtains are strategically placed between the greenhouse's upper and lower sections to optimize shading. However, for simplicity and due to the constraints of the simulation software, the model treated these shading elements as if they were fully integrated within the structure. Additionally, the lack of precise data on evaporative cooling led to the reliance on default software values, further contributing to the discrepancies observed. This study underscores the importance of accurate data and the need for refinement in simulation models to closely mimic real-world conditions.

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## Acronyms

Agri-PV: Agri Photovoltaics DBS: Dynamic Building Simulation DHI: Diffuse Horizontal Irradiance DNI: Direct Normal Irradiance DT: Digital Twin GH: Greenhouse GHI: Global Horizontal Irradiance LAI: Leaf Area Index PV: Photovoltaic

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## Building Archetypes Supporting the National Building Renovation Plan

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#### Abstract

The national building renovation plan is a key element in the recently approved version of the Energy Performance of Buildings Directive. The plan will provide a comprehensive overview of the energy and environmental performance of both the residential and non-residential building stock. To achieve the objective of mapping the energy *status* of urban configurations, the exploitation of building typologies, representative of different climatic zones, building use categories, and construction periods, has shown to be a useful approach.

The huge data uncertainty related to the building archetype generation necessitates a deeper analysis of the variation of crucial inputs that have repercussions on the energy performance assessment of the building stock.

This work begins with the Urban Building Energy Model data classification aimed at identifying the fundamental inputs needed to run an urban large-scale energy analysis. Then, the paper proceeds with the review and categorisation of the existing Italian databases, exploitable to mitigate the high uncertainty related to the input data. Once the requisite information is collected and the databases classified, the application part progresses with the probabilistic building archetype schema generation from the energy performance certificates of the Aosta Valley Region, taken as a case study. A local large-scale sensitivity analysis, obtained varying one at a time the thermophysical parameters of the building fabric and the window-to-wall ratio of a residential stock located in Aosta, was carried out. The study highlights how variations in statistical ranges of inputs, particularly regarding the performance of opaque building envelope components, impact the assessment of building energy needs.

#### 1. Introduction

#### 1.1 Background Analysis

The implementation of the national building renovation plan (European Commission, 2024), to track the decarbonisation of the building stock, involves the development of Urban Building Energy Models (UBEMs). UBEM, a complex object using a bottomup engineering model, aids urban planners, public administrations, energy agencies, and validation bodies to map the energy and environmental status of a block, a district, or a city. UBEMs require huge amount of information that is usually limited and lacks accuracy. The data restriction is influenced by privacy policies (Hosseini Haghighi et al., 2022; Johari et al., 2023) affecting the availability of building data at the city scale. Building energy consumptions are sensitive data, usually inaccessible for a portfolio of buildings. In large-scale energy models, a consequence of this issue is reported by Oraiopoulos & Howard (2022), who pointed out that just 9 % of UBEMs are validated. On the other hand, the inaccuracy of data is attributable to the non-interoperability between databases, the absence of controls to enhance data quality, and the lack of standardised format and harmonised procedures to collect data between local, regional, and national informative systems (Chen et al., 2019).

To bridge the data uncertainty at large-scale energy analysis, the collected data flow into the generation of the building archetypes (BAs). However, according to Swan and Ugursal (2009), the utilisation of archetypes is a possible approach but not the only one used in UBEMs. The BA approach is a trade-off to reduce complexity and enhance the model's accuracy in energy analysis. BAs, prototypes (Carnieletto et al., 2021), or building typologies (Dascalaki et al., 2011) are sets of geometric, in UBEMs directly extracted from GIS, and non-geometric properties that represent the heterogeneity of the building stock characteristics. Although a harmonised and shared methodology to generate BAs does not exist (Borges et al., 2022), archetyping is generally composed of two steps, i.e., the segmentation and the characterisation of the building stock (Pasichnyi et al., 2019). The segmentation phase refers to the taxonomy of similar buildings based on different criteria, such as climatic zone, building use category, construction periods, etc. The characterisation process corresponds to defining representative parameters that generalise the performance of the building stock. This aspect influences the structure of the BA dataset since archetypes may include deterministic or probabilistic parameters. From this perspective, Cerezo et al. (2017) investigated and compared simulation results for four groups of BAs, creating two with deterministic and two with probabilistic metrics. To discover the impact of different input parameters, Pernetti et al. (2021) applied different sensitivity analyses (SA) to rank the life cycle cost of eleven zero-energy buildings in Europe.

#### 1.2 Aim of the Research

The data uncertainty for a single-building energy model grows significantly in large-scale energy analyses. The BA, which represents the mean characteristics of a building stock, helps mitigate this source of error. However, it is crucial to evaluate how variations in key inputs impact the overall energy performance of the building stock.

This work first explores UBEM data for large-scale analysis and then classifies sources to gather the required information. Next, considering a UBEM archetype-based approach, a local SA varying one relevant thermo-physical parameter at a time, included in the probabilistic BA schema, applied to a residential block located in the municipality of Aosta (Italy) was carried out. Using CitySim Pro (Robinson et al., 2009), this analysis emphasises the order of error in the building's energy need linked to the variability of significant input parameters within their confidence interval. It highlights the possible deviations in estimating energy needs of the building stock. The novelty of this study lies in addressing the high uncertainty levels in UBEM and identifying the information in the BA schema that requires greater accuracy.

#### 2. Methods

The proposed methodology comprises: a) UBEM data classification, which provides a standardised overview of the required data to build a large-scale energy model, b) database cataloguing, including the listing and classification of recognised Italian local, regional, and national databases, c) definition of a probabilistic BA dataset (archetyping), and d) SA to assess the impact of relevant thermo-physical parameters in a non-validated UBEM scenario. The first three points of the proposed methodology fall into the "Urban Reference Buildings for Energy Modelling" (URBEM, 2024) project approach. The scope of URBEM-which is an Italian national research project financed under the PRIN 2020 Programme-is to create an Italian library of representative buildings to be used by UBEM tools.

#### 2.1 UBEM Data Classification

UBEM is a bottom-up physical-based model (Reinhart & Cerezo Davila, 2016), aimed at determining the energy and environmental performance of the building stock.

The purpose of the simulation, the spatial and temporal granularity of data, and the calculation methodology integrated into the large-scale energy programs influence the UBEM input data needed. UBEM can be delineated into distinct layers: input data, mathematical model, and output data. The UBEM input data can be grouped into five different categories: geometrical information, properties of transparent and opaque building envelope components, occupancy data, technical building system characteristics, and climatic data. A detailed description about the simplifications and assumptions made in UBEM from the Building Energy Model (BEM) can be found in Piro et al. (2023).

However, the primary objective of the UBEM data classification is to distinctly identify basic and

common input data, enabling a comprehensive evaluation of the energy performance of building stocks, regardless of the simulation tools used. The defined dataset is the minimum set of parameters to run a dynamic simulation on an hourly or subhourly basis.

#### 2.2 Database Cataloguing

Data availability, data quality, and data accessibility at the city scale represent future challenges of our societies (Goy et al., 2020). Especially public administrations must face this difficult task since they are responsible for collecting the data. In this regard, achieving standardised data formats, harmonised procedures, and minimum data requirements between different Regions could reduce the efforts required to UBEM developers. In this context, the categorisation of the existing local, regional, and national information systems plays a pivotal role in contributing to informed decision-making and sustainable development.

The attribution of the BAs to the analysed building stock is typically accomplished using the following criteria: climatic zone, building use category, and construction period. The subdivision of climatic zones is conducted at the national level. In more challenging scenarios, the determination of the building use category may involve on-site inspection or rely on the modeller's expertise. However, the identification of the ages of buildings poses difficulties, particularly because open GIS maps and regional geographical databases seldom contain such information. To address this issue, Zagarella (2019) proposed a systematic procedure to determine the prevailing construction period of buildings depending on building-related parameters. Without such a method, attributing the BA to the analysed urban configuration becomes very complicated, making the building archetype-based approach less effective in mitigating data uncertainty. Furthermore, building energy consumption is sensitive data that is usually not released due to privacy issues. In UBEM, this information is indispensable for calibrating or validating energy models.

Once the UBEM data classification has been set, the necessity is to review, list, and organise the available existing Italian information systems to collect the relevant data to generate the BAs. In the UR-BEM project (URBEM, 2024), the databases were grouped into the following categories: i) "source type", which indicates the origin of the information, ii) "accessibility", which denotes the constraint levels of the informative systems, iii) "database digitalisation", connected to the presence of data either in digital online or offline form or in paper-based documents, and iv) "data granularity", associated to the measure of the level of detail of the information. In Fig. 1, the criteria for classifying local, regional, or national databases for each of the categories proposed are depicted.



Fig. 1 – Database cataloguing criteria adopted in URBEM (2024)

#### 2.3 Archetyping and Sensitivity Analysis

The BAs embed the most common and typical technologies shared by a group of similar buildings. A significant research advancement in this field can be attributed to the well-recognised and pioneering TABULA project (TABULA, 2009-2012), which harmonised the building typology approach across numerous EU countries.

The BA encapsulates both geometric and nongeometric data that summarise the building's stock energy performance. The data integrated into the BA schema can be presented from either a deterministic or probabilistic standpoint. However, the association of the confidence interval to the data included in the BA schema contemplates and manifests the high uncertainty related to UBEM development.

To emphasise the importance of having a statistical range to guide the UBEM modeller's decisions, conducting a SA becomes imperative. This approach enables observations of how variations in crucial input data influence the model's output, particularly in terms of the building's energy need.

## 3. Application

The probabilistic BAs simulated in CitySim Pro were generated using data extracted from the energy performance certificate (EPC) database of the Aosta Valley Region. This Italian Region was chosen within the framework of the URBEM project. Then, a local large-scale sensitivity energy analysis was conducted on a residential block located in the municipality of Aosta, highlighting the significant impact of key UBEM inputs on the overall performance of the building stock.

## 3.1 CitySim Pro

CitySim Pro-developed by the Solar Energy and Building Physics Laboratory of EPFL (L'École Polytechnique Fédérale de Lausanne)—is one of the most recognised and used UBEM tool (Robinson et al., 2009). The calculation engine of the software is CitySim Solver (CitySim Solver, 2024) on which the KAEMCO company developed a graphical user interface. CitySim Pro is a dynamic hourly energy model with a Resistive-Capacitive system that discretises the building envelope components into nodes of temperature, thermal resistances, and heat capacities (Emmanuel and Kämpf, 2015).

#### 3.2 Case Study

The case study examines a real residential block situated in the municipality of Aosta (583 m a.s.l.). This city block consists of twenty-one buildings, five of which are single-family houses (SFHs), while the others are apartment blocks (ABs). The construction period range of these buildings was determined based on the findings of D'Alonzo et al. (2020). Fig. 2 presents the residential building stock analysed, including details such as the building code, size and shape, construction period range, and compactness ratio.

The Level of Detail (LOD) of the urban geometry scene was improved through a series of steps. Initially, the building footprint (LOD0) was established using data from the OpenStreetMap database. Then, the objects were extruded (LOD1), capturing the slopes of the roofs (LOD2). Additionally, further adjustments were made to enhance the accuracy of the assessed objects, such as converting incorrect volumes into shading elements (see Fig. 3).



Fig. 2 - Satellite view of the city block (source GoogleMaps)



Fig. 3 – Urban scene imported in CitySim Pro

The interquartile ranges of the building fabric performance parameters, encompassing thermal transmittance of walls  $(U_{wl})$ , floors  $(U_{lf})$ , roofs  $(U_{uf})$ , and windows  $(U_w)$ , and the WWR were calculated from the data included in the EPC database of the Aosta Valley Region. The EPCs were categorised considering the different climatic zones, building use categories, construction periods, and size and shape for residential buildings (e.g., SFHs and ABs). Following the determination of the first  $(Q_1)$ , second  $(Q_2)$ , and third  $(Q_3)$  quartiles of thermal transmittances, the layers of the building components and thermal characteristics of the materials were extracted from UNI/TR 11552 (UNI, 2014). To propose an example, Table 1 presents the thermal transmittances of the walls per building construction types, quartiles, and construction period ranges.

The building construction type was assigned to the building based on the statistical prevalence derived from the EPCs of each specific cluster. Before 1945, load-bearing stone masonry was the predominant type, transitioning to reinforced concrete structures with brick walls and load-bearing brick masonry thereafter. SFHs were assumed to have floors adjacent to the ground, while the thermal transmittance of the floors facing unconditioned spaces was considered for ABs. The floors of the ABs D1 and F2 are elevated *pilotis* storeys. Additionally, the roofs are differentiated whether the upper floor is flat or sloped.

Table 1 – Thermal transmittances of the walls per building construction type and construction period (a)

$U_{ m w1}$	1	919-4	5	1	946-6	51	1	962-7	'1
(W·m <sup>-2</sup> ·K <sup>-1</sup> )	$Q_1$	$Q_2$	$Q_3$	$Q_1$	$Q_2$	$Q_3$	$Q_1$	$Q_2$	$Q_3$
<b>S</b> (*)	1.01	1.64	2.01	0.70	1.57	2.10			
С	0.66	1.02	1.30	0.80	1.10	1.23	0.85	1.10	1.22
В	0.64	1.18	1.43	0.77	1.10	1.34	0.76	1.13	1.27

(\*) S = load-bearing stone masonry; C = reinforced concrete skeleton with brick walls; B = load-bearing brick masonry

Table 2 – Thermal transmittances of the walls per building construction type and construction period (b)

$U_{ m w1}$	1972-81			1982-91		
(W·m <sup>-2</sup> ·K <sup>-1</sup> )	$Q_1$	$Q_2$	$Q_3$	$Q_1$	$Q_2$	$Q_3$
С	0.82	1.10	1.23	0.51	0.88	1.08

For the various construction period ranges, the *WWR* is differentiated between SFHs and ABs. The calculated window-to-wall ratio was assumed to be the same for every building orientation. The *WWR* extracted from the EPCs issued for single building units was used for the whole apartment blocks. The median values representing the glazing ratio are between 9 % and 18 %, with the *WWR* of SFHs generally lower than those of ABs.

The window glazing type was used to cluster the  $U_w$  values. An example is depicted in Fig. 4 for different construction periods. The total solar energy transmittance of glazing was derived from a technical standard (CTI, 2021), depending on the glazing types adopted.

The Typical Meteorological Year file elaborated by the Italian Thermo-technical Committee (CTI, 2024) was used in the simulation. Moreover, the schedules and intensities of the internal heat gains (occupants, appliances, and lighting) were derived from the draft of the Italian National Annex of UNI EN 16798-1 (CTI, 2022). An infiltration rate equal to  $0.30 h^{-1}$  was assumed for every building.



Fig. 4 - Glazing type share per construction period

#### 3.3 Sensitivity Analysis

A local large-scale SA was performed by varying one at a time different features of the building envelope, such as the thermal transmittance of opaque walls, floors, roofs, and windows, as well as the *WWR*, within their respective interquartile ranges.

Three groups of simulations (OP\_, W\_, and WWR\_) were conducted. These groups evaluate the variation of the performance of the opaque  $(U_{wl}, U_{lf}, and U_{uf})$  and transparent  $(U_w)$  building envelope components, as well as different *WWR* values. Each group comprises two scenarios, defined based on the values of the first quartile  $(Q_1)$  in the first case and the third quartile  $(Q_3)$  in the second for each considered parameter. These scenarios were compared with the baseline, which was determined by assuming the median values for each parameter.

#### 4. Results and Discussion

The Aosta municipality experiences a climate dominated by space heating. Therefore, only the variation in the building's energy need for space heating  $(EP_{H,nd})$  for the different configurations has been evaluated, thus excluding the cooling need.

In **Error! Reference source not found.**, the outcomes of the three model configurations, each with two scenarios—considering  $Q_1$  and  $Q_3$  values,

respectively—are compared with the outcomes of the simulation carried out with the median values applied. The opaque building fabric's performance reveals to be the most impactful factor influencing the variation of the  $EP_{H,nd}$ , with percentage fluctuation between – 33 % and 37 %. Across various buildings, the trend remains consistent: as the thermal transmittance of the building envelope components decreases, the thermal energy need decreases (OP\_Q1), whereas the opposite pattern is observed in OP\_Q3.

A similar trend is observed when analysing the thermal performance of different windows (W\_Q1 and W\_Q3), but the percentage impact (between – 6 % and 3 %) is an order of magnitude lower compared to the previous case, due to limited *WWR* compared to the opaque fraction.



Fig. 5 - Results of the SA. Space heating variation of the city block for different scenarios of the building envelope parameters

In the SA for the *WWR*, reducing the glazing fraction (WWR\_Q1) decreases the heat transfer through transmission, thereby reducing the  $EP_{H;nd}$ . Conversely, increasing *WWR* in configuration WWR\_Q3 leads to the opposite trend. Notably, a reverse pattern can be observed for well-sunexposed buildings C1, C4, and F4, where the solar heat gains compensate for and exceed the heat losses through transmission. Globally, the percentage variation of WWR\_Q1 and WWR\_Q3 scenarios is between – 4 % and 6 %. The incidence of *WWR* accounts more during the summer season since the energy need for space cooling decreases reducing the *WWR*, and vice versa.

#### 5. Conclusion

The variation in heating energy need was assessed ranging one at a time the key input indicators within their confidence intervals. The BA workflow from the generation to the exploitation phase was evaluated to support the development of a national building renovation plan in a UBEM environment. The UBEM data classification, which involves cataloguing the required input data, was carried out. Then, the review and organisation of existing Italian local, regional, and national databases to derive the thermal properties of the building envelope, the technical building system characteristics, the building occupancy, and the climatic data were identified. Next, considering a UBEM archetypebased approach, the effect of the variation of the building fabric performance and WWR within the confidence interval of their BA schema was explored for a case study located in the northern part of Italy. The SA showed the major impact on the output resulting from the different characterisation of the thermal performance of the opaque building envelope components. This aspect suggests the need for precise determination of the thermal transmittances of walls, roofs, and floors. However, the limitations of this work are related to the limited information available in the EPCs.

The spread in the distribution of the outcomes for the analysed city block highlights the need for more reliable and representative statistical samples to define the BA schema. The validation of BAs is of foremost importance above all when low-quality input data are used in the analysis.

The future steps of the work will focus on implementing and validating the created BAs to be used in UBEMs. Then, according to the methodology proposed in this work, a future implementation will be focused on detailed SA obtained by combining the variation of different parameters in a single simulation to assess if the discrepancies would be increased or compensated.

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#### Nomenclature

#### Symbols

EP	energy performance (kWh·m <sup>-2</sup> )
U	thermal transmittance (W·m <sup>-2</sup> ·K <sup>-1</sup> )
WWR	window-to-wall ratio (%)

#### Subscripts

Н	heating	uf	upper floor
lf	lower floor	W	window
nd	need	wl	wall

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# Integration of Machine Learning-Based CIE Standard Skies Model With Daylight Simulation for Building Energy Performance Analysis

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#### Abstract

Daylight illuminance data is required for daylight scheme evaluations.while the adoption of daylight-linked control (DLLC) systems is a useful strategy for attaining energy savings on lighting. For evaluations of these daylighting schemes and DLLC, determining the sky conditions through sky luminance distributions is required. Moreover, through these distributions, the 15 CIE standard skies can be identified and daylight illuminance for any surface of interest can be derived. The crucial issue is that sky luminance data is sparingly measured. Recent studies have shown that the use of accessible climatic data and machine learning (ML) models for determining the standard skies can be viable alternatives. In this study, an ensembledbased Light Gradient Boosting Machine (LGBM) was used to identify the standard sky types in Hong Kong. The predictions of the LGBM model were then integrated with RADIANCE and EnergPlus for daylight and building energy simulations of a generic shopping mall. The simulation was carried out by comparing the Best fit, ASRC 1992 and the All-weather models against the measured data. Findings show that when tested, the LGBM model correctly classified the sky types over 70% of the time. Similarly, when used for daylight and energy simulations acceptable predictions were obtained from all models. Finally, it was found that the impact of the sky luminance distribution model on illuminance prediction is higher than that for energy estimation.

#### 1. Introduction

In Hong Kong, energy spent on lighting contributes 10% to the electricity demand (Electrical & Mechanical Services Department [EMSD], 2023). Hence, attaining a balance between the provision of adequate lighting and the reduction of building energy consumption on lighting is crucial for energy-efficient designs (Aghimien et al., 2021). Even when daylight is admitted into buildings, occupants tend to rely on artificial lighting. Technically, daylight is preferable because it provides visual comfort and energy savings (Aghimien et al., 2022). One of the approaches for attaining daylight energy savings is the use of daylight-linked control (DLLC) systems since these can reduce building energy consumption without compromising the visual comfort in a room (Bellia et al., 2016). In cases where measurements are not possible to evaluate these controls, simulation techniques are used.

Furthermore, for daylight assessment, the daylight illuminance in a room is hugely dependent on the sky luminance distributions. Unfortunately, ground measurement of luminance distributions is rarely carried out, and the sky scanners used for such measurements are expensive (Granados-López et al., 2021). In 2003, the International Commission on Illumination (CIE) proposed using the 15 CIE standard skies which covers the whole spectrum of skies in the world to classify the skies (CIE, 2003). Apart from actual measurement, daylight illuminance data can be obtained and the sky condition, determined. However, the criteria for determining the sky conditions using this approach are sometimes based on the vertical and zenith illuminance or irradiance data which are not readily available (Lou et al., 2017). Moreso, meteorological parameters can be used for identifying the skies. However, whether these parameters can correctly identify the sky conditions is still a major point of discussion (Aghimien et al., 2022). In this study, an ensemble-based machine learning (ML) model called Light Gradient Boosting Machine (LGBM) is proposed to identify the 15 CIE standard skies using readily available climatic variables. The rationale behind using ML is that it provides an alternative approach to sky classification (Aghimien et al., 2022; Granados-López et al. 2021; Lou et al., 2016). Nevertheless, recent works have shifted focus to the use of ensemble ML models as these can provide better predictions, they can boost the performance of traditional ML and perform well even under noisy data (Mienye et al., 2022). Importantly, ensemble models perform well when the data to be predicted is imbalanced which is the case for most real-life classification problems (Khan et al., 2024; Mohammed & Kora, 2023). Nonetheless, ensembles have not been widely explored in previous CIE standard skies studies. Moreover, the previous ML works in CIE standard sky classification did not attempt to determine the energy performance of these methods in actual energy simulation scenarios (Granados-López et al., 2021; Lou et al., 2017). Neither is the comparison of the ML-based CIE standard Skies against other sky distribution models considered in the previous energy analysis. Thus, in this study, the daylight illuminance and building energy prediction from the proposed LGBM model and for a generic commercial building infused with DLLC systems were investigated. The objectives of this study were to (i) develop an LGBM CIE standard sky classification model (ii) simulate daylight illuminance based on the LGBM and other acceptable sky distribution models (iii) determine energy savings from using DLLC systems and the sky models.

## 2. Study Methodology

Ten-minute measurements obtained from the City University of Hong Kong measuring station between 2004 to 2005 were used in this study. These data consist of solar irradiance, daylight illuminance, sky luminance distributions, geographical and meteorological variables. The measurements were done using Kipp & Zonen CM11 thermopile pyranometers, the MS- 80 Pyranometer, the T-10M illuminance sensor and the EKO MS 300LR sky scanner. Similarly, the meteorological variables such as sunshine duration (*sun*), cloud cover (*cld*), visibility (*vis*) e.t.c were collected from the Hong Kong Observatory (HKO). These meteorological inputs also covered the same measurement period as the solar measurements.

Upon measurement, data quality control was carried out to clean the data as described in Aghimien et al. (2022). Upon cleaning, a total of 16,118 and 10,747 datasets were obtained for years 2004 and 2005, respectively. The 2004 data was further divided using the ratio of 80 to 20% for training and initial testing. This splitting ratio provides sufficient data for learning and still gives room for evaluating the model against unseen data. Next, the 15 CIE standard skies were determined as outlined in Li et al. (2013). Therefrom, the sky classification model was developed using LGBM and the 2004 input climatic data. Upon model development, the LGBM was used to classify the 15 standard skies using the 2005 test data. By using the model against the 2005 data, the ability of the model to make predictions against a whole year's worth of data was determined. For daylighting and energy calculations, a generic shopping mall was assumed and, the standard skies obtained from the LGBM were used to simulate daylight illuminance in RADIANCE using a climate-based daylight modelling (CBDM) approach. For a more robust conclusion, the LGBM classification was compared with the Best fit skies (i.e., the 15 CIE standard skies as classified by the sky luminance modelling method), the All-weather model (Perez et al., 1993), and the ASRC-1992 (Perez et al., 1992). Finally, the energy savings as obtained from the different sky models, the top-up DLLC system and other building parameters were investigated using EnergyPlus. Importantly, for the daylight and the building energy simulation, the 2005 weather data was used. The methodology flow chart is shown in Fig. 1.



Fig. 1 - Flow chart of research methodology

## 3. Case Study and Model Description

#### 3.1 Case Study

The generic case study is a 70 m by 70 m 4-storey shopping mall in Hong Kong. The mall has typical floor plans comprising retail shops, restaurants, back-ofhouse, circulation areas, supporting plant rooms, and atria as shown in Fig. 2. In terms of glazing, the overall skylight-to-roof and window-to-wall ratios were 5% and 44.6%, respectivelyand the visible transmittances for the skylight and window were 0.9 and 0.8. The lighting power densities for the retail shops, restaurants and circulation areas were 10, 9 and 5 W/m<sup>2</sup>, respectively. Similarly, the design illuminance for the retail shops, restaurants, and circulation areas was 300 lux, 200 lux and 100 lux, respectively. A fan-coil unit was provided for retail shops and restaurants while a variable-air-volume system was used in circulation areas. Water-cooled chillers were used for space cooling. The operating hours for the retail shops and circulation areas were 09:00-21:00 while the restaurants were 09:00-01:00. All parameters were chosen following the Hong Kong local requirements (EMSD, 2021). DLLC systems were equipped in the perimeter zones, and these were twice the window height while the reference point for lighting control was placed in the middle of the room. Finally, obstructions of 56.3° were positioned in all four major principal orientations (i.e., north, east, south and west). The atria, ground and third-floor plans were considered in this analysis.



Fig. 2 - Floor plan and section of case study building

#### 3.2 CIE Standard Skies Classification

The CIE standard skies contain five clear, five intermediate and five overcast skies, and these cover the whole spectrum of skies in the world (CIE, 2003). These 15 CIE skies are derived from a number of mathematical expressions which are mainly composed of the relative distribution, the standard gradation function and the relative scattering indicatrix function (Li et al., 2013).

Full details of the 15 CIE standard skies and its modelling approach using the sky luminance method can be found in Aghimien and Li (2022). This method was used in this study (Section 4.1) as the baseline method for comparing the LGBM sky classification performance.

#### 3.3 Light Gradient Boosting Machine

Ensemble models combine several ML models to build a single and more powerful model than its original constituents (Mohammed & Kora, 2023). These models are widely adopted due to their ability to reduce overfitting and efficiency when dealing with imbalance data (Khan et al., 2024). The LGBM is a highly efficient ensemble of decision trees (DT) used to minimize a loss function (Ooba et al., 2023). This model has been widely adopted and hence, used in this study.

Before model development, the relationship of the inputs was first checked using Pearson's correlation analysis. This helps to determine the model input relationship and prevent multicollinearity. The findings show no likelihood of collinearity in the data. For the model structure, thirteen input variables were used and these consist of solar altitude angle ( $\alpha$ ), clearness index ( $K_t$ ), diffuse fraction ( $K_d$ ), turbidity  $(T_v)$ , atmospheric pressure (atp), cloud cover (cld), sunshine duration (sun), visibility (vis), relative humidity (*rhm*), dew point temperature (*dpt*), dry bulb temperature (*dbt*), wet bulb temperature (wbt) and wind speed (wsp). While the output was the 15 CIE standard skies identified by the sky luminance method. Furthermore, the output data were encoded since they have categorical attributes, and then the data was split. The 2004 data was used for training and initial testing in the ratio of 80 to 20%. Next, the split data were separately scaled using the min-max method to prevent data leakage. Then, the Grid search method was used to optimize the model while K-fold cross-validation was used to prevent overfitting. Upon optimization, the best LGBM hyperparameters were; column subsampling by the tree: 0.9, learning rate: 0.01, number of estimators: 300, number of leaves: 60, and subsample: 0.8. After model development, the 2005 data were scaled and used as additional new sets of data to retest the model's performance. Finally, the model was assessed using accuracy (Accu), precision (Pre), recall (Re), F1-score (f1) and receiver operating characteristic (ROC). By using these arrays of metrics and setting their average as "weighted", issues related to data imbalance were catered for. Details of these evaluation metrics can be found in Hossin and Sulaiman (2015).

## 4. Results and Discussions

#### 4.1 CIE Skies Luminance Classification

As shown in the frequency of occurrence (FOC) plot in Fig. 3, the overcast skies (Skies 1 to 5) represented 32.1 % of the sky condition. Partly cloudy skies (Skies 6 to 10) and clear skies (Skies 11 to 15) represented 44.3% and 23.5%, respectively. Skies number 1, 8 and 13 were the most represented sky types with FOCs of 17.5, 37.0% and 16.0%. These also represented the most represented sky types for each typical sky. Overall, the FOC result showed that the data (i.e., predicted sky types) was imbalanced as expected. Thus, making the use of the LGBM model a good alternative.

#### 4.2 LGBM Standard Skies Classification

The statistical performance of LGBM on the 2004 test data was assessed. The ROC for the identified skies and the micro average value were presented. As shown in Fig. 4, the area under curve (AUC) of the identified skies ranged from 0.87 (i.e., Sky 5) to 0.99 (i.e., Skies 13 to 15). Similarly, the micro average ROC had an AUC of 0.98. A perfect classifier will usually have an AUC of 1.00. Hence, the findings show that the ROCs were quite close to a perfect classifier. This result means that the LGBM model can classify the 15 CIE standard skies with reasonably good accuracy and there is a tendency to obtain high recall and low false positive rate across the skies during classification.



Fig. 3 - FOC of the best fit 15 CIE Standard Skies

Next, the LGBM performance was evaluated by using the confusion matrix in Fig. 5. The lighter brown box in the matrix shows instances where predictions were accurate. As expected, Skies 1, 8 and 13 were the most correctly classified skies and these had correct predictions of 482, 1098 and 2310, respectively, which is generally in line with the observed FOC of the skies (i.e., Section 4.1).

Lastly, the model's performance on the initial and new sets of test data (i.e., 2004 and 2005, respectively) is presented in Fig. 6. It was observed that for the 2004 data, the *Accu* was 74.7% while the *Pre Re* and *f1* were also above 70%. As expected, the

performance dropped for the new 2005 test data. Nonetheless, its *Accu* and *Re* were above 70% while the *Pre* and *f1* were 66.91 and 67.77%, respectively. Overall, the result shows that for most of the predictions, the LGBM correctly identified the 15 CIE standard skies for more than 70% of the instances. This implies that good predictions were obtained.







Fig. 5 - Confusion matrix of LGBM model on 2004 test data



Fig. 6 – Performance of LGBM on 2004 and 2005 test data

#### 4.2.1 LGBM feature importance

The feature importance of the LGBM model was assessed using the permutation importance method. As shown in Fig. 7,  $K_d$ ,  $T_v$  and  $K_t$  were the most important inputs. Next to these, were  $\alpha$ , *cld* and *sun*. Since these variables have been extensively used as sky clearness indicators, this result validates their high level of relevance. However, other meteorological variables had lower importance. From this analysis, the important features can be subsequently used in places with limited data for developing simpler sky models.



Fig. 7 - Feature importance of LGBM inputs

#### 4.3 Daylight Illuminance Simulation

For daylight illuminance simulation, the Best fit standard skies, the LGBM-based standard skies and other luminance distribution models were integrated with RADIANCE and the analysis was conducted as described in Section 2.0. Precisely, five scenarios were considered for discussion. These scenarios include the south atria, then the north and south orientations of the ground and third floor, respectively. By selecting these scenarios, extreme and less extreme cases were covered. For example, the ground and third floors, depict daylight predictions with more and less obstruction, respectivelywhereas north and south orientations show the effect on sun-shaded and less shaded surfaces, respectively. The prediction error was evaluated using %root mean square error (%RMSE) and %mean bias error (%MBE). The %RMSE compares forecasting errors of different models, while the %MBE

determines the tendency of a model to overestimate or underestimate. Details of these evaluation metrics can be found in Despotovic et al. (2015). As observed in Table 1, all models tend to provide better predictions (i.e., lower %RMSE) on the ground floor compared to the third and on the north orientation compared to the other orientations. Since the model was proposed with consideration of obstruction, the reason for this might be the likelihood of the south orientation, third floor and atria being exposed to more of the sky. Overall, the models gave predictions of reasonable accuracy and this was more obvious in the Best fit and LGBM models. In fact, the Best fit prediction ranged from 10.17 to 23.73%, while the LGBM ranged from 11.5 to 26.17%. Strictly speaking, models with %RMSE < 20% are considered to have higher accuracy (Despotovic et al., 2015). Hence, showing the efficacy of both models. Nevertheless, the All-weather and ASRC-1992 also gave acceptable predictions with the latter performing the least. Also, the observed %MBE indicated that most of the time, the predictions were not so far from the daylight illuminance values. Furthermore, the ASRC-1992 and All-weather models mainly overestimated the daylight illuminance, while the Best fit and LGBM mostly underestimated. Importantly, for the proposed LGBM the %MBE ranged from -0.03 to -3.35%. This implies that most of the time, the average difference between the measured illuminance and the predicted value from the proposed LGBM will be around 3%.

Table 1 – Statistical performance of models in predicting daylight illuminance using RADIANCE simulation

Scenarios	Metrics	Best	ASRC-	LGBM	All-
		nt	1992		weather
Atrium (South)	%RMSE	23.73	33.83	26.17	28.57
	%MBE	2.08	-5.43	2.17	-1.57
GF (North)	%RMSE	10.17	25.67	11.5	16.93
(- (- (- (- (- (- (- (- (- (- (- (- (	9/ MPT	0.12	0 7E	0.02	4.45
	/olVIDE	0.15	0.75	-0.05	4.43
GF (South)	%RMSE	19.53	34.63	22.95	27.03
(,	% MRE	1 29	0 00	2.06	2.22
	/olVIDL	-1.56	0.00	-2.00	3.23
3F (North)	%RMSE	11.84	25.56	13.44	16.99
	0/MRE	0.17	9 77	0.28	2 76
	/olVIDL	-0.17	0.77	-0.28	5.70
3F (South)	%RMSE	20.77	39.75	24.87	28.32
/	0/MRE	2 40	11.04	2.25	2.00
	/01VIDL	-2.49	11.04	-3.35	2.99

Note: GF represents the ground floor while 3F represents the third floor.

#### 4.4 Energy Performance Simulation

Although indoor lamps help improve visual comfort, they dissipate heat, which will impact the indoor cooling requirement. Similarly, by setting the DLLC to the target indoor illuminance, significant energy savings can be achieved. Based on the predicted illuminance, the building energy consumption is estimated by EnergyPlus. The energy simulation result in terms of the energy savings of the measured sky and different models are presented in Table 2. As pointed out in Section 2, there were only 10,747 sets of valid data, which is equivalent to about 1,791 hours and about half of the daytime for the simulation period. Thus, it should be noted that the findings in Table 2 only cover half of the year's daylight conditions. As observed, the addition of DLLC systems caused energy savings on lighting for the measured sky luminance data and the sky models. This energy saving on lighting ranged from 38.1 (i.e., measured sky luminance data) to 38.6% (i.e., ASRC 1992). Similarly, for cooling-related end uses like fans, and heat rejection there is also a considerable energy savings actualized from the use of the DLLC system. This had maximum values of 6.0 and 4.0%, for fans and heat rejection, respectively. Other savings of about 2.5 % were derived from pumps while end use without a direct relationship with DLLC systems such as equipment and heating had no energy savings. Furthermore, it was observed that the energy savings for the different models was not so far from the measured data and all savings from these models were of similar magnitude. The reason for this might be because the lux level and visible window transmittance used in the analysis were low. Moreover, the presence of obstruction might be of concern since the analysed spaces were mainly dependent on the diffuse and reflected illuminance. Generally, shopping centers have long operating hours and relatively low illuminance requirements, hence, larger savings may be obtained if it is applied to office buildings. Nevertheless, the closeness of the predicted energy savings from the sky models to that of the measured sky luminance data shows that acceptable predictions were obtained.

## 5. Conclusion

This paper shows the potential of using the LGBM model and accessible climatic variables to determine the 15 CIE standard skies. The findings show that for over 70% of the time, the LGBM model could correctly classify the sky types. Hence, the proposed model could provide acceptable predictions. The important features in the LGBM model were determined. It was shown that sky clearness indicators like  $K_d$ ,  $T_v K_t$ ,  $\alpha$ , *cld* and *sun*, were the most important features. Therefrom, the LGBM model alongside the Best fit, ASRC-1992 and all-weather models were used for daylight and energy simulations of a generic shopping mall. For daylight simulation, it was observed that surfaces more exposed to the skies like the south and upper floors (e.g. third floor in this study) are more prone to error during daylight predictions. In terms of %RMSE, the Best fit model gave the best predictions while the ASRC-1992 performed the least. It was also observed that from the %MBE obtained, the difference between the measured and predicted illuminance from the proposed LGBM will be around 3% on average. Finally, electricity consumption was predicted and findings show that all models gave predictions which were close to the measured data. Most of the savings only deviated within 2 MWh which is equivalent to about 1.5% of the saving. Generally, an approach for determining the skies which can be incorporated into simulation software has been proposed. Nevertheless, more work using other ensemble models, larger databases and different locations is required.

End Uses	Sky luminance	Best Fit	LGBM	All- weather	ASRC 1992
Lighting	38.1	38.2	38.2	38.5	38.6
Equip- ment	0.0	0.0	0.0	0.0	0.0
Fans	5.9	5.9	5.9	5.9	6.0
Heating	-3.9	-3.9	-3.9	-3.9	-4.0
Cooling	0.0	0.0	0.0	0.0	0.0
Heat Re- jection	3.9	4.0	4.0	4.0	4.0
Pumps	2.4	2.4	2.4	2.5	2.4

Table 2 – Energy savings f	for all four sky	models with	Top-up control
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Note: Energy savings are expressed as percentages (%)

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# A Design Assistant Tool for Optimised Building Energy Retrofit

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#### Abstract

The construction sector is a major contributor to global resource depletion and environmental impacts. Most buildings still lack energy efficiency, necessitating substantial renovations to reach European climate neutrality by 2050. Energy efficiency measures typically prioritize investment cost and targeted energy performance, often neglecting the environmental impact associated with the production and disposal of the selected materials. This paper presents the development of a design assistant tool that combines sustainability indicators with cost and energy performance, aiming to foster sustainable renovation. Through automated data exchange between Autodesk Revit, CasaClima software and Microsoft Excel, the tool identifies optimal retrofit solutions. Users can choose materials and systems and visualise different retrofit alternatives through a user-friendly interface. The paper describes how the tool is structured to quickly evaluate a wide range of energy efficiency measures.

#### 1. Introduction

The European Union's strategy for achieving climate neutrality by 2050 necessitates a significant transformation in the construction sector due to its high resource and energy consumption. It accounts for about half of globally extracted materials and 25-30% of waste generated in the EU (EURIMA, 2024). Moreover, buildings account for 40% of the EU's energy consumption and 36% of greenhouse gas (GHG) emissions (EURIMA, 2019). Considering that most of the building stock is relatively old and energy inefficient, retrofitting plays a key role in achieving European targets (ECSO, 2021). Retrofitting usually concerns building envelope and systems, prioritising investment cost and targeted energy performance. The embodied emissions associated with materials production and disposal, and those associated with the construction process are often neglected despite they account for 21% of buildings' total emissions (EURIMA, 2023). According to (ECSO, 2021) along with improving energy performance, retrofitting should prioritise an efficient use of resources considering the entire life cycle of a building. This has the potential to significantly reduce emissions, especially if implemented already at the design stage.

Recent studies explore holistic frameworks that consider cost, energy efficiency and environmental sustainability. (Chen et al., 2020) stress the importance of holistic evaluations that incorporate both quantitative and qualitative assessments-like energy consumption, cost analysis, carbon emission reductions, and social perspectivesparticularly for residential buildings in Norway. (Rosso et al., 2020) explore the use of genetic algorithms in multi-objective optimisation for building retrofits in the Mediterranean climate, showing how these can tailor retrofit solutions to specific regional needs. (Li et al., 2021) developed a simulation-based optimisation model that assesses design alternatives to balance energy demand with thermal comfort, providing a basis for making informed decisions in retrofit projects. (Fourchal et al., 2017) introduced a decision support tool that automatically generates and ranks building retrofit alternatives based on energy performance, user requirements, benchmarks, and regulations. The tool uses the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method for multi-criteria ranking, offering a systematic approach for selecting optimal retrofit solutions.

Despite the development of holistic frameworks, there is often a disconnect between these assessment tools and project design software. (Stratbücker & Mitterhofer, 2017) and (Lai et al., 2023) emphasize the need for better integration between assessment tools and platforms like Building Information Modelling (BIM) to enhance the accuracy and efficiency of retrofits. Regarding this, (Jalaei & Jrade, 2014) propose a methodology that links BIM with energy analysis tools and green building certification systems, facilitating sustainability evaluations at the design stage. (Thravalou et al., 2023) present an integrated approach to propose cost-effective energy efficiency upgrade measures for historic buildings, considering the building envelope, efficient systems, and renewable energy systems using Heritage-BIM tools. However, challenges such as data interoperability still hinder the effective use of BIM as noted by Pereira et al. (Pereira et al., 2021). In fact, sustainability assessment tools such as CasaClima software often operate independently, leading to fragmented and timeconsuming assessment processes. Moreover, the literature still indicates a gap in accessible tools that provide this level of integration in a userfriendly interface, which is essential for broad adoption.

In response to these gaps, this paper introduces a design assistant tool that leverages automated data exchange between Autodesk Revit, CasaClima software, and Microsoft Excel to provide a comprehensive analysis of building retrofits. By integrating these platforms, the tool facilitates the identification of optimal retrofit solutions that balance cost, energy performance, and environmental sustainability. Its user-friendly interface allows for easy selection of materials and systems, visualisation of retrofit alternatives, and informed decisions based on a multi-criteria evaluation process.

The choice of the aforementioned software is driven by the goal of creating a useful tool for companies in the South Tyrol region, since the development of the design assistant tool is funded by the South Tyrol Fusion Grant Fund, which aims to foster collaboration between research institutes and companies in South Tyrol, Italy, to promote innovation and development within local businesses. The structure of the paper is as follows: Section 2 illustrates the methodology for addressing the above-mentioned challenges; Section 3 describes the resulting design assistant tool; Section 4 draws conclusions and gives a brief outlook for possible directions of further research.

#### 2. Method

The methodology applied for the development of the design assistant tool, illustrated in Fig. 1, is based on an in-depth analysis of the CasaClima software and its simulation requirements.



Fig. 1 - Overview of methodology

CasaClima is a comprehensive software used to assess the energy performance and sustainability of buildings, ensuring they meet specific energy efficiency standards outlined in European Directives such as EU 2018/844, 2010/31/EU, and 2012/27/EU. The software evaluates the energy consumption of buildings, helping architects and engineers design energy-efficient and environmentally sustainable projects. In addition to energy efficiency, CasaClima assesses the environmental and health impacts of buildings, including the eco-compatibility of construction materials, water usage, and indoor environmental quality (Agenzia CasaClima, 2024). Running a simulation with CasaClima requires users to manually input extensive building information, including geometry, materials, insulation properties, windows, and HVAC system details, into an Excel spreadsheet. Therefore, to promote sustainable retrofitting, the design assistant tool needs to enable users to quickly evaluate various retrofitting options during the design stage, minimising the manual input required. It must also provide a user-friendly interface that not only displays the CasaClima evaluation results but also includes cost data.

The design assistant tool development follows a multi-phase approach. The initial phase focuses on developing an Autodesk Revit plugin to extract data efficiently, enabling automated input into the evaluation software. The second phase introduces a user interface designed to gather additional required data, such as information on heating, ventilation, and air conditioning (HVAC) systems, which cannot be automatically retrieved from the 3D model. Following this, the CasaClima software (Pro CasaClima 2018 v1.1) calculates energy performance and sustainability indicators, with the results being showcased via user interface. The last phase involves integrating the costs of each retrofitting option, determined using the Life Cycle Cost (LCC) method, into the user interface.

Excel Macros combine the data obtained from the various phases by returning a final result while a C# code allows interoperability between Autodesk Revit, CasaClima software, and Microsoft Excel.

#### 2.1 Phase One: Autodesk Revit Plugin

Within the scope of this study, a workflow for efficient data extraction and transfer from Autodesk Revit to the Pro CasaClima 2018 v1.1. software is developed and implemented. Autodesk Revit is a widely used design and engineering software in the construction sector. It is particularly valuable for its capability to create detailed 3D models that are enriched with several data.

For effective assessment, data to be extracted include dimensions, orientations, material information and function of all the building elements. Specifically, this includes every wall, slab, roof, window, and door element that is either facing the external environment or non-heated rooms of the building as well as the area of both non-heated and heated rooms.

To identify the relevant building elements, Revit's built-in categories properties are extended with a set of custom boolean properties. Users must edit these properties before the data extraction to indicate the boundary condition of the building elements. This boundary condition can be either external, terrain or non-heated room. Additionally, users must specify roof types as either pitched roof, flat roof, or non-heated attics, and distinguish between heated and non-heated rooms. This setup does not require users to manually input this information for every individual element. Revit works with so called *types*. Every instance of the same type will have the same properties assigned. For example, all wall elements of the same wall type have the same layer stratigraphy, materials and boundary condition assigned.

Moreover, a materials library in ASDKLIB file format is created to provide detailed materials information. This library contains materials commonly found in existing buildings, such as brick, EPS and XPS insulation, and lime. Each material in the library is defined by properties crucial for assessment, including thermal conductivity (W/mK), density (kg/m<sup>3</sup>), and specific heat capacity (KJ/kgK). These property values are sourced from the CasaClima software materials library, ensuring accurate and reliable calculations.

The Revit's C# programming interface is used to implement the exposure of the custom properties and the automated data extraction into a plugin. These two functionalities of the plugin are exposed through two buttons that are added to the Revit user interface automatically on startup.

Finally, since the CasaClima software is implemented in a Microsoft (MS) Excel spreadsheet, all extracted data could be directly transferred seamlessly by the Revit plugin using MS Excel's C# programming interface, which enables reading and writing data to and from MS Excel spreadsheets through C# code.

#### 2.2 Phase Two: User Interface

In addition to the Autodesk Revit plugin, a user interface is designed to gather additional data related to the building's design, location, and systems. The user interface is implemented within an Excel spreadsheet, organised into four distinct sections to simplify the data entry process. In particular, the data entry sections are:

- Section 0: Project Requirements; this section is designated for entering information related to the number of building's units, area, volume, and the municipality where it is situated.
- Section 1: Existing Building; this section enables the input of details concerning the HVAC system and the roof type (pitched, flat etc.) of the building before retrofitting.
- Section 2: Refurbishment; this section is for entering information about the retrofit solution, including the adjustment of costs if the predefined ones are unsuitable.
- Section 3: Life Cycle Cost; this section allows for the modification of the predefined costs mentioned in section 2.3.

Moreover, the Excel spreadsheet features two additional sections dedicated to displaying the results for energy performance, sustainability indicators, and costs. Specifically, the data output sections are:

- Section 4: Simulation; this section showcases the values associated with different retrofitting solutions in a tabular format.
- Section 5: Analysis; this section presents the results through a series of charts.

To initiate the assessment process and obtain these results, the interface incorporates three buttons created using Excel Macros. Moreover, to evaluate and compare different retrofit alternatives, the Excel spreadsheet includes a retrofit matrix linked to the data entry cells. Each row of the matrix represents a distinct retrofit option. Once the assessment process is started, an Excel macro reads the data from the first row of the matrix, inserts it into the corresponding fields of the CasaClima software, retrieves the result, and writes it into the dedicated sections of the user interface. This process is repeated for each row of the matrix.

Finally, the Excel spreadsheet has instructions accompanying each input and output field to ensure clarity and ease of use.

## 2.3 Phase Three: Life Cycle Cost (LCC)

The cost evaluation employs a custom-developed Excel spreadsheet, designed based on the LCC method. This spreadsheet primarily calculates the initial investment cost by aggregating expenses associated with the building envelope, HVAC system installation, general site setup, and any technical costs. To ensure accuracy in these calculations, data is sourced from the provincial price list of Bolzano (Provincia Autonoma di Bolzano – Alto Adige, 2024) and directly from user inputs via the interface. Moreover, the spreadsheet adds other costs associated with the building's entire lifecycle to the initial investment cost, facilitating a comprehensive assessment of the total cost. This assessment includes the following costs:

- Energy costs from ARERA (ARERA, 2024) and the Bolzano Consumer Protection Center (CTCU, 2024).
- Maintenance costs from the UNI 15459:2008 (UNI Ente Italiano Di Normazione, 2008).
- Public incentive programs, calculated to be 50% of the total costs and amortised over 10 years.

The assessment excludes replacement costs and residual values to streamline the evaluation. After completing these calculations, the user interface mentioned in section 2.2 displays the costs of different retrofitting options in a tabulated and graph format. This is done by an Excel function that connects the LCC calculation spreadsheet to the user interface, facilitating data exchange.

## 3. Results

The results of the design assistant tool consist in a series of data presented in an alphanumeric format. The data are visualised both in tabular format and as graphs. The tabular format offers an overview, enabling users to quickly identify the optimal refurbishment strategy. The solutions are ranked, beginning with the optimal one, based on a comprehensive set of criteria. This arrangement allows for an immediate comparative analysis across different options. The information provided for each solution is categorised into three sections:

- Technical Specifications: This section includes the technical details of each solution, including, but not limited to, the thickness of insulation materials and the type of HVAC systems employed.
- Energy Performance and Sustainability: Here, the outcomes derived from the CasaClima calculations are displayed, offering insights into the energy efficiency and sustainability impacts of each refurbishment option.
- Cost Analysis: Costs are detailed in this section, outlining the investment required for each refurbishment strategy.

Through an interactive interface, users can initiate the design assistant tool, with the flexibility to update its input parameters and subsequently refresh the results. Specifically, it allows them to perform the calculation and view the results regarding the building before retrofitting and to obtain the list of possible retrofitting options.

In addition to the tabular representation, users can visualise the results through a series of graphs. Each point on the graph correspond to a different retrofit solution and is linked to its detailed technical specifications listed in the abovementioned table.

To test the automated data exchange capabilities of the tool, a case study is conducted on a multistorey residential building in South Tyrol, Italy. The focus is on verifying the automated workflow and data exchange between Autodesk Revit, CasaClima software, and Microsoft Excel, rather than on the accuracy of the calculations. A BIM model of the building is created using Autodesk Revit as shown in Fig. 2.



Fig. 2  $\,$  – BIM model of the multi-storey residential building case study

The building has double-glazed wooden windows and wooden doors. It has external brick walls covered with lime plaster and a pitched roof made of glulam structure and shingles. The model's component and associated materials technical data are detailed in Table 1.

Using these data and user inputs via interface, the tool identified possible renovation alternatives, demonstrating the correct functioning of the automated data exchange. The tool generated several solutions featuring options such as 120 mm, 140 mm and 160 mm EPS or mineral wool insulated walls, upgrading to triple-glazed wooden windows, installing a heat pump and photovoltaic panels, as well as opting for a condensing boiler, biomass heating, or district heating connection.

Fig. 3 and Fig. 4 provide examples of possible results produced by the tool. They illustrate, respectively, the sustainability indicator "Nature" (Agenzia CasaClima, 2024) and the investment costs. The "Nature" indicator scores each solution based on a combination of factors. These include overall energy efficiency of the building, environmental impact of construction materials, efficient use of water resources, high air quality and low-emission materials, measures for radon gas protection, use of natural light, and acoustic comfort. The investment indicator covers the aspects described in section 2.3 of this paper, illustrating the financial implication of each retrofit solution.

These results confirm that the automated workflow functions correctly, enabling efficient data exchange and the generation of renovation alternatives. For being able to discuss the accuracy of the specific values from the results, further evaluations have to be done. This was not part of this study but will be included in future works. Nevertheless, we successfully demonstrated the functionality of the entire toolchain, including the cor-

Table 1 – Technical data of materials in the BIM model

rect implementation of automated data transfer between Autodesk Revit, CasaClima software, and Microsoft Excel.

Material	Building component	Thickness [mm]	Thermal conductivity [W/mK]	Specific heat capacity [KJ/kgK]	Density [kg/m³]	Thermal trasmittance [W/m²K]
Hollow clay bricks	External wall	400	0,37	0,88	850	-
Hollow clay bricks	External wall	100	0,37	0,88	850	-
Lime plaster	External wall	20	0,7	0,93	1400	-
Lime plaster	External wall	15	0,7	0,93	1400	-
Glulam timber	Roof	270	0,13	2	495	-
Glulam timber	Roof	70	0,13	2	495	-
Breathable membrane	Roof	0,8	0,16	0,9	1390	-
Clay shingles	Roof	15	1	0,9	1800	-
Glass	Double-glazed windows	24	-	-	-	3,3
Wood-aluminum	Windows frame	65	-	-	-	1,8

#### NATURE [Points]



Fig. 3 – Graph illustration of the sustainability indicator for each retrofit solution

#### INVESTMENT [€]



Fig. 4 – Graph illustration of the investment cost for each retrofit solution

#### 4. Conclusions and Outlook

In this paper a design assistant tool for optimised building energy retrofit is proposed and described. The tool aims to foster sustainable renovation by facilitating the identification of optimal retrofit solutions that balance cost, energy performance, and environmental sustainability. To this aim, the tool ensures an automatic data flow between Autodesk Revit, CasaClima software and Microsoft Excel, returning retrofit alternatives through a user-friendly interface.

The tool has proven effective in automating data exchange, significantly reducing the amount of manual data entry required for CasaClima software and minimising associated errors. Despite these improvements, there is great potential for further development.

Firstly, the tool could be enhanced by automating the extraction of HVAC system data directly from the BIM model, which currently requires manual input by the user through the interface. Additionally, the calculation and export of thermal volume, as well as the building's position, could be automated directly from the Autodesk Revit.

Moreover, the current design of the tool is closely tied to the CasaClima software and its parameters, which limits its flexibility. If users wish to evaluate materials not included in the CasaClima database, the tool cannot perform the necessary calculations. This is because the building model must be set according to a specific Autodesk Revit library of materials based on the CasaClima database. Therefore, the tool and the materials library could be expanded to allow for evaluations using other available market software, not just CasaClima software, broadening its applicability and utility. Finally, since this paper primarily focused on implementing and verifying the functionality of the automated data exchange workflow, less emphasis was placed on verifying the accuracy and reliability of the calculation process and its results. Future development will involve applying the tool to actual case studies to validate its effectiveness and accuracy in real-world scenarios.

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# A Simulation Study on the Performance of Machine Learning Daylight-Linked Lighting Control Under Urban Topography

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#### Abstract

Daylight-linked lighting control (DLLC) system has been recognized as one of the effective measures for improving indoor illuminance distribution and energy performance. However, the system is often considered ineffective due to poor calibration and commissioning of the system and lack of design guidelines (Bellia et al., 2016). Among different causes, the positions of photosensors play a crucial role in DLLC systems. The position affects the DLLC system in two major aspects. First, the location of the sensor needs to reflect the illuminance level on the working plan level where it would not be affected by a strong source of sunlight. Secondly, under normal circumstances, DLLC is controlled by a single photosensor which leads to over-dimming in the rear part of the room or overprovided electrical lighting at the front part of the room. Traditionally, the use of open-loop and closed-loop controls makes it impossible to change the dimming ratio of artificial lighting due to indoor illuminance distributions and climatic conditions. Hence, an artificial neural network (ANN)-based machine learning (ML) is used to identify the correlation between artificial lighting and photosensors under different operating conditions. This paper focuses on identifying the major input parameters for the ANN model. Findings show that the input parameters (features) have strong correlations with the dimming output. Also, the ANN model performed very well with very small errors in most of the cases.

## 1. Introduction

Tsang et al. (2021) assessed the performances of closed-loop and open-loop DLLC systems under urban topography. Open control system is highly affected by the external lighting environment especially reflected direct sunlight from opposite façade.

The view angle of the photosensor is important and a narrower or shielded photosensor is preferred to provide a steadier system performance (Kim & Song, 2007; Do et al., 2023). For a closed-loop lighting control system, installing narrow-view-angle photosensors at the rear part of the room ensures sufficient illuminance of the room and prevents the photosensor from being interfered with by direct or reflected sunlight. Generally, the major focus for closed-loop DLLC and its associated method of testing and commissioning is to ensure the minimum illuminance is achieved in the working zone of the room. Hence, when a photosensor is designed for the rear part of the room to meet the design illuminance values, the front part of the room will always be over lit especially under clear sky conditions. This shortcoming is difficult to eliminate for traditional closed-loop DLLC systems. Hence, machine learning (ML) seems to offer the opportunity of introducing variable lighting output to photosensor signal ratio according to external weather conditions and solar positions. Beccali et al. (2018) suggested that the artificial neural network (ANN), which is the chief ML algorithm (Sevedzadeh et al., 2018), can provide a sensor signal match with a working plane illuminance level. The coefficient of determination achieved using ANN in this study exceeded 0.75. Wagiman et al. (2020) proposed the use of advanced control algorithms such as fuzzy logic to control multiple photosensors and multiple sets of lighting systems. Furthermore, ANN was used to design an adaptive smart indoor lighting control by Seyedolhosseini et al. (2020). This method was asserted to effectively respond to variations in daylight, deal with the non-linearity of lighting systems and reduce power consumption. Similarly, an ANN

control method for optimizing lighting conditions in an LED-based lighting system was proposed by Mohaghegi et al. (2017). In all these studies, ANN proved to be viable for modelling DLLC systems. Based on the possibilities inherent in the use of ML in previous studies, this paper explored the use of ML in DLLC in urban topography. Specifically, an ANN with four interconnected layers was used in this study. To accomplish this, the best ANN algorithm and training method for DLLC in urban topography was first selected based on simulation methods. Next, the performance of DLLC by ANN were analysed. Lastly, major parameters affecting the performance of DLLC with ANN are discussed.

## 2. Case Study

#### 2.1 Building Model

This study analysed the DLLC system in a typical office in an urban location of Hong Kong. Fig. 1 shows an existing cellular office of 4.55 m (W) × 4.8 m (D) × 3 m (H) employed. The office is equipped with nine recessed LED luminaires. The overall lighting power density was 9.47 W/m<sup>2</sup> which is slightly less than the allowable value of the local building energy code (Electrical & Mechanical Services Department, 2021). The working plan illuminance ranged from 320 to 640 lux with an average of 500 lux during night operation while the room setpoint was 500 lux. Usually, those locations with a lower working plane illuminance level are at the corners or closed to walls or windows will not be used for normal office work. The normal operating hours of the office lighting was from 08:00 to 18:00. The minimum lighting output can be reduced to 0% whereas the minimum power consumption was 5%. Also, the power input and lighting output have a linear relationship. While to simulate the effect of reflected sunlight, the north-facing room was chosen for the study.



Furthermore, the building had a height of five floors, and the obstruction also had the same height as the office building. The ratio of separation between the two buildings and obstruction height was 1:3 which is the minimum ratio required by the local regulations (Hong Kong Government, 1956). To model the building in heavily obstructed urban topography, a continuous type of obstruction was modelled. As shown in Fig. 2, the office building and obstruction were extended to five times the modelled office's width. Details including fins, mullions and ceiling panels were modelled according to installation details. Finally, the glazing had a visible transmittance of 0.3 while the reflectance for obstructions, ceilings, interior walls, and floors were 0.35, 0.7 0.5 and 0.2, respectively.



Fig. 2 – External obstruction arrangement to model the urban topography

# 2.2 Daylight-Linked Lighting Control System (DLLC)

A DLLC system aims to maintain the required interior illuminance level and to reduce the reliance on artificial lighting. Hence, by the using DLLC system, the lighting energy consumption can be reduced without affecting indoor occupants. As the purpose of this study is to explore the application of ML in DLLC, there were significant differences in lighting system modelling compared with a previous study (Tsang et al., 2021). Nine luminaires were assigned to three different control groups as shown in Fig. 1. Luminaires under the same group will have identical dimming ratios. Five downward facing photosensors to simulate the actual DLLC setup were installed in the centerline of the ceiling with equal spacing. Three types of photosensors were selected for this study including wide, medium, and narrow spatial sensitivity which has corresponding angles of incidence of 90°, 30° and 15° respectively (Di-Laura & IESNA, 2011). In addition, the vertical illuminance on the centre of the window facing external obstruction and sky was also calculated.

# 3. Study Methodologies

This study employed climate-based daylight modelling (CBDM) and measured climatic data to predict natural and artificial illuminance. A tailor-made programme was written to calculate the dimming ratio of each group of lighting. The dimming ratios and other parameters were then used to train the ANN. Then, the abilities of ANN to predict the dimming ratios were analysed. Finally, the trained ANN DLLC system was used to predict the system response and indoor daylighting performance.



Fig. 3 – Sequence of methodology

# 3.1 Lighting Simulation

## 3.1.1 Simulation package

RADIANCE is a backward ray-tracing program which has been used and tested by some researchers (Li & Tsang, 2005; Mardaljevic, 2000; Reinhart & Walkenhorst, 2001). In this study, version 5.2 was used. A few parameters affecting the accuracy of a computational model are the number of reflections, sampling, and resolution. These settings were considered for controlling these ambient parameters. To ensure the setting can ensure the accuracy of simulation results according to the complexity of the simulation model, a convergence test by tighten the setting until stable results were obtain was carried out. The values of ambient bounce (ab), ambient division (ad), ambient subdivision (as), ambient resolution (ar) and ambient accuracy (aa) were 5, 1024, 512, 1024 and 0.08, respectively.

## 3.1.2 Climate-based daylight modelling

Daylight simulation is time-consuming, and it is impossible to conduct long-term assessments via the traditional step-by-step simulation method. Tregenza and Waters (1983) proposed a daylight coefficients (DC) approach which is a ratio of indoor illuminance level and brightness of the sky patch. By the DC approach, once a set of DC has been determined, it can be used again even if the sky luminance distribution pattern is changed. Mardaljevic (2006) proposed the use of CBDM based on the DC approach and sky luminance distribution model to estimate the indoor illuminance for a typical weather data. In this study, instead of the sky luminance distribution model, the actual sky luminance distribution data based on measurement was used.

#### 3.1.3 Weather data measurement

A measuring station was set up at the City University of Hong Kong to record the solar radiation, illuminance, sky luminance and radiance distribution patterns. Irradiance was measured by Kipp & Zonen CM11 thermopile pyranometers. While the Minolta T-M10 illuminance meters were used to measure the horizontal global and diffuse illuminances. Similarly, EKO MS 300LR was used to measure the sky luminance and radiance distributions. In this study, the meteorological data measured between January 2004 and December 2005 were used in the analysis. Due to the need to remove erroneous measured data, the data quality control test was carried out as described in (Aghimien & Li, 2022). In total, 16,118 and 10,747 sets of valid data for 2004 and 2005, respectively were used.

# 3.2 Determine the Optimal Dimming Ratio

An optimal dimming ratio of artificial lighting provides minimum lighting to maintain the working plane illuminance level to reach the design value or the illuminance values during night conditions. A program was written to tune up the light output until the sample point with the lowest illuminance level reached the setpoint values. The processes were repeated until the illuminance level for all sample points fulfilled the lighting requirement. Then the programme verified if any over lit condition exists. In case of over lit, then the corresponding group of light fitting will tune down. The process was continued until the optimal dimming ratio was reached.

# 3.3 Model Development and Artificial Neural Network (ANN) Description

Before model development, correlation analysis was conducted to determine the data relationship. The 2004 data was used for training and validation using a ratio of 80 to 20% while the 2005 data was used for testing. After splitting, all training and test data were separately scaled using the min-max approach. The technique of separately scaling the data helped to prevent data leakage. Consequently, artificial neural network (ANN) models were developed.

The ANN is the most popular and powerful ML algorithm (Li et al., 2022). Hence, it is regarded as the chief ML algorithm and used in most energy estimations due to its ability to model nonlinear and complex systems (Seyedzadeh et al., 2018). In this study, three supervised ANN models for different spatial sensitivity photosensors (narrow, wide, and medium sensors) were used to predict the dimming ratio of the artificial lighting for the 1st, 3rd and 5th floor, respectively. Hence, nine ANN models were developed in total. The model inputs were vertical illuminance, illuminance levels in photosensor, solar altitude ( $\alpha$ ), solar azimuth ( $\phi$ ), clearness index (Kt), diffuse fraction (Kd) and Turbidity. The structure of all models is similar. Each model is a feedforward network consisting of 4 interconnected lavers (i.e., an input layer, 2 hidden layers and an output layer). For both hidden layers, 63 and 128 hidden neurons were used, respectively while the rectified linear unit (ReLU) activation function was used to address vanish gradient problems. Furthermore, model optimization was done using the Adaptive Moment Estimation (Adam) while "Early stopping" of the training iterations was used in the model development to prevent overfitting.

# 3.4 Predicting Dimming Ratio by ANN

The lighting performances of the ANN DLLC system were evaluated. Dimming ratios were determined by illuminance level on photosensors and climatic parameters. Afterwards, the total illuminance levels for the working plan and photosensors were updated. Hence, the updated photosensor illuminance became the new input parameters for the ANN DLLC controller. Iteration was continued until the dimming ratio became steady. Then the indoor lighting conditions were assessed according to Bellia and Fragliasso (2017).

# 4. Data Analysis

#### 4.1 Features Importance

In the ANN training, input parameters are commonly known as features. Thus, the significance of these features for the 1<sup>st</sup>, 3<sup>rd</sup> and 5<sup>th</sup> floor according to Altmann et al. (2010) is presented in Fig. 4.



Fig. 4 - Feature importance of dimming ratio

In general, the influence of the illuminance level received from photosensors whether attached to the ceiling or mounted on windows vertically is more important than other climatic parameters.

In this paragraph, the issue related to photosensors is discussed. First, the importance of photosensors located at the rear part of the room (photosensors 1-3) is higher than those located at the front of the room. This may be because the sensor at the front tends to achieve very high illuminance values and hence it is not a good indicator to represent the distribution of indoor illuminance as well as the optimal dimming ratio of the lighting. Second, for less obstructed cases, the importance of the deepest photosensor (photosensor 1) outweighed almost all other parameters. The permutation importance of medium and narrow view angles in that a photosensor can reach 7.26 and 18.38, respectively while other features are only around 2 or less. For an unobstructed indoor environment, the deeper the photosensor the higher is the importance in forming an ANN DLLC system. Third, for photosensors located close to the window, photosensors with a wider view angle have a higher permutation importance. For locations with a heavier obstruction or at the rear part of the room, a narrower field of view for photosensors is much better. Fourth, the importance of outside vertical illuminance is higher than the photosensors close to the window (photosensors 4 & 5) for a less obstructed environment. Using a vertical illuminance sensor can help to improve the performance of a wide-angle sensor.

Under most situations, climatic parameters are less important with a permutation importance less than 0.2. However, based on Fig.4, the importance of the clearness index increases substantially for less obstructed rooms. For less obstructed cases more light flux enters the room from the sky directly so the influence of climatic parameters increases.

## 4.2 Correlations and Errors of ANN Model

To appraise the training for ANN, coefficient of determination (r<sup>2</sup>), mean bias error (MBE) and root mean square error (RMSE) were reviewed. As pointed out in Section 3.3, the year 2004 was divided into training and validation sets while the year 2005 was used for testing. Fig. 5 shows the r<sup>2</sup>, MBE and RMSE.

For most of the training and validation sets, the r<sup>2</sup> was around 90% or higher. The features (lighting level received by photosensors and climatic parameters) have a strong correlation with the lighting dimming ratio. As expected, the test set data shows a poor correlation compared with training and validation sets. Most of the r<sup>2</sup> are under 0.9 while some of them can be as low as 0.74. The photosensors with a wider field of view have a lower correlation. Among all floors, the 3<sup>rd</sup> floor has the lowest r<sup>2</sup>. For the wide-angle photosensors, the lighting group 1 has the worst performance. It might be due to a lower dimming ratio and very high illuminance level received by photosensors which resulted in a lower correlation.



Fig. 5 –  $r^2$ , MBE and RMSE for ANN model

In terms of error, the behaviours are similar to the r<sup>2</sup>. In general, the ANN model tends to slightly underestimate the dimming ratio of lighting for moderate or heavily obstructed scenarios (3rd and 1st floors) whereas it overestimates the dimming ratio for the less obstructed cases (5th floor). For the lowest floor, most of the MBEs are low. The highest MBE occurred in lighting group 1 (closest to the window) with only about -0.05 and the corresponding RMSE is 0.126, i.e. on average about 5% deviated from the optimal setting. On the topmost floor, the MBE can reach 0.07 and this occurred in the lighting group 2 with narrow spatial sensitivity photosensor. The largest MBE and RMSE were found on the 3<sup>rd</sup> floor with wide-view-angle photosensor. The first group of lighting reached an MBE of -0.104 and RMSE of 0.18. Even though several points have very large relative errors, most of the points can provide satisfactory performance.

#### 4.3 Lighting System Performance

The performance of the ANN DLLC system was examined according to Bellia and Fragliasso (2017). Intrinsic light excess (ILE) is the light that exceeds design values which cannot be avoided unless there are changes in the lighting system configuration. Light deficit (LD) is the lighting provided less than the requirement and light waste (LW) is lighting supplied more than an ideal system. The summary of ANN DLLC system performance with different types of photosensors and locations is tabulated in Table 1.

Table 1 – Lighting performance of ANN DLLC system with different spatial sensitivity photosensors

	S	patial sensitivit	у
	Wide	Medium	Narrow
1/F (ILE% = 0.	06%)		
LD (%)	4.22	5.89	24.1
LW (%)	6.61	4.13	1.77
3/F (ILE% = 0.	11%)		
LD (%)	8.69	10.31	16.31
LW (%)	5.21	4.45	2.88
5/F (ILE% = 0.	78%)		
LD (%)	43.91	35.45	24.76
LW (%)	0.66	2.21	12.02

Each ideal ANN DLLC system has been calibrated carefully. The lighting was divided into three different groups, and each can be controlled individually. The lighting level is close to setpoint and hence a very low ILE was recorded for all the floors. As the floor level increased, the variation of natural lighting inside the room increased and hence there was a slight increase in the ILE.

The LD and LW for the topmost floor (5<sup>th</sup> floor) were very large. This is because daylight can provide sufficient lighting for most of the cases, hence, the total light requirement (LR) is reduced. As the denominator (i.e. LR) of LD and LW dropped, the percentage increased. In contrast to the correlation study, the wide and medium spatial sensitivity photosensors provided better LD and LW under moderately and heavily obstructed room while a narrower photosensor increases the LD. However, for the topmost floor, a photosensor with narrow spatial sensitivity can reduce the LD. This may be due to large illuminance level variations on the working plan level, and it is required to reduce the view angle to ensure sufficient illuminance level for underlit locations. Similar observations can be found in closedloop control (Kim and Song, 2007; Do et al., 2023).

# 5. Conclusion

The feasibility of using multi-photosensor and multi-lighting controllers by the ANN system has been covered in this study via simulation techniques. CBDM and measured sky luminance distribution patterns were used to model the indoor illuminance levels which covered most of the weather conditions. Based on the importance study, it is noted that the photosensor located at the rear of the room is more important than other parameters. For less obstructed cases, outdoor vertical illuminance is also one of the key features. Except for the topmost floor, climatic parameters are not so important as under heavily obstructed cases, the light flux received by photosensors may also be able to reflect the climatic parameters to a certain extent. As more sky can be "seen" by the indoor working plan, Kt becomes more important. To evaluate the ANN's ability to predict the optimal dimming ratio of lighting, correlation and error analysis were conducted. In most cases, r<sup>2</sup> of 0.9 or above were achieved. Major errors were found in the topmost floor, or the points closed to windows. It is believed that these variations are due to strong daylight in these cases. The ANN DLLC system performances were also analysed and it performed very well. For wide or medium photosensors, the LD and LW can be lower than 10% under moderately or heavily obstructed cases. For the topmost floor, the percentage error is larger. However, it may only be because the lighting required is very small and resulted in a larger relative error. This study can be used to set design guidelines on selecting the location of photosensors. This is not applicable to the ANN controller; it is also applied to other type of DLLC system. More should be conducted based on this approach to generalise the best practices which allow better calibration of DLLC system during testing and commissioning processes. The applications of ANN DLLC should be further compared with traditional controllers such as closed-loop controllers. Hence, further work is needed.

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# BIM2FEM: From Building Information Modelling to Finite Element Analysis – An Automated Open Source-Based Workflow

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#### Abstract

We propose an open-source-based workflow which connects Building Information Modelling (BIM) with thermal Finite Element (FE) - Analysis. We use the open IFCstandard for data interoperability and leverage opensource FE software packages for both 2D and 3D thermal analysis. The Finite Element Method (FEM) represents a highly flexible state-of-the-art approach for thermal analysis in construction engineering. With the recent increase in computing power, even complex 3D FE models can be analysed within a feasible amount of time. However, the integration of FE-Analysis into BIM-workflows remains an active area of research. Especially, a consistent and automated flow of material and boundary condition information is a challenging task to realize. The aim of this work is to contribute to the advancement of automated and open-source-based solutions for thermal analysis of buildings. The proposed workflow has the potential to decrease the time needed for evaluation of energy efficient building designs, especially in early design-phases. Its open-source nature promotes transparency, reproducibility, and collaboration in the building industry. The implementation of the proposed workflow results in a software prototype, which is tested based on a selected use case.

## 1. Introduction

Data interoperability is still one of the main issues in the construction industry today. Many data exist already in today's building information models, but they are in many cases not used for tasks that go beyond the pure design of a building or a built structure. Especially the information about the structure of the building envelope like wall stratigraphies or window details with material information are of high value for building performance analysis. Often missing interfaces and tedious manual input of data – that theoretically already exists in building information models – hinder the efficient analysis of building performances.

The Finite Element Method (FEM) is a numerical technique widely used in engineering and mathematical modelling to solve complex physical problems. The FEM is highly suitable for Building Energy Performance Simulation (BEPS), due to its ability to model complex geometries, provide high spatial resolution with low computational times, and adapt to specific accuracy requirements.

It could be shown by multiple recent studies that the integration of FEM into Building Information Modelling (BIM) workflows carries a high potential. Jia et al. (2022) present an innovative approach to automate the conversion from BIM to FE models, leveraging Industry Foundation Classes (IFC) and ontology systems. Their methodology aims to enhance the efficiency and quality of data conversion and information transfer, critical aspects in the structural design phase. Leonardi et al. (2024) demonstrate how open-BIM can be used to facilitated structural analysis of historic masonry structures. Fedorik et al. (2016) explore the integration of BIM and FE analysis to automate engineering design processes for buildings and bridges. The integration of BIM with FEM tools was shown to facilitate the efficient transfer of data, reducing manual inputs and errors, and ultimately improving the quality of engineering designs.

Furthermore, in the field of BEPS the integration of BIM and the exploitation of BIM data for more efficient simulations is a subject of current research. Andriamamonjy et al. (2019) conducted a combined scientometric and literature review to understand BIM research trends and its integration with BEPS. They identified a lack of established strategies for interoperability between BIM and BEPS, noting the potential for improvement in building system and control modelling during the operational phase.

Ahmad Mohammad Ahmad et al. (2022) stress the importance of a coherent life cycle information flow within BIM projects for effective energy analysis, developed through literature review and expert interviews. Li et al. (2020) explore BIM-based energy simulation for building operations, specifically addressing interoperability issues between BIM tools and energy simulation software, proposing a technical framework for information transfer to support accurate energy simulations.

Integrating BIM with energy modelling tools, as shown in the works of Carvalho et al. (2021) and Pezeshki et al. (2019), provides valuable opportunities to improve building sustainability and energy efficiency from the early design stages.

The automation of data conversion and information transfer processes, as explored by Jia et al. (2022), represents a critical area for advancement, offering the potential to significantly enhance the efficiency and accuracy of both structural analysis and energy modelling.

Ou et al. (2017) leverage BIM models specifically for thermal FE Analysis to evaluate the thermal building performance. The authors demonstrated the transfer of an IFC model to a commercial FEA software and highlight the capabilities of FE models to accurately represent geometric information from original IFC model. However, one drawback of their approach is the limitation to a specific commercial FE software.

The integration of BIM with FEM and BEPS is a dynamic and evolving field, offering significant potential to advance building design, structural analysis, and energy efficiency. While challenges remain, particularly in interoperability and data exchange, ongoing research and development in this area hold promise for creating more sustainable, energy-efficient buildings. By proposing an automated open source-based workflow that enables a consistent flow of geometrical and non-geometrical data between BIM and FE analysis we want to address interoperability issues and increase automation for BEPS. A high degree of automation can reduce manual input errors and especially for large building models it has the advantage of reducing the amount of tedious manual input work.

This paper is structured as follows. In the following Section 2 we introduce our developed workflow from a methodical point of view. In Section 3 we demonstrate its application through a selected casestudy. In Section 4 we discuss the performance and possible drawbacks that were found conducting the case-study. In Section 5 we draw conclusions and give a brief outlook for possible directions of further research.

# 2. Methodology

The objective of this study is to create an automated workflow which takes a digital building model as input and returns results of a thermal FE simulation as output. These results can then be used to calculate a variety of different metrics to indicate the performance and necessary dimensioning installations of the corresponding building.

The overall workflow to achieve this is shown in Fig. 1. It consists of three primary steps:

- 1. IFC-Processing (Section 2.1)
- 2. Geometry discretization (Section 2.2)
- 3. Thermal FE simulation (Section 2.3)

We implemented all three steps in the Python programming language and made use of free and opensource Python libraries.



Fig. 1 – Overall workflow with used software, libraries and file formats

#### 2.1 Processing of IFC Model

The starting point of our workflow is an IFC-file containing a digital building model. The IFC file format is an open standard and widely used for exchange of construction data. Hence, every common building design and engineering software like Autodesk Revit, Nemetschek Allplan or Graphisoft Archicad support nowadays the export of models in IFC format.

We leveraged the capabilities of IfcOpenShell (Krijnen, 2023) and PythonOCC (Paviot, 2023) libraries to develop a Python module for the efficient processing and manipulation of 3D geometries derived from IFC models. This module encompasses two primary functions:

Firstly, the function designated for extracting geometrical representations selectively filters and refines 3D objects from the IFC model and extracts material information. The output is a curated Python dictionary with 3D geometries, each associated with specific object and material names.

Objects of type *IfcSpace* play a special role, as heat sources will be placed into them at later stages of the thermal simulation. To identify these elements later, their names are prefixed with 'Air\_body' followed by a sequential number.

Secondly, we implemented a function aimed at exporting the processed geometries into a STEP file format. The STEP format is extensively recognized for its compatibility with various Computer-Aided Design (CAD) and meshing software for FE analysis. All geometries apart from the *IfcSpace* objects carry their original name as in the input IFC model. Due to limitations regarding STEP file importing in the consequent discretization step (see Section 2.2) the material information of the geometric objects is stored in a separate JSON-file and not directly in the STEP-file itself. The JSON-file contains a mapping between the geometry names and their material names.

#### 2.2 Discretization

For the execution of FE simulations, it is imperative to discretize geometries into finite elements, a process commonly referred to as meshing. One commonly used free and open-source meshing software is Gmsh (Geuzaine & Remacle, 2009). Gmsh encompasses a comprehensive set of robust meshing algorithms suitable for both 2D and 3D discretization. In addition, it is equipped with a Python programming interface, thus enabling access to all functionalities via Python code. Additionally, Gmsh supports processing the STEP file format as an input.

In the context of this study, we have developed a Python module that harnesses the meshing capabilities of Gmsh. We have also devised an algorithm that automatically identifies all external boundaries of the processed geometrical model. The algorithm iterates through entities of the geometric model, which are one dimension lower than the model itself (surfaces in 3D models or lines in 2D models).

For each entity, it examines the adjacent higher-dimensional entities. If an entity is adjacent to only one higher-dimensional entity (e.g., a surface adjacent to only one solid in 3D), it is considered part of an external boundary. This is based on the premise that external boundaries will not be shared by multiple higher-dimensional neighbours.

Gmsh offers several configurable parameters to tailor the meshing process. The parameters of paramount importance include the meshing algorithm, the size of the resulting mesh elements, and the mesh output file format. For the sake of file format compatibility with Elmer FEM, the software employed for thermal FE simulation (refer to Section 2.3), we have opted for the UNV as mesh output file format. The remaining parameters are designed to be adaptable, allowing for customization based on specific use-case scenarios. Detailed discussions on the parameters selected for the case-study examined within this study are provided in Section 3.

In this step, our objective is still to maintain the material information preserved during the IFC processing (see Section 2.1), while also incorporating details about the external boundaries. The UNV file format is limited to representing only the geometrical aspects of the stored mesh, lacking the capability to include metadata such as materials, object names, or tags identifying external boundaries. To overcome this limitation and ensure the retention of this essential metadata, we once again employ a JSON file. This file facilitates a linkage between the 3D mesh geometry IDs and their respective materials, in addition to enumerating the IDs of any detected external boundaries. Both the 3D geometry IDs and the boundary IDs are cross-referenced in the UNV file.

#### 2.3 Thermal FE Simulation

Leveraging the discretized geometry model and associated metadata obtained from the preceding step, we employ Elmer (CSC - IT Center for Science, 2023), an open-source finite element software for multiphysical problems to solve a steady state heat equation (1) with at least one internal heat source.

$$-\nabla \cdot (k\nabla T) = \rho h \tag{1}$$

Where *T* is the temperature, *k* is the thermal conductivity,  $\rho$  is the density and *h* is the heat source. Heat sources are placed in all 3D objects that carry the 'Air\_body' tag placed during the IFC processing step (see Section 2.1). In our workflow, these objects

are meant to represent the indoor air volume inside of the building model and should simulate the heating of a building. Elmer exposes a functionality called Smart Heater Control that adjusts the intensity of the prescribed heat source. This adjustment ensures that a given target temperature is reached at a designated point within the heated object. Utilizing this feature, we aim to regulate the desired indoor room temperature effectively. The initial value of the heat source is set to a predetermined default in our code. However, the target indoor temperature remains adjustable, allowing the flexibility to accommodate various use-case requirements. We simulate the indoor air with equation (1) which is a simplification. Instead of applying an indoor heat transfer coefficient, we model the indoor air as a volume with high thermal conductivity (see Section 3 for the specific value).

As an external boundary condition, we apply a boundary condition which simulates the heat transfer between the external boundaries and the surrounding environment of the building model using a heat transfer coefficient (2).

$$q = \alpha \cdot (T - T_{ext}) \tag{2}$$

Where *q* is the heat flux,  $\alpha$  denotes the heat transfer coefficient (combined convective and radiative) and  $T_{ext}$  refers to the external temperature.

Due to the fact that Elmer does not provide a builtin Python interface, we made use of the library pyelmer (Wintzer et al., 2023) which enables the setup of the Elmer simulation through Python code. Elmer processes UNV files and converts them into mesh files readable by the Elmer solver. With pyelmer we were able to assign the boundary condition to all detected external boundaries from Section 2.2. The material parameters for the different geometries are queried from a YAML file that contains the density and thermal conductivity of a predefined set of materials. This material database can be easily extended by inserting the desired material information into the YML-file.

When the materials and boundary conditions are set, the Elmer solver is triggered. The output of the solver is a VTU file that contains a calculated temperature for every mesh point. Furthermore, the Elmer solver also returns the tuned heating power of the heat sources. These results can be used to identify thermal bridges, to calculate heat and cooling loads and seasonal heating or cooling demands. For visualization and postprocessing purposes tools like ParaView (Ahrens et al., 2005) can be used.

#### 2.4 Two-Dimensional Case

In addition to the 3D case, we implemented the possibility to run a 2D thermal simulation on a horizontal cross-section of the digital building model. For this we added a function to the IFC processing module that takes a given height as input parameter and creates a horizontal cross-section of processed geometries at this height. The rest of the algorithm then works analogously to the 3D case following the workflow described in Sections 2.1 to 2.3.

#### Application and Case Study

To test the developed workflow, we modelled a simple 3D building which serves for demonstration purposes in this study. The model was created with Autodesk Revit (Autodesk, 2022) and exported in IFC-format (see Fig. 2). It is a two-storey residential building with two separated apartments (one per storey). The outer walls consist of 30 cm of sandlime bricks, followed by 12 cm of external insulation (EPS), and a 1-cm thick layer of plaster on both the interior and exterior surfaces. All external horizontal structural elements like slabs and roof consist of 20 cm reinforce concrete, 10 cm of external insulation (EPS) and in case of the roof also of a 1-cm thick exterior finishing layer. There are six one-winged wooden windows and two double-winged wooden terrace doors. Both windows and terrace doors are modelled with simple rectangular wooden frames. The glass is modelled as a 5 cm thick monolithic block with equivalent thermal conductivity to simplify the modelling of a triple-paned window and avoid the modelling of the gas layers. For simplicity reasons internal walls and rooms were not modelled. The model contains two elements of type IfcSpace (one per storey) which represent the air volumes inside ground floor and first floor storey respectively.



Fig. 2 - Digital building model in IFC file format

We use this model as input for our automated workflow. In the first step the trees, the hand railing and the external stairs are filtered out then the STEP file with the remaining processed geometries is generated.

As meshing algorithm, we conducted the Delaunay algorithm (Gmsh Developers, 2024) which generates a mesh of linear tetrahedral elements. The target mesh size was set to 5 cm. Fig. 3 shows the result of the meshing process: the discretized model with all meshed geometries. The mesh consists of nearly 3 million elements with a total of approximately 510 000 nodes.



Fig. 3 – Discretized model with meshed geometries in UNV file format

For the Elmer FE simulation we set the external temperature  $T_{ext}$  to 277.15 K (4 °C). We applied a uniform value of 25 W/(m<sup>2</sup> K) for the heat transfer coefficient  $\alpha$ , which represents linearised radiative and convective heat transfers. The internal temperature at the control point of Elmer's *Smart Heater* was set to 293.15 K (20 °C). The thermal conductivity k of the most relevant materials that appear in the model are listed in Table 1.

In Fig. 4 we show a visualization of the obtained results after the simulation finished. The figure shows a screenshot from the visualization tool ParaView with the temperature distribution of the simulated model. Through this, a first plausibility control of the results can be done. The temperature on the surface of the building model is almost constant in all points. Only the window frames have a slightly higher temperature compared to the rest of the surface. We chose a well-insulated building as use case because this is how new buildings today are designed and planned. However, another interesting use case would be an existing historic building with poor thermal insulation characteristics and extensive thermal bridges.

A more detailed view is shown in Fig. 5. Here a cross-section of a window in the upper storey of the model is depicted. The temperature distribution inside the insulated wall and the connection to the window can be observed. The concrete roof slab has a significantly higher thermal conductivity than the sand-lime brick wall, which can also be observed in the figure.

The total heat source power was calculated to 3850 W and the computing time of the whole work-flow was 408 seconds (6.8 minutes). In Table 2 the induvial computing times for every workflow step can be found. It was run on a machine with an Intel Core i7-1165G7 (2.80 GHz) processor.

Table 1 –	Primary	materials	and	their	thermal	conductivity
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Material	Thermal conductivity (W/(m K))
Sand-lime-brick	0.560
Reinforced concrete	2.300
EPS	0.035
Plaster	0.500
Window wooden frame	0.130
Window glass (modelled as mono- lithic block)	0.033
Air volumes (ground and first floor)	1000



Fig. 4 – Visualized simulation results (temperature distribution on building envelope) in VTU file format



Fig. 5 – Cross-section view of window, wall and roof from the upper storey of the building model, temperature contour lines

Table 2 - Computing times of individual steps

Workflow step	Computing time (s)
IFC Processing	3.89
Discretization	102.44
Thermal FEM simulation	301.93
Total	408.27

# 4. Discussion

Because we expose relevant parameters both for meshing and FE simulation, the workflow is highly adaptable and can be used for a wide range of different use-cases. However, a drawback that we found was that the solid air volume inside the building, represented by IfcSpace elements, must be modelled quite accurately in order to avoid gaps between the internal air volume and the building structure. This can be a tedious modelling task especially when dealing with complex window geometries or other openings. Another possible approach here would be to use the same procedure as for the external boundaries and apply a boundary condition with heat transfer coefficient also to the internal boundaries with an internal temperature instead of using the air volume with a heat source. In this case it would be more complex to detect all boundaries automatically. It might be necessary then to have some sort of user selection to distinguish the internal and external boundaries and to apply the desired temperature.

In terms of computation time, our implementation has still potential for optimizations. The meshing algorithm can be fine-tuned to have adaptive mesh sizes depending on the complexity of geometries. The FE simulations is now running in a single process, but Elmer also supports multiprocessing, so there is potential for parallelising the simulation and to reduce the computation time significantly, always depending the machine the simulation is running on.

## 5. Conclusions and Outlook

We developed and implemented an automated open source-based workflow to efficiently interface BIM with FE thermal simulations. The corresponding simulation results can be used to evaluate the building energy performance. The key features of our workflow are the consistent data flow of geometry and material information and high degree of automation, in specific the automatic assignment of boundary conditions.

With the conducted case-study we were able to demonstrate that our workflow produces plausible results within a short computing time and little need of manual configuration. Furthermore, we offer a high degree of flexibility since the relevant parameters can be configured based on the needs of specific use-cases. Due to its open-source nature the workflow and algorithms are easily reproduceable and extendable.

The proposed workflow has the potential to be integrated in digital twins in order to run simulations based on real-time sensor-data and assist prediction models. In future work the encountered drawback of missing flexibility in terms of the assignment of different boundary conditions for different areas of the digital model must be addressed. The optimization of meshing and parallel processing could also be subjects. An additional possibility for further enhancements could be to leverage thermal properties or any other properties related to materials that are already integrated in the digital building model instead of retrieving them from a separated material database. Furthermore, the workflows' evaluation and testing on a broader range of different use cases (e.g. existing historic buildings) should be included in future works. In terms of simulation capabilities, the integration of time-dependent dynamic simulations including solar radiation would be a valuable enhancement.

## Nomenclature

#### Symbols

Т	Temperature (K)
k	Thermal conductivity (W/(m K))
ρ	Density (kg/m³)

h	Heat source (W/kg)
$\nabla$	Nabla operator (-)
q	Heat flux (W/m <sup>2</sup> )
α	Heat transfer coefficient (W/(m <sup>2</sup> K))
T <sub>ext</sub>	External temperature (K)

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# Hygrothermal Analysis of Most Common Historical Slabs in Hungary

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#### Abstract

In Hungary and generally in Central Europe, a significant part of the existing building stock is constructed using traditional technologies that were widespread in the 19th and 20th centuries. Due to a lack of quality building materials, it was common practice to build structures using materials that were not specified and not following the prescribed layering scheme, so even a simple renovation project could typically be problematic. Moisture generated during the use of the building, condensation, and the initial construction moisture also have significant effects on building structures. In many cases, the reconstruction works are carried out due to a change of function, which can cause various external and internal moisture effects to affect the structure. To reduce the energy needs of the existing building stock, an increasing number of experts are starting to work on thermal and hygrothermal simulation of building structures. Numerical simulations of the distribution of humidity and temperature inside buildings can be used to determine the behavior of a building element during its life cycle, which can facilitate, among other things, the maintenance of architectural heritage and the design of renovations for energy efficiency. Within the framework of this research, detailed thermal and coupled heat and moisture transport simulations based on finite element methods were carried out to evaluate the energy performance of the most common traditional slab structures in Hungary. There were significant differences in both heat losses and thermal conductivity depending on whether only thermal or hygrothermal simulation was used and in general, hygrothermal simulations can provide much more accurate and detailed results. The simulations showed that none of the historic slab structures meet today's minimum energy and durability requirements, but with the suitable renovation method, heat losses for example, can be reduced by up to 25-60 %.

#### 1. Introduction

By the late 19th century, Budapest had grown into a metropolis along with other Central European capitals, leading to a dramatic increase in the housing stock and multi-storey apartment blocks were built. In the early 1800s, wooden slabs and domes were the main horizontal load-bearing structures, replaced by bent steel beams later in the century. By the 1910s, reinforced concrete developed, and post-World Wars, prefabrication led to prestressed and formwork slab systems. Due to climate change and decreasing energy supplies, experts now focus on the thermal properties of buildings to reduce heat losses and maintenance costs. Recent changes in building energetics have been driven by technical progress and stricter regulations, increasing the need to reinforce and renovate existing structures. EU regulations require renovated structures to meet thermal standards, but 100-year-old slabs often fail to comply. Energy performance calculations must consider thermal bridges, described by linear thermal transmittance, while moisture bridges are also advised to be considered due to conservation reasons.

In the field of heat, air and moisture transport (HAM) in building and systems, much progress on the modeling and simulation tools has been established. However, the use of these tools in an integrated building simulation environment is still limited, since they mostly neglect or simplify building structures and thermal bridges. This is mainly caused by the lack of reliable thermophysical input data for building materials as well as by some intrinsic limitations in the simulation models, especially in describing the geometric features and peculiarities of the heritage buildings (Akkurt et al., 2020). Another issue is due to its long calculation time, since dynamic thermal analysis and HAM simulations are currently recommended only for research purposes (Nagy et al., 2022). Based on the research of the last years, it can even be said that the hygrothermal simulations of building elements and building structures (Sýkora et al., 2013), such as porous building materials (Abahri et al., 2011), solid masonry walls (Sýkora et al., 2009), prefabricated panels (Pihelo et al., 2016), insulated masonry or concrete (Ibrahim et al., 2014), lightweight concrete walls (Colinart et al., 2016), lightweight timber walls (McClung et al., 2014) or various cladding structures (Pihelo et al., 2016) are becoming more and more common. Less has been published on the hygrothermal analysis of building construction joints as wallslab joints (Bianchi Janetti et al., 2012) and installation of openings (Nagy et al., 2018), which are largely responsible for thermal bridges according to Nagy (2019). Another less publicized topic is historic building structures (Cho et al., 2020; Gutland et al., 2022; Qin et al., 2024) and materials (Oumeziane et al., 2021; Jaros et al., 2023), even though urban modernization is progressing and the renovation of old buildings, especially historic buildings, is a priority for urban renewal.

This paper presents finite element simulations using COMSOL Multiphysics to compare thermal and moisture transmittances, including thermal bridges, of common slab structures (Prussian-, Monier-, Horcsik-, Bohn- and E-beam slab) under monthly design conditions, and to assess the impact of neglecting moisture transfer."Based on the performance of the analyzed slab types, renovation options were developed that can be of great help in practice. The results can be used and provide a reliable database for typology-based hygrothermal modeling of historic buildings and analysis based on dynamic simulations.

## 2. Methods

## 2.1 Numerical Model

Within the framework of this research, steady-state coupled heat and moisture transport simulations were performed by using Comsol Multiphysics 5.6 software, taking into account the latest EN 15026:2023 standard. The steady-state simulation was chosen instead of performing time-dependent hourly-based simulations because the main goal of the research was to compare surface, linear, and point thermal and moisture transmittances of the building constructions considering heating design conditions, and also to evaluate the effect of neglecting moisture transfer.

The first part of the partial differential equation (PDE) for steady-state heat transfer shown by Eq. (1) considers heat fluxes due to heat conduction, the second part takes into account heat fluxes due to evaporation.

$$\nabla q = \nabla [\lambda_{eff} \nabla T + L_v \delta_p \nabla (\phi p_{sat}(T))] = 0$$
(1)

If only a thermal simulation is performed on solids, only the first part is considered and given by Eq. (2).

$$q = -\lambda_{eff} \nabla T \tag{2}$$

In the case of steady-state moisture transfer, the PDE for solids is defined by Eq. (3), in which the first member of the equation represents the liquid transport of moisture fluxes, while the second part is responsible for moisture fluxes from vapor transport.

$$\nabla g = \nabla [\xi D_w \nabla \phi + \delta_p \nabla (\phi p_{sat}(T))] = G = 0$$
(3)

The partial differential equations shown by Eq. (1) and Eq. (3) were implemented into COMSOL Multiphysics' Heat Transfer Module, which uses the EN 15026:2023 standard for HAM simulations.

## 2.2 Geometry

The geometric models of the analyzed 5 types of slabs were created and defined as solids in Auto-CAD 2023, then exported in dwg to COMSOL Multiphysics. However, due to improved computational efficiency, simplifications were made in the geometry models. In the cases of PS and BS, the reinforcement was modeled separately as an octagonal prism instead of a cylinder, the reinforced slabs and ring beams were modeled with a higher equivalent thermal conductivity, and the coupling elements fixing the beams to the walls were neglected. To determine the heat losses of the wall surfaces and joints, 4 geometric models were made for each type of slab, giving a total of 20 models as follows: 2-way wall-slab corner connection, wall corner design, wall-slab connection parallel and perpendicular to the load-bearing direction. The geometric model of the Prussian slab is shown in Fig. 1. Since all slab types are beam slabs, 2 beams, and 1.5 slab fields were considered in the modeling, and the length of the wall connections was determined according to EN ISO 10211:2017.



Fig. 1 - 2-way wall-slab corner connection of Prussian slab in COM-SOL Multiphysics

## 2.3 Material Properties

With hygrothermal analysis, material properties that vary with temperature and moisture content can be considered, giving a better approximation of the real thermal behavior of materials. Material properties such as thermal conductivity, temperature and moisture dependent conversion factor, water vapor resistance factor were determined according to EN ISO 10456:2007, moisture storage curves and liquid transport coefficient were determined based on WUFI PRO 6.6 database. Table 1 shows the applied material properties, and Fig. 2 shows the sorption isotherms of the historical materials and materials of the renovation. While in the thermal simulations, the thermal conductivity of each material was given as a constant value as an input parameter, in the hygrothermal simulations it was calculated according to Eq. (6).

$$\lambda_{\rm eff} = \lambda_1 * f_{\rm T} * f_{\psi} \tag{6}$$

Table 1 - Applied material properties	according	to EN ISC	D 10456
and WUFI PRO 6.6 database			

Material	λ <sub>eff</sub> [W/mK]	fт [1/K]	fΨ [m³/m³]	μ [-]	Dw80 [m²/s]	D100 [m²/s]
plaster	0.80	0.001	4	10	1.09 × 10 <sup>-10</sup>	2.49 × 10-8
fired clay	0.80	0.001	10	10	3.00 × 10 <sup>-5</sup>	7.57 × 10-8
concrete	2.00	0.001	4	100	1.84 × 10 <sup>-8</sup>	2.00 × 10 <sup>-7</sup>
reinforced concrete	2.50	0.001	4	130	1.84 × 10 <sup>-8</sup>	2.00 × 10 <sup>-7</sup>
wood	0.18	1.400	80	5	4.00 × 10 <sup>-12</sup>	5.00 × 10 <sup>-12</sup>
slag fill	0.45	0.001	4	10	7.46 × 10-9	7.00 × 10 <sup>-5</sup>
mortar	0.80	0.001	4	10	1.09 × 10 <sup>-10</sup>	2.49 × 10-8
rebar	50.00	-	-	1000	-	-
mineral insulation	0.045	0.003	10	3	-	-
insulating plaster	0.05	0.001	4	10	-	-
internal plaster	0.155	0.001	4	10	-	-



Fig. 2 - Sorption isotherms of applied materials

#### 2.4 Boundary Conditions

When determining the boundary conditions of moisture transport, it is possible to use local weather data, therefore in this paper, the values are based on the research of Nagy (2019), which takes

into account the average January weather in Budapest. Internal conditions of air and equivalent vapor diffusion thicknesses of the boundary layers were set according to the EN 15026:2023. The temperatures were set to  $T_{int} = 20$  °C for internal,  $T_{ext} = 3.6$  °C for external. The external air and surface relative humidity were set to  $\phi_e = 0.74$  and  $\phi_{se} = 0.41$ . The equivalent vapor diffusion thickness of the boundary layer was set to  $s_{d,si} = 0.008$  m on the internal and  $s_{d,se} = 0.0023$  m on the external surface. Surface heat transfer coefficients were set based on EN ISO 6946:2017. The heat transfer coefficients were set to  $h_{si} = 7.69$  W/(m<sup>2</sup>K) for internal and  $h_{se} = 25$  W/(m<sup>2</sup>K) for external surfaces.

#### 2.5 Evaluation

Both thermal simulations and hygrothermal simulations were carried out to determine the point thermal transmittance and minimum temperature of the internal surfaces of the models. In the coupled heat and moisture transport simulations, the geometric models and material properties are the same as previously used in thermal simulations, but latent heat fluxes and the behavior of the materials against moisture were considered so that more accurate results can be expected. The heat losses can be used to determine the heat flux per m<sup>2</sup> of surface generated by a temperature difference of 1 K. The minimum temperature of the internal surface can be used to calculate the temperature factor which is useful when dealing with conservation problems. A calculation methodology according to EN ISO 10211:2017 was used.

To calculate the  $\chi$  point thermal transmittance for the given structural design, the following Eq. (4) were used: L<sub>3D</sub> were calculated for the junction, U<sub>i</sub> thermal transmittance of the wall surfaces and  $\Psi_j$ linear thermal transmittances of the length of connections based on Eq. (4).

$$\chi = L_{3D} - \sum_{i=1}^{N_i} U_i * A_i - \sum_{j=1}^{N_i} \Psi_j * l_j$$
(4)

To check the durability and hygrothermal deterioration of the structures, the temperature factor is used for verification. According to DIN 4108-2:2010, if the value is less than 0.7, the design of the structures is inadequate and there is a risk of mold growth.  $f_{Rsi}$  temperature factor of the junctions can be calculated as follows on Eq. (5).

$$f_{Rsi} = \frac{T_{s,min} - T_e}{T_i - T_e}$$
(5)

#### 3. Results and Discussion

The results have been evaluated by comparing surface, linear, and point thermal transmittances, and temperature factors in tabular and graphical form. Based on the methodology described in the previous chapter, the first step was to retrieve the temperature distribution, the total heat and moisture flux magnitude, and the relative humidity for each junction design from the numerical simulation. Due to the limitations of the presented paper, only relevant figures of one slab type (HS) are shown, but similar results are obtained for all slab types. The temperature distribution and the conductive heat flux magnitude of the 2-way wall-slab corner connection in case of only steady-state heat transfer considered are illustrated in Figs. 3-4. The temperature distribution and the total heat flux magnitude of the 2-way wall-slab corner connection of steadystate coupled heat and moisture simulation are shown in Fig. 5-6. In general, it is visible in all cases that there are large heat losses and thermal and moisture bridges, but typically these do not occur at the junction of the wall-joint but along the longitudinal joints of the wall-slab. This is partly because a decade ago, when most similar slab structures were built, there was no consideration of the need for a design that would be adequate in terms of durability, materials such as thermal insulation did not yet exist that could effectively reduce heat losses, and in many cases the knowledge of the material properties is uncertain. Comparing the result plots of thermal and hygrothermal simulations, we can see that both the temperature and the heat flux density distribution are similar, but the scaling of the plots is different, which means that different simulations lead to different results. These differences have been investigated in tabular and graphical form below in Figs. 7-10.



Fig. 3 – Temperature distribution [°C] of 2-way wall-slab corner connection of Horcsik-slab in case of thermal simulation



Fig. 4 – Heat flux magnitude  $[W/m^2]$  of 2-way wall-slab corner connection of Horcsik-slab in case of thermal simulation



Fig. 5 – Temperature distribution [°C] of 2-way wall-slab corner connection of Horcsik-slab in case of hygrothermal simulation



Fig. 6 – Heat flux magnitude  $[W/m^2]$  of 2-way wall-slab corner connection of Horcsik-slab in case of hygrothermal simulation

Fig. 7–8 shows that the difference between the simulation results was more significant for the linear thermal transmittance. It means the thermal bridges usually occur along the longitudinal joints of the wall-slab as previously shown in Figs. 3–6. and there is a risk of underestimating their magnitude if only thermal simulations are performed.



Fig. 7 – Comparison of  $\Psi_{2Dpar}$  paralel to the load-bearing direction of thermal and hygrothermal simulations



Fig. 8 – Comparison of  $\Psi_{\text{2Dperp}}$  perpendicular to the load-bearing direction of thermal and hygrothermal simulations

According to Fig. 9 MS and BS have such small heat losses that in these cases it is not necessary to perform 3D simulations to determine the heat losses of the junction. On the other hand, the HS and EBS have much higher excess heat losses at the junction, these slab types are designed with ring beams, so the large difference in the thermal conductivity of the materials also contributes to the higher heat losses. The negative value obtained for the PS means that the loss is only along the length of the wall-slab junction.



Fig. 9 – Comparison of  $\boldsymbol{\chi}$  of junction design of thermal and hygrothermal simulations

As seen in Fig. 10, the temperature factor based on hygrothermal simulations are below 0.7 (except for the hygrothermal simulation of MS), while the results of the thermal simulations for the PS, HS, and EBS are below 0.6., that means there is a high risk of mold growth. The lower values of thermal simulations are explained by the minimum temperatures of the internal surfaces being much lower than in the hygrothermal simulations and by the temperature difference between the external and internal surfaces being larger.



Fig. 10 – Comparison of  $f_{\mbox{\scriptsize Rsi}}$  of junction design of thermal and hygrothermal simulations

For thermal conductivity, only the main findings are presented in this article. The evaluation of the results shows that the results obtained from the hygrothermal simulation are always higher than the design values, but while in none of the cases do the wall, ceramic, and infill deviate by more than 5 % from the design values used in the thermal simulations, for the other materials the average thermal conductivity considered in the hygrothermal simulation can differ by up to 15–18 %.

Table 2 shows by what percentage the results of the hydrothermal simulations differ from the results of the thermal simulations. In most cases, if only thermal simulations are performed, this will lead to an underestimation of heat losses.

Table 2 – Differences between the results of thermal and hygrothermal simulation [%]

Case	PS	MS	HS	BS	EBS
Ψ <sub>2Dpar</sub> [W/mK]	5,5 %	11,3 %	9,8 %	30,5 %	23,0 %
Ψ <sub>2Dperp</sub> [W/mK]	14.5 %	16.3 %	-2.8 %	28.1 %	23.7 %
$f_{Rsi} \left[ ^{\circ} C \right]$	8.0 %	30.8 %	45.6 %	9.6 %	12.3 %

#### χ [W/K] -40.3 % 160.6 % 16.7% 142.4 % 60.2 %

# 3.1 Design of Renovation for Energy Efficiency

As the results presented earlier show, none of the junction designs meet the energy and durability requirements. For listed buildings, renovation of the façade is generally not an option, therefore options with different thicknesses of internal thermal insulation and thermal insulation plaster were investigated. For each type of slab, at least 1 renovation option was developed based on hygrothermal simulations to achieve a temperature factor of 0.7 to meet the durability requirements, and the energy efficiency of the design was improved over the original condition.



Fig. 11 – Comparison of  $f_{Rsi}$  for renovation options of different slabs

As shown in Fig. 11, the following renovation options were selected for each slab type to provide the requirements of durability:

- PS: 3-3 cm ext. and int. insulating plaster
- MS: 2-2 cm ext. and int. insulating plaster
- HS: 3-3 cm ext. and int. insulating plaster
- BS: 5 cm int. insulation with 2 cm plaster on the inside + 2 cm ext. insulation plaster
- EBS: 5 cm int. insulation with 1 cm plaster on the inside + 1 cm ext. insulation plaster

Although the thermal transmittance of the walls of listed buildings does not have to comply with the requirement ( $U_{wall} \leq 0.24 \text{ W/(m^2K)}$ ), the effectiveness of renovation options in reducing the  $U_{wall}$  has been investigated.

Based on Fig. 12, even 1 - 1 cm of insulation plaster on the inside and outside can significantly reduce  $U_{wall}$  by up to 35 %. Of course, the greatest reduction can be achieved by applying some form of thermal insulation to both the inside and the outside, in this case, 5 cm of insulation on the inside and 2 cm of exterior insulation plaster can achieve a reduction of more than 70 %.



Fig. 12 – Comparison of  $U_{\mbox{wall}}$  for renovation options

# 4. Conclusion

One of the main tasks of the research is to investigate and develop options for energy-efficient retrofitting of the existing slab structures and create a reliable database for typology-based hygrothermal modeling of historic buildings and analysis based on dynamic simulation.

- Based on only 6 % difference between the results of thermal and hygrothermal simulation for the 3-dimensional thermal transmittance may lead to the conclusion that there is no need for 3D simulations, but the difference for the linear thermal transmittance (up to 30 %), the temperature factor (up to 45 %) and the heat losses (up to 160 %) was more significant.
- The deviation of the thermal conductivity from the design value is highly dependent on the material, since there are cases where the deviation is only 1-2 %, but there are also cases where the design value is 15 – 18 % less than the value obtained from the hygrothermal simulations.
- The results show that by choosing the most appropriate renovation method, heat losses, for example, can be reduced by up to 25 60 %. The best solution is to reduce the amount of heat fluxes on both the inside and the outside, so either we can apply thermal insulation on the inside with external insulating plaster or, for buildings that are not listed we can apply external thermal insulation.

One of the limitations was that standard material properties were considered, hence further research can be done to determine material properties in laboratory measurements specific to Hungary. By refining the models, extending the input physics, such as the consideration of airflow in the case of hollow slabs, and investigating more slab types, more comprehensive and complete results can be obtained.

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#### Nomenclature

#### Symbols

$\nabla(\frac{\delta}{\delta x}, \frac{\delta}{\delta y}, \frac{\delta}{\delta z})$	nabla vectorial diff. operator
q	heat flux [W/m²]
$\lambda_{eff}$	temp. and vol. moist. cont. de-
	pendent thermal cond. [W/mK],
	based on EN ISO 10456
Т	temperature [K]
$L_{\nu}$	latent heat of evaporation [J/kg]
$\delta_p {=} \delta_a \!/\! \mu$	vapor permeability [kg/(msPa)]
$\delta_{a}$	vapor permeability of still air de-
	pending on air temp. [kg/(msPa)]
μ	water vapor resistance factor [1]
$\rho_{sat}$	sat. pressure of water vapor [Pa],
	depending on temp.
g	moisture flux
$\xi = \delta w / \delta \phi$	diff. moist. capacity [kg/m <sup>3</sup> ]
W	moist. cont. [kg/m3] according to
	the moist. stor. func. of the mat.
φ	relative humidity [-]
φ <sub>e, se</sub>	ext. air and surface rel. humidity

λ	thermal conductivity [W/(m K)]				
fт	temp. dependent conv. factor [-]				
$f_{\psi}$	moist. dependent conv. factor [-]				
$D_{w,s}$	liquid transport coefficient [m <sup>2</sup> /s]				
Sd,s	equivalent vapor diffusion thick-				
	ness [m]				
hs	heat transfer coefficient [W/(m <sup>2</sup> K)]				
χ	point thermal transmittance				
	[W/K]				
L3d	3-D thermal transmittance [W/K]				
$U_{i}$	thermal transmittance [W/(m <sup>2</sup> K)]				
Ai	interior surfaces [m <sup>2</sup> ]				
$\Psi_{\rm 2Dperp/par}$	linear thermal transmittance per-				
	pendicular or parallel to the load-				
	bearing direction [W/(m K)]				
lj	length of connections [m]				
$f_{\mathrm{Rsi}}$	temperature factor [-]				
Ts,min	min. int. surface temperature [°C]				

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# Energy Flexibility Study of a Hotel Using TRNSYS

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#### Abstract

In this work, a TRNSYS model of a five-story hotel located in Northern Italy is used to evaluate simple energy flexibility strategies for the cooling season to be used in a possible smart grid integration. The strategies are demandside and include energy efficiency and load shifting. Two models are used, one of the building envelopes, to evaluate the instantaneous heating and cooling demands, and the HVAC system model, used to simulate the heating and cooling production by two multifunctional heat pumps and two heat pump boosters for the domestic hot water production. The flexibility strategies are applied in the building model controlling the room thermostats while the heating and cooling demands are calculated using measured occupation profiles. On the other hand, the hot and cold-water tanks set point temperatures are used to implement the energy flexibility of the HVAC system. In both cases, the target is to shift the loads in the PV panels production hours, reducing the electricity demands from the grid during the other hours.

#### 1. Introduction

With the target of reducing greenhouse gas emissions, energy production is expected to shift from a centralised power grid, based on fossil-fuel generation, to a diversified renewable energy production. This change will also affect the energy availability and cost, which will depend on weather conditions and daylight intermittence. To optimise these conditions, building operations should be able to be managed (demand side management) to concentrate the energy demand during daylight hours, shifting the loads at the PV production hours. This capability, together with the possibility of reducing or shifting the load peaks when needed, is known as energy flexibility. In alignment with the United Nations' Sustainable Development Goals 7 (affordable and clean energy) and 11 (sustainable cities and communities), this paper focuses on the energy flexibility of a hotel in Northern Italy.

Hotels are high energy consumption buildings, not only due to the Heating Ventilation and Air Conditioning (HVAC) operation, but also to other services provided to the guests. The average energy consumption for the Italian hotel sector in 2016 has been estimated by Bianco et al. (2017) to be 203 kWh/m<sup>2</sup>. For this reason, it is relevant to study efficiency strategies for the existing hotels to optimize energy consumption. Moreover, when the building is integrated with renewable energy supply such as photovoltaic (PV) panels and thermal solar panels, it is important to match the energy produced in situ with the energy demand through load shifting methods, thanks to electrical or thermal energy storage and the implementation of advanced control. With these methods, it is possible to improve the energy demand flexibility to increase PV self-consumption and the integration of buildings in smart grids.

Examples of regulation strategies to exploit the energy flexibility of a single building to increase the PV self-consumption are presented in Pinamonti et al. (2020), where the utilization of modulating heat pumps and thermal energy storages allows reduce the grid energy demand up to the 22%, depending on the climate and the building characteristics.

The considered hotel is monitored by a supervision system, a common management practice. The system is designed to report the monitoring of the main hotel services, such as HVAC, lighting and charging stations for electric vehicles, together with the hourly production of electricity and heat from PV and solar panels on a dashboard. The monitoring systems can also overwrite settings in each room to reduce energy waste by keeping energy saving conditions in empty rooms. The temperature and energy consumption measurements are recorded hourly and stored by the hotel management system. In this research, following Libralato et al. (2023), the utilization of these measurements as calibration and validation variables is explored with the aim of developing an energy model of the hotel, increasing the energy efficiency of the building-HVAC system, also using the heat storage properties of the building envelope to shift and shave the peaks of power demands. Control rules that allow a better match between electrical energy demand and availability, developed, and tested using the building energy model, are used with the final goal to prepare the inclusion of the hotel in a Smart Grid or a Renewable Energy Community, to perform energy sharing strategies as presented, for example, in Franzoi et al. (2021).

# 2. Methods

The energy flexibility of the hotel is studied comparing the building cooling and heating demand and the plant electricity demand. These are calculated using simulations of the building and the plant with different control strategies using the TRNSYS 18 simulation environment (Klein et al., 2018). The building model is calibrated manually, while the DHW loads are measured by the monitoring system.

The control strategies are implemented at the building level, changing the thermostat settings in the rooms, and at the plant level, changing the thermostat settings of the water tanks. The aim of the study is to maximise the PV consumption shifting the loads of the building/HVAC system using the heat pumps and storing thermal energy in the building envelope and in the water storage tanks.

#### 2.1 Case Study

The building is a  $1600 \text{ m}^2$ , a five-story hotel in a tourist town on the seaside in Northern Italy. The hotel is a new construction with a high efficiency envelope that should allow the implementation of flexibility strategies (Foteinaki et al., 2018); the thermal transmittance of the wall and windows are 0.20 and  $0.13 \text{ W/(m^2K)}$ .

The hotel is heated and cooled with two multifunctional air-to-water two-stage reversible heat pumps (MHP) connected with two tanks (hot water tank and cold-water tank both of 0.9 m3) that serve 4-pipe fan-coils in every room and common zone and an air handling unit. The fan coils and the ventilation system are turned off in the rooms, when the windows are opened. Domestic hot water (DHW) is heated by two water-to-water two-stage heat pumps (boosters), used as boosters from the hot water tank to heat the water in other two 0.9 m<sup>3</sup> hot water tanks (DHW tanks). The DHW tanks are also supplied with hot water produced with a total of 14 m<sup>2</sup> thermal solar panels. The building is also served by 36 photovoltaic (PV) panels for a total of 16 kWp; for this work the presence of batteries was not considered since they are not currently installed.

The MHPs have a cooling capacity of 80 kW (EER = 2.91, system side water heat exchanger 12 °C / 7 °C with external air at 35 °C) and a heating capacity of 84 kW (COP = 3.28, system side water heat exchanger 40 °C / 45 °C with external air at 7 °C) in standard conditions. When cooling and DHW are required simultaneously, then the cooling capacity is 87 kW and the heating capacity is 111 kW, with a power consumption of 25.9 kW (the water exchanger to the total recovery side is 45 °C while the water to the system side heat exchanger at 7 °C). The Boosters provide 56.7 kW of heating capacity with a COP = 3.48 (70 °C / 78 °C water user side, 35 °C / 30 °C water source side).

#### 2.2 TRNSYS Models

The building-plant system is modelled with two separate decks in the TRNSYS 18 simulation environment. The first deck simulates the building envelope, while the second, uses the heating and cooling demands of the first model to simulate the behaviour of the HVAC system. Both simulations are performed from the 1<sup>st</sup> of May 2023 to the 31<sup>st</sup> of August 2023, with a preconditioning period of 1 month (from the 1<sup>st</sup> of April).

#### 2.2.1 Building envelope

The building envelope is modelled using Type 56 as a multizone building (Fig. 1), with 34 double zone hotel rooms and common zones, for a total of 94 thermal zones.

The used weather file is obtained from the measurements of a nearby weather station (kindly supplied by ARPA FVG (OSMER)), and it is included in the simulation using Type 15, used also to perform the radiation calculations for the Type 56 model. The effective sky temperature is calculated using Type 69b.

The room occupancy recorded by the hotel supervision system is used to define the internal loads and the thermostat settings. The thermostats of the rented rooms (occupied and not occupied) are set to 22 °C by default while the temperature of the DHW is set to 47 °C, which is sufficient to meet the occupants' satisfaction during summer. The DHW tank does not require thermal shock cycles thanks to the chemical-based disinfection for Legionella. The internal loads are estimated considering 115 W (sensible load) per person and the illumination devices loads (from 45 W to 280 W, depending on the room size) activated only when the occupancy is detected, and a constant load to consider other electric devices (7 W).



Fig. 1 – Hotel building geometry used in TRNSYS 18 Type 56

The temperature recordings of the month of November 2023 of the hotel supervision system are used to manually calibrate the building energy model. In this period the temperature of the hallways of every floor were recorded and the HVAC system was not active. The free-floating behaviour is measured for few zones, allowing to perform a partial manual calibration of the building envelope model. This preliminary and partial calibration allowed us to estimate the air infiltrations of the hallways and the thermal capacity of the rooms. The thermal capacitance of every room has been increased of 8 kJ/(K·m<sup>2</sup>) to model the presence of furniture. The simulated temperatures resulted in an average RMSE of 1 K, which has been considered acceptable, given the low accuracy of the sensors (1 K, with a resolution of 0.5 K) and the preliminary state of the study. The building simulation is performed with a 15 minutes timestep. The building energy model is then used to test control strategies to reduce energy consumption (energy saving strategies) end to match the HVAC system power demands with the PV panels production (flexibility strategies).

#### 2.2.2 HVAC and DHW system

The HVAC and DHW systems scheme are shown in Figure 2. The Fan coils and AHU are modelled as ideal systems, providing sensible heating and cooling loads to the thermal zones without losses. The heating and cooling production of the MHPs are modelled with performance mappings (Type 581c) provided by the producers, depending on the inlet water temperature and on the external air dry-bulb temperature.

The MHPs can provide both heating and cooling using the "recovery mode"; in this mode the performance does not depend on external air, but on the inlet water temperatures of the heating and cooling circuits. The heat pumps are controlled with PID controllers (Type 23) controlling the water tank thermostats, the water tanks are modelled with Type 158, the PV panels with Type 103b. The MHPs and the boosters are programmed to keep their working condition for at least 5 minutes to avoid rapid oscillations between ON and OFF states. To approximate this behaviour, the simulation is performed with a 5-minute time step. For this work, the DHW demand and the Solar thermal panel production have been considered calculating the thermal load on the boosters from the electricity consumption monitoring, using the Boosters model to calculate the heating demand on the DHW tanks.



Fig. 2 – HVAC and DHW system scheme

## 2.3 Energy Flexibility Analysis

This paper presents a preliminary analysis of the utilization of the building and plant energy flexibility performed comparing three building thermostat scenarios and three plant control strategies in summertime. Concerning the building, the flexibility is implemented changing the thermostat settings.

The "Standard" thermostat setting is 24 °C for the rooms that are not booked, while, when a room is booked, the temperature is set to 22 °C.

The "Flexible" thermostat setting proposed in this paper is 24 °C for the unoccupied room, 22 °C when the room is occupied, 20 °C when the room is unoccupied, and the PV panels' energy production is larger than 2.8 kW (25% of the maximum simulated PV power). This setting is intended to reduce the power demand in the evening taking advantage of the room heat capacity. In both conditions, the comfort of the occupants is not significantly affected.

With these two settings, an energy saving one is also considered, the "Energy Saving" combination, with 26 °C in free rooms and 24 °C for occupied rooms.

The settings of the plant used to implement the energy flexibility are the hot, cold and DHW water tanks' thermostats. The standard setting for the tank temperatures is 42 °C for the hot water tank, 12 °C for the cold-water tank and 47 °C for the DHW tank. This setting is used in the cases "Flexibility", "Standard" and "Energy Saving". To increase the utilization of the PV produced electricity, an

alternative tank setting is tested using the building demands calculated with the "Flexibility" configuration. The setting is the "Temperatures" tank setting, obtained increasing the temperature set point proportionally with the PV production of 2 K for the hot water tank, decreasing by 2 K the cold-water tank, and increasing by 4 K the DHW tank. Another case is also considered, the "Tank Size" case, based on the "Temperatures" case, with larger tanks, increased by a factor of 1.5.

#### 3. Results

The effects of the load shifting are presented in Figure 3. It is possible to see that reducing the temperature settings of the thermostats during the PV production, the loads are slightly reduced for the first hours of the evening at the expense of a significant energy consumption. The obtained value is also slightly lower than the energy saving setting, with all the thermostats reduced of 2 K.

As reported in the literature (Hedegaard et al., 2019), it is expected that a load shifting strategy could cause the generation of new peaks, also larger than the former.



Fig. 3 – Cooling demand calculated with the building simulation with the three studied thermostat strategies (15 minutes timestep). The Flexibility setting allows to reduce the demand in the evenings

The overall effects of the thermostat strategies are presented in Fig. 4. The monthly cooling demands are reduced respect to the "Standard" strategy, except for the month of May. The cooling demand reduction from the "Standard" strategy of all the four months is reduced by t 3% with the "Flexibility" strategy and by 15% with the "Energy Saving" strategy.

Figure 5 presents the monthly electricity demands for the HVAC and DHW systems of the room thermostat strategies. The "Energy Saving" always has lower electricity demands to the grid but presents the lower utilization of the PV panels production ("PV not used" negative values).



Fig. 4 – Monthly cooling demand calculated with the building simulation with the three studied room thermostat strategies. The "Standard" and "Flexibility" strategies have similar performances

The "Flexibility" configuration is an implementation of flexibility using only the building thermal mass as energy storage and the fixed thermostats for the tanks. In the following, the flexibility will be quantified with the percentage of PV usage, also reported in Table 1.



Fig. 5 – Monthly electricity demands of the hotel's HVAC and DHW systems, with the three-room thermostat strategies. The "-PV" columns represent the net energy demand (considering the PV production instantly used), while the "PV not used" columns represent the energy produced by the PV not instantly used by the system

The "Flexibility" case registered 36.1% of PV usage (calculated as the ratio between the PV energy used by the HVAC system and the total PV energy produced), just 3.9% more than the "Standard" case. The net energy demand, calculated adding the energy demands of the MHPs and the boosters and subtracting the PV energy production, is comparable in both the "Flexibility" and the "Standard" cases, while the "Energy Saving" allowed to save about 3 MWh.

In Figure 6, the HVAC system control strategies are compared. Changing the temperature settings of the water tanks allows for the storage of more energy, but requires a higher electricity consumption, due to the lower efficiency of the heat pumps with higher temperature differences. As expected, the "Temperature" case obtained higher electricity consumptions, but had a higher PV energy consumption (42.2%) 10% more than the "Standard" mode. The PV covers 7.7% of the energy demand, but the total net energy is increased by 2.4 MWh.

The last study case "Tank size" involves the addition of 50% of the tank volumes and it is not actually feasible in the real hotel, due to the lack of space in the technical rooms. Nevertheless, it has been included to quantify the relevance of hot and cool water storage systems. With the additional storage, not only is the PV usage high, but also the net energy consumption is lower than the "Energy Saving" setting, while keeping the "Flexibility" room thermostat settings.



Fig. 6 – Monthly electricity demands of the hotel's HVAC and DHW systems, with the three tank thermostat strategies based on the "Flexibility" cooling demands. The "-PV" columns represent the net energy demand (considering the PV production instantly used), while the "PV not used" columns represent the energy produced by the PV not instantly used by the system

Table 1 presents a summary of the five cases studied in this work. The "Net Demand" is calculated as the sum of the HVAC and DHW electricity demands minus the PV electricity production. The PV demand coverage shows the fraction of the demands covered by the PV panels, while the "PV usage" is selected as the flexibility indicator, since the load shifting strategies aim at maximizing the consumption during the PV production hours. The "Standard" strategy is used as the reference case. Despite the building demand shifting, the energy demands of the heat pumps are concentrated only in some timesteps during the day, due to the small size of the tanks (the tanks reach the setpoint temperatures after less than 5 minutes). For this reason, the electricity produced by the PV panels is not used in every time step and its usage is limited to 32.2% in the "Standard" strategy. The "Flexibility" strategy allows an increase of the PV usage of only 3.9% while the "Temperatures" strategy that considers a flexibility strategy in both building envelope and tanks, reaches the higher PV usage, with an increase of 10.6%. The "Tank size" strategy allowed us to reduce net electricity demand, saving 3.4 MWh during the four months, and to increase the PV usage of 6.2%. Finally, the "Energy Saving" strategy, provided a low net electricity demand, similarly to the "Tank size" strategy, but at the cost of changing the thermostat settings in the building at higher temperatures during summertime and slightly reducing the comfort of the occupants. The PV usage of this strategy is also lower, 1.9% less than the "Standard" strategy, with a 6.1% PV cover of the total electricity demand. In all the cases, the strategies did not allow to significantly increase the PV total demand coverage (the increase from the "Standard" strategy is always less than 2%).

Table 1 – Net demand of electricity for all the studied flexibility strategies from May to August, with the demand coverage by the PV panels production and the percentage of the usage of the PV energy produced.

Case	Net Demand [MWh]	PV demand coverage	PV usage
Standard	36.7	6.3 %	32.2 %
Flexibility	36.2	7.1 %	36.1 %
Energy Saving	33.5	6.1 %	28.3 %
Temperatures	39.1	7.7 %	42.8 %
Tank Size	33.3	8.1 %	38.4 %

While most of the strategies reduced the electricity demand, the "Temperature" strategy increased it in all the four months and the "Flexibility" strategy increased it in May. This consumption increase is the energy cost of the flexibility that is "paid" to shift the loads to the PV production time. These electricity increase depends on the PV electricity production, which is not sufficient to cover the load during the production time (no increase in load is expected during the other hours). To evaluate when this shift is economically advantageous, the minimal energy discount to reach economical advantage of flexibility is calculated as follows:

$$\Delta C_{\text{s}} = (E_{f} - E_{s}) \cdot 100\% / E_{\text{St}}$$
 (1)

and represents the minimum discount that is necessary on the energy during PV production time to meet the same costs of the "Standard" strategy, considering the installed PV panels. If the "Flexibility" strategy has a low energy cost and implies a slight increase in economic cost, the "Temperatures" strategy, on the other hand, requires a discount of about 13% at most, in May, during solar production hours to become economically advantageous. This scenario could be plausible in the context of a smart grid where energy supply costs are lower during PV production hours.



Fig. 7 – Monthly energy cost of flexibility operations of load shifting. The "Temperatures" strategy requires the consumption of more energy during the PV availability to allow the load shifting strategy

# 4. Conclusion

In this work the energy flexibility of a hotel has been evaluated during the cooling season. Two flexibility strategies are implemented at the building level, changing the thermostat set points of the rooms to shift the loads during the PV electricity production hours, while two other strategies are implemented at the thermal storage components of the HVAC and DHW plants, changing the thermostats and increasing the size of the tanks. The results showed that it is possible to increase the PV energy usage by 10% just changing the thermostats of the rooms and the tanks during the PV production hours with a relatively small increase of the energy demand ("Temperatures" strategy). Moreover, increasing the tanks' sizes would reduce energy demand and would increase the PV energy usage, more than increasing all the thermostats in the hotel rooms of 2K. The proposed strategies did not allow us to significantly increase the PV total demand coverage suggesting that other storage systems should be included in the plant.

Future work will focus on extending the monitoring system in the studied building to obtain a fully calibrated model of the building envelope and of the HVAC and DHW systems, including the possibility to apply the flexibility strategies on the real building, measuring the real load shifting capabilities. Other energy storage systems and strategies will be considered.

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#### Nomenclature

#### Abbreviations

AHU	Air Handling Unit
DHW	Domestic Hot Water
HVAC	Heating Ventilation and Air Condi-
	tioning
HP	Heat Pump
MHP	Multifunctional Heat Pump
PV	Photovoltaic

#### Symbols

$\Delta C_{\%}$	Minimal energy discount to reach
	economical advantage (%)
$E_{\rm f}$	Energy required during the PV pro-
	duction time to shift the loads (kWh)
$E_{\rm s}$	Shifted Energy load (kWh)
$E_{St}$	Energy demand obtained with the
	"Standard" strategy (kWh)

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# The Impact of Classroom Acoustics on Student Well-Being and Noise Disturbance at the University of Pescara, Italy

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#### Abstract

Concerns about noise conditions in schools have led many countries to introduce standards or guidelines for school acoustics design.

The aim of this paper is to investigate the extent to which classroom acoustics affect perceived well-being and noise disturbance at the University of Pescara in Italy. Approximately 100 students aged between 20 and 30 participated in the study, during which room acoustic measurements were taken, and noise levels were monitored in accordance with the national standard UNI 11532. To validate the measurements, a questionnaire was used, following the ISO 12913 standard.

In addition to the empirical study, a numerical model was developed using ODEON, a widely recognized room acoustics simulation software. This model was employed to simulate and analyze the acoustic conditions in the classrooms under various scenarios, providing additional insights into the acoustic environment.

The results of the correlation between subjective responses and objective measurements will be used to design more positive and inclusive learning environments.

#### 1. Introduction

The Indoor Environmental Quality (IEQ) stands as a critical determinant of the holistic educational experience, significantly influencing the well-being, concentration, and performance of students within the confines of school environments (Tahsildoost et al., 2018). From an acoustic quality standpoint, ensuring adequate speech intelligibility is crucial. Students positioned in the front rows, adjacent to the professor, experience better auditory clarity compared to those seated at the back of the classroom. It is evident that in the rear sections of spacious classrooms, the teacher's voice weakens, and excessive reverberation poses challenges to effective listening (Bin Yahya et al., 2010; Burfoot et al., 2022).

Addressing high background noise levels presents a complex challenge in the context of school buildings. Background noise stands out as a pivotal factor influencing speech intelligibility. Essentially, ambient noise levels (external noise), student behaviour, and noise from internal service equipment significantly contribute to the overall background noise (Bistafa et al., 2000).

The acoustic quality of classrooms can significantly impact students' learning, concentration, and overall well-being (Caniato et al., 2022; Granzotto et al., 2022). An environment that is too noisy or has acoustic issues can compromise the effective transmission of information, negatively affecting teaching activities (Recalde, 2021).

Since most learning activities in classrooms involve oral communication, the intelligibility of spoken words, defined as the percentage of correctly understood speech items in relation to the overall speech, is crucial for successful development (Mealings, 2023; Di Loreto, 2023).

Literature extensively explores students' evaluations of teachers' speech intelligibility. However,
there is a noticeable research gap regarding teachers' perception of students' speech intelligibility, particularly within the realm of classroom acoustics. In the context of the (Subramaniam, 2019) project, the practice of graduate students routinely conducting presentations and talks in classrooms was examined. This practice is subject to evaluation and grading, contingent on their communication skills and delivery.

In Pellegatti et al. (2023) good acoustic quality in classrooms becomes essential to create an optimal learning environment, in fact in the last year soundscape research in indoor environments has been gaining attention for its potential to contribute to the design of supportive, healthier, and more comfortable spaces.

Visentin et al. (2023) addressed the indoor soundscape of classrooms for primary school children aged 8 to 10 years. Utilizing questionnaires based on pictorial scales, the study explores perceived loudness and affective dimensions such as pleasantness and arousal. Both the actual soundscape and the children's ideal soundscape are investigated. The study reveals that the most frequent sounds in classrooms come from the students themselves, including voices and movements, followed by traffic.

The aim of this study is to identify challenges related to the acoustics of university classrooms using a holistic approach. This approach encompasses not only traditional measurements of acoustic parameters but also psychoacoustic factors, taking into account the subjective perception of students. Throughout the research, a calibrated numerical model was developed using empirical measurements, complemented by a listening test to assess students' satisfaction and perceived pleasantness. The results reveal a significant correlation between objective measurements and the listening test outcomes, providing valuable insights for classroom design. This correlation offers a comprehensive understanding, considering not only conventional acoustic parameters but also students' perception and satisfaction levels, to optimize the acoustic environment of university classrooms. In this work, two sections are included. In the first, the case study, the measurements equipment of the room and the calibration of numeric model are evaluated. In the second section, the outcomes of the

simulations are compared with the subjective findings from the acoustic survey conducted in the same classroom.

#### 2. Material and Methods

## 2.1 Room Acoustics Metrics and Measurements Equipment

The university building is situated in the central area of Pescara city, near road traffic and other environmental noise sources. For the assessment of acoustic quality, the A34 classroom, belonging to the engineering Faculty of the G. D'Annunzio University, was chosen as a case study.

Classroom R-34 has a volume of 771 m<sup>3</sup>, an average height of 4 meters and a base area of 192.2 m<sup>2</sup>.

The classroom does not have a sound-absorbing acoustic ceiling and has wooden chairs and tables. The windowed surface occupies 1/3 of the total surface of the concrete perimeter walls. Fig. 1 shows the R-34 classroom, and the measurement positions as required by UNI 11532-2:2020 (2020).



Fig. 1 - Plan of R-34

The equivalent sound pressure level of the noise level of technological systems was measured in accordance with UNI EN ISO 16032 in phase - stationary conditions (ISO, 2005).

The acoustic measurements highlighted: the background noise and the equivalent sound pressure level in the classroom when the mechanical system was on. The measurement of RT time (T30) was performed according to the ISO 3382-2 standard (ISO, 2008) which requires measurements to be made for at least two source positions and three microphone positions. The measurement of the Speech Transmission Index (STI) was derived from the impulse response measures and background noise measures with the indirect methodology proposed by the EN 60268-16 standard (ISO, 2020).

For the STI parameter, the UNI 11532 standard requires measurements to be made for at least one source position and four microphone positions.

All investigations were carried out using the SAM-URAI Room Acoustic commercial software (licensed by SPECTRA S.p.A).

The sound field, in the case of intelligibility measurements, was excited using a self-built directional sound source, NTi-Talkbox, in compliance with 11532, consisting of a speaker with a diameter of 100 mm, powered by an MLS signal; the measurements of the RT time were carried out by means of a dodecahedral source, fed with a line-sweep signal. The acquisition of impulse responses was achieved by taking the output signal of a B&K 2250 sound level meter.

Table 1–3 shows the results of measurements for each measurement point and the STI mean value.

Table 1 - Results of rt measurements by octave bands

Frequency [Hz]	RT-full Classroom [s]	RT occupated by 80% of people [s]
125	2.16	1.71
250	2.57	1.58
500	2.09	1.25
1000	2.12	1.20
2000	2.35	1.15
4000	1.88	1.02

Table 2 – Results of full Lamb	and L <sub>int</sub> measurements by octave
bands	

Frequency [Hz]	Lamb-full Class- room [dB(A)]	Lint-full Classroom [dB(A)]
125	24.6	36.7
250	33.7	42.8
500	31.9	44.6
1000	32.1	47.9
2000	28.2	47.0
4000	20.2	34.0

Table 3 – Speech transmission index (sti) for sinle point, mean and speech quality in accordance with cei en 60268-16.

Measurments Positions	STI	STI, mean Classroom	Speech quality in accordance with CEI EN 60268-16
P1	0.36		
P2	0.23	0.26	RAD
Р3	0.22	0.26	BAD
P4	0.22		

The psychoacoustic analysis to evaluate the sound level perception of the classroom was measured in accordance with ISO 532-2 (ISO, 2017) with head and torso simulator B&K, type 4100. The head and torso simulator enables maintaining the shape, size and acoustic impedance of the head and torso of the listener; it is also able to maintain unaltered the directionality of the sound.

Fig. 2 shows the results of measurements for Loudness during the lesson in frequency range from 20 Hz to 20 kHz.



Fig. 2 – Specific Loudness N' (ISO 532-1). Channel 1 is the right ear and Channel 2 is the left ear of the binaural head

Table 4 shows the results of psychoacoustic parameters calculated from the binaural recording.

Table 4 – Psychoacoustic parameters divided into right and left channel

Parameters	Channel 1	Channel 2
Loudness [Phone]	88,3	89,2
Sharpness [Acum]	1,56	1,54
Fluctation Strenght [Vacil]	0,082	0,135
Roughness [Asper]	0,34	0,51

## 2.2 Questionnaire and Subjective Evaluations

Qualitative analysis was conducted through subjective responses provided by students during a listening test, focusing on their overall impression of acoustic comfort, annoyance, pleasantness, and unpleasantness of sounds, as well as the general environmental comfort encompassing temperature and lighting within the classroom. The questionnaire, developed based on ISO 12914-2 (Aletta et al., 2019) with modifications addressing general comfort aspects, was shared with students during academic lessons. Participants were specifically instructed to describe the sound environment within the classroom and their experiences during lessons. The questionnaire was administered in Italian, and the ensuing results highlight significant and distinctive elements identified throughout the evaluation. The decision to carry out the analysis in Italian underscores the emphasis on capturing participants' subjective experiences within their specific cultural and linguistic context.

Fig. 3 shows the results of the subjective investigation about participants.



Fig. 3 – Demographic characteristics pie chart

A total of 98 respondents completed the questionnaire. Most of the respondents came from students (82%). Other respondents were from a professor and researcher (18%). The majority (62%) reported visiting room 34 every day, the minority (6%), reported irregular visits.

The overall perceived acoustic quality of the sound landscape is low, as participants rated it an average of 2.1 on a scale from 1 to 5.

Specifically, 56.2% of participants reported poor acoustic quality, 19.5% indicated it as sufficient, and only 4.9% characterized it as good.

These findings indicate a notable discrepancy between objective measurements of background noise, which comply with regulations, and the subjective perception of individuals, who did not express a positive judgment.

## 3. Results and Discussion

#### 3.1 Statistical Analysis

Considering the results of simulations and according to the background literature, a statistical analysis was conducted for the case study. The proposed correlation model between the measurements of acoustic quality versus the subjective test response is based on a polynomial function, according to the following Eq. 1:

$$y = ax^3 + bx^2 + cx + d$$
 (1)

Where:

- Y represents the subjective test response,

- X denotes the acoustic quality measurements,

- a,b,c,d are the coefficients of the polynomial function.

This polynomial model was selected based on its versatility in capturing non-linear relationships, and Eq. 1 provides a mathematical expression to quantify the correlation observed in the case study.



Fig. 4 – Best fit polynomial curve and residuals of the measured value vs subjective value

Table 5 - Result of the polynomial regression

DFE	SSE	<b>R</b> <sup>2</sup>	adRs	RMSE
1	0.17	0.81	0.14	0.28

The result of the correlation shows the statistical significance is indicated by the  $R^2 = 0.89$  and this represents a good correlation between the variables (Fig. 4; Table 5).

This data shows interesting relationships offering a nuanced understanding of the complex interplay between measured acoustic quality and subjective responses.

Despite the objective measures in accordance with the background noise legislation, there is a significant discrepancy with the subjective perceptions of the participants. For example, although a relatively low percentage of participants rated the acoustic quality as poor, subjective data shows a positive correlation with objective measurements. This indicates the complexity of interpreting acoustic quality based solely on technical measurements, suggesting the need to also consider the subjective perspective of individuals. The correlation between measurement data and listening test results provides a more comprehensive and multifaceted picture of the acoustic quality of the soundscape, underlining the importance of an integrated approach to acoustic analysis.

## 3.2 Numerical Model

In order to create positive and inclusive learning environments, a simulated model utilizing ODEON room acoustic software was developed. The process began with calibrating the model through measurements acquisition. This involved applying absorption coefficients to a geometric model, which, in turn, simulated the acoustic phenomena using a ray tracing algorithm. ODEON's material optimization system employs eight independent genetic algorithms, each corresponding to a specific octave band. The algorithm initiated with a random step, generates individuals in the population with varying absorption coefficients within a user-defined range, forming an initial generation. The evolutionary process ensues, filtering and selecting the best individuals as parents to produce offspring inheriting advantageous traits. This iterative process continued until solutions converge based on predefined criteria. The calculation persists until reaching a solution minimizing errors, aiming to reduce them to a minimum, though not necessarily achieving perfection. In the case study simulations, a tuning process adjusted absorption coefficients of the temple structure to ensure simulated average reverberation times closely matched on-site measurements, with a deviation of no more than 1 JND (5%) for each octave band frequency. In Fig. 4 are reported the best fitting and last error decrease between measured and calibrated absorption in the frequency range from 125 to 4000 Hz (Fig. 5).



Fig. 5 - Best fitting and last error decrease of the GA model

Table 6 presents the main absorption coefficient values used in the simulations after the described correction.

Table 6 – Absorption coefficient after calibration with GA in Odeon from 125 Hz to 4 KHz

Material	125 Hz	250 Hz	500 Hz	1000 Hz	2000 Hz	4000 Hz
Windows	0.418	0.127	0.153	0.031	0.016	0.019
Plaster	0.043	0.020	0.030	0.047	0.039	0.030
Desks	0.161	0.148	0.150	0.161	0.124	0.146
Doors	0.309	0.138	0.106	0.007	0.026	0.016
Floor	0.011	0.012	0.053	0.042	0.052	0.033

Fig. 6 shows the result of the reverberation time after calibration and measurement.



Fig. 6 - R34 simulation: T30 measured vs calibrated

The implemented process played a crucial role in formulating acoustic correction solutions. Notably, it was decided to introduce a 40 cm acoustic baffle with predetermined absorption coefficients, adhering to the UNI 11532-2 standard.

Fig. 7 shows the result of the reverberation time after acoustic correction and calibrated model.



Fig. 7 - R34 simulation: T30 acoustic correction vs calibrated

By implementing the simulated model using ODEON room acoustic software, calibrated with meticulous measurements and an evolutionary process guided by genetic algorithms, we aimed to create more positive and inclusive learning environments. The extensive efforts involved in simulating acoustic phenomena, fine-tuning absorption coefficients, and minimizing errors have culminated in a successful outcome. By strategically incorporating a 40 cm acoustic baffle with well-defined absorption coefficients, in accordance with the UNI 11532-2 standard, the acoustic correction solutions were thoughtfully chosen. As a result of these interventions, the room's acoustics have now reached an optimal state.

This is verified also to evaluate the intelligibility in the simulated R34 room.

Table 7 shows the result of STI for single points in room R34 after the acoustic correction.

Table 7– Speech transmission index (sti) for single point, mean
and speech quality in accordance with cei en 60268-16

Measurements Positions	STI	STI, mean Classroom	Speech quality in accordance with CEI EN 60268-16
P1	0.65		
P2	0.62	0.(1	EVCELLENT
Р3	0.60	0.61	EACELLENI
P4	0.59		

The meticulous approach to this process has allowed us to accomplish our intended goal of creating an environment that not only meets but surpasses the desired acoustic standards, contributing to a more conducive learning atmosphere.

# 4. Conclusion

The study emphasizes the importance of incorporating subjective perspectives into the design of educational spaces, surpassing mere adherence to acoustic regulations. Utilizing acoustic simulations, specifically with ODEON, the environment was tailored based on loudness—an objectively measured parameter. This approach, centred on objectively evaluating environmental pleasantness, yielded more robust outcomes. Designing classrooms to meet both regulatory requirements and incorporate subjective considerations, particularly through loudness management, proved effective in creating spaces that transcend silence, fostering a pleasant and reassuring atmosphere.

Future research will focus on implementing and

refining this approach. The study's scope will extend to the entire university campus for a comprehensive evaluation. Hearing tests will be repeated, adjusting methodologies based on initial results. This extension will strengthen conclusions, providing a solid foundation for designing and optimizing academic environments. The goal is to integrate practices that consider acoustic subjectivity, contributing to environments that meet technical regulations and user-perceived needs.

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# Environmental Quality Analysis in School Environment by Measurements and Numerical Methods

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#### Abstract

Energy consumption and its consequences are inevitable in modern-age human activities, particularly in the school environment.

School buildings require significant energy inputs for heating and air-conditioning, and the majority of the occupants are adolescent students, whose health and cognitive performance are vulnerable to poor indoor air quality (IAQ), thermal discomfort and acoustic noise sources.

The present study employs measurements and numerical methods to improve Indoor Environmental Quality (IEQ) and reduce energy consumption in school buildings.

Accurate measurements enable the quantification of various environmental parameters, from indoor air pollutants to temperature and relative humidity levels. These measurements form the basis for informed decision-making and interventions to improve the environment.

Numerical methods, on the other hand, offer a means to model and simulate the impact of different factors on environmental quality. Advanced computational tools allow for the assessment of scenarios, enabling stakeholders to identify optimal solutions for achieving and maintaining high standards of environmental quality in schools.

#### 1. Introduction

Due to the SARS-CoV-2 pandemic, there has been a critical need to explore and implement novel approaches aimed to study virus airborne transport (D'Alessandro et al., 2022) and enhance indoor air quality. Several studies indicate that the risk of contagion escalates in enclosed spaces as the number of

occupants and their duration of stay inside rises (Braggion et al., 2023; Dowell et al., 2022; Goodwin et al., 2021).

In Papadopoulos et al. (2022), studying IEQ is important to ensure the thermo-hygrometric comfort of occupants within a room, especially in school buildings whose classrooms are continuously occupied by a considerable number of people. In particular, assessing the variation of parameters that influence indoor air quality (IAQ) allows for increased student performance and the prevention of undesirable health effects (Amoatey et al., 2023).

The school ventilation system serves as a fundamental tool in creating a safe, comfortable, and healthy indoor environment conducive to effective learning (Calama-González et al., 2019). Beyond merely regulating temperature, proper ventilation is essential for maintaining acceptable indoor air quality (IAQ), which is vital for promoting optimal educational and health outcomes among students and staff alike (Ali et al., 2009). Thermal comfort, alongside acceptable IAQ standards, directly influences students' ability to concentrate, engage in learning activities, and perform academically (Asrani & Shah, 2019). Inadequate ventilation can lead to stuffy, stale air, which not only affects concentration levels but also increases the risk of spreading airborne contaminants, including viruses and allergens. By prioritizing effective ventilation systems within educational facilities, schools can create environments that support the physical and cognitive well-being of occupants (AiCARR, 2022; De Giuli et al., 2015; Serpilli et al., 2022). This ensures that students have the best possible conditions for learning and thriving academically, while also fostering a healthier and safer atmosphere for everyone within the school community.

This study introduces a methodological approach to studying indoor air quality in educational settings. This approach assesses the effectiveness of existing air-conditioning systems while considering the potential implementation of controlled mechanical ventilation (VMC) systems.

The methodological approach unfolds in two distinct phases. Firstly, a measurement phase is conducted wherein characteristic parameters of the target classroom are acquired using sensors deployed within a specially designed setup. Subsequently, a modeling phase follows, wherein the acquired measurement data serves as both input parameters for the model and verification benchmarks for ensuring the accuracy of simulated outcomes. The numerical model is implemented utilizing the COM-SOL Multiphysics software (COMSOL), which offers a comprehensive platform for managing all aspects of the analysis within a unified study framework. This approach allows for a thorough examination of various factors influencing indoor air quality and facilitates the evaluation of potential interventions, such as the introduction of controlled mechanical ventilation systems, to enhance overall air quality and occupants' well-being within educational environments.

## 2. Material and Methods

#### 2.1 Indoor Environmental Parameters

To assess indoor comfort and air quality, key parameters including indoor air temperature, relative humidity, and CO<sub>2</sub> concentration were meticulously measured. Within enclosed spaces, such as classrooms, air quality is influenced by a spectrum of indicators and pollutants.

Elevated levels of CO<sub>2</sub>, in particular, can detrimentally impact classroom occupants' attention, leading to symptoms such as headaches, drowsiness, and reduced concentration abilities (Braggion et al., 2023). For the measurement of air temperature and relative humidity, the technical reference standard EN ISO 7726:2002 (ISO, 2002) was adhered to, while EN ISO 16000-26:2012 (ISO, 2012) was employed for CO<sub>2</sub> measurement. These standards provide guidelines for assessing indoor environmental parameters. In educational settings, adherence to specific limit values for these parameters is crucial. These values are outlined in Italian regulations DM 18/12/75 (Decreto Ministeriale, 1975) and technical standard UNI EN 16798-1:2019 (UNI, 2019), which serve as benchmark for maintaining acceptable indoor air quality levels.

## 2.2 Classroom Description and Measurements Equipment

In the preliminary phase of the research, which will also involve high schools at a later stage, classroom A34 at the University of Studies "G. D'Annunzio" of Chieti-Pescara is the starting point for the study. The classroom is in the "Pindaro Pole" of the Pescara campus. It is a corner classroom, positioned between the North-East and North-West sides of the ground floor near the entrance to the faculties of Engineering and Architecture (Fig. 1). Classroom A34 has a volume of 772.8 m<sup>3</sup>, a height of 4 m, an area of 193.2 m<sup>2</sup> and has 4 large windows (2 on the North-East side with an area of 18.56 m<sup>2</sup> and 2 on the North-West side with an area of 17.6 m<sup>2</sup>).



Fig. 1 – Location of classroom A34

The air-conditioning system in room A34 was recently modified. It consists of a cross-flow air handling unit that supplies the classrooms and the corridor on the north-east side of the building.

The classroom therefore has two supply channels with four vents each. The change of air is provided by 2 return vents (one on each side) and by the opening of 2 entrance doors (corridor side) and 2 emergency exits on the street side (Fig. 2).



Fig. 2 – Description of air-conditioning system in Classroom 34

The measuring system consists of several sensors placed on a stand. The aluminum support is designed to allow the sensors to be positioned so that they do not clash with each other. It allows the sensors to be handled in a compact position on an easyto-transport telescopic tripod. Fig. 3 shows the mounted sensors and their position within the measurement set-up.



Fig. 3 - Measurement set-up

The sensors involved are a VOCs sensor, a psychrometer, a geothermometer, a net radiometer and a CO<sub>2</sub> sensor. The measured quantities and measuring range from each sensor are shown in Table 1. The acquisition system, also mounted on the crossmount, consists of two E-log terminal blocks with slave function and one alpha-log in master function. Both devices are supplied by LSI LASTEM. The alpha-log device is connected via Ethernet cable to a PC and then controlled via the 3Dom software.

Table 1 – Measuring range of each sensor

Transducer	Measures	Measuring Range
1) VOCs sensor	VOCs	0 [ppm] – 2000 [ppm]
2) Psychrometer	Temperature	-5 [°C] – 60 [°C]
	Relative Humidity	0 [%] – 100 [%]
3) Globo thermometer	Globe Temperature	-30[°C] – 70 [°C]
4) Net Radiometer	Radiation Net	-1500 [W/m <sup>2</sup> ] – 1500 [W/m <sup>2</sup> ]
5) CO <sub>2</sub> sensor	CO <sub>2</sub>	0 [ppm] – 5000 [ppm]

In the measurement phase, the position of the instrument was chosen so as not to interfere with normal classroom activities (Fig. 4).



Fig. 4 - Position of the instrument within the classroom

The measurements were carried out continuously over five days, from Monday 4 March 2024 to Friday 8 March 2024 during both the night period and during lessons and daily activities. During the daytime period, three students monitored the proper functioning of the system and transcribed observations such as the number of occupants and their location, as well as the duration of air changes if present.

#### 2.3 Numerical Simulation

The numerical model of classroom A34 was created with version 6.1 of the COMSOL Multiphysics software.

Due to the classroom configuration and the imbalance in vents mass flow rate, the entire geometry was analysed considering the presence of people and closed doors and windows.

The adopted approach relies on continuity and Reynolds-Averaged Navier-Stokes (RANS) equations in their steady, incompressible form as follow:

$$\rho \nabla \cdot \boldsymbol{u} = 0 \tag{1}$$

 $\rho(\boldsymbol{u} \cdot \boldsymbol{\nabla})\boldsymbol{u} = \boldsymbol{\nabla} \cdot [-p\boldsymbol{I} + \boldsymbol{K}] + \boldsymbol{F} + \rho \boldsymbol{g}$ (2) with

 $\boldsymbol{K} = (\boldsymbol{\mu} + \boldsymbol{\mu}_T)(\boldsymbol{\nabla}\boldsymbol{u} + (\boldsymbol{\nabla}\boldsymbol{u})^T)$ (3)

In the above equations, standard constitutive relations for Newtonian fluid were considered. Moreover, Boussinesq's approximation was employed to consider the buoyancy, and the system closure was guaranteed by k- $\epsilon$  turbulence model, here not reported for sake of compactness.

Furthermore, the energy equation was considered:

 $\rho C_p \boldsymbol{u} \cdot \boldsymbol{\nabla} T + \boldsymbol{\nabla} \cdot \boldsymbol{q} = Q + Q_p + Q_{vd} \qquad (4)$ in which Fourier's law was introduced to describe the heat thermal flux:

$$\boldsymbol{q} = -k\boldsymbol{V}\boldsymbol{I} \tag{5}$$

Finally, Fick's law describes vapour (v) and carbon dioxide (CO<sub>2</sub>) diffusion in ambient air as follows:

$$M_{v}\boldsymbol{u}\cdot\boldsymbol{\nabla}c_{v}+\boldsymbol{\nabla}\cdot(-M_{v}D\boldsymbol{\nabla}c_{v})=G$$

$$\boldsymbol{u}\cdot\boldsymbol{\nabla}c_{co_{2}}+\boldsymbol{\nabla}\cdot(-D_{co_{2}}\boldsymbol{\nabla}c_{co_{2}})=R_{co_{2}}$$
(6)
(7)

The acquired measurement data was used as input parameters for the computations such as the vents inlet and outlet air velocity and the external surfaces temperature.

## 3. Results and Discussion

In the following Table 2, the average values for thermal comfort parameters, together with CO<sub>2</sub> concentration, for A34 room, are presented.

Table 2 – Operative condition of A34 classroom divided into three period of observation

Time	Type of Measure	Avg	Number of people	Observation
From	Temperature [°C]	19.0	0	System On
8:00 to	Relative			
9:00	Humidity [%]	49.6		
a.m.	CO <sub>2</sub> [ppm]	487.4		
From	Temperature [°C]	21.8	49	System On
1:00 to	Relative			All Door-
3:00	Humidity [%]	44.6		windows
p.m.	CO <sub>2</sub> [ppm]	612.4		open
From	Temperature [°C]	21.4	70	System On
6:00 to	Relative			All Door-
7:00	Humidity [%]	43.8		windows
p.m.	CO <sub>2</sub> [ppm]	926.9		closed

The values presented refer to the average indication of all sensors for the periods the classroom was crowded and not; these periods, including the number of students.

In Fig. 5 the air temperature, relative humidity and  $CO_2$  concentration of the 6<sup>th</sup> of March from 8:00 to 9:00 a.m. (empty classroom), from 1:00 to 2:00 p.m. (occupied classroom with open door), from 18:00 to 19:00 p.m. (occupied classroom), are presented.



Fig. 5 – Air temperature, relative humidity, and CO2 concentration during the measurement period

Fig. 6 shows the results of the calculated variables on selected section planes. Sections A and B were made at the inlets, while section C at the outlet in the left side of the room.

These results were calculated by imposing the conditions for 6<sup>th</sup> March from 6:00 pm to 7:00 pm.



Fig. 6 – Air temperature, relative humidity, and CO2 concentration calculated by COMSOL Multiphysics

The results were consistent with the set boundary conditions.

In particular, in section C, the variables are changed in concentration due to convective motions driven by the air-conditioning system.

In fact, when the inputs are at the occupant's head (position B), the trend is upward. However, when the vent is placed at a certain distance from the oc-

cupant (position A), the trend is downward.

In addition, on the left side of sections A and B, there is a high concentration of parameters caused by poor air circulation. In fact, measurements of the air velocity coming out of the vents on the left side of the room show that the system is unbalanced on that side.

A correct comparison with the experimental data can be made by taking the average of the data for the first half-hour of acquisition. Indeed, in this period, the data do not undergo great fluctuations and are comparable with steady-state simulations.

The air temperature, relative humidity and  $CO_2$  concentration evaluated in the simulation at the points corresponding to the position of the sensors are presented in Table 3.

Table 3 – Conditions evaluated in the simulation at the points corresponding to the position of the sensors.

Time	Number of people	Type of Measure	Avg (first half- hour)	Comsol point
6th of	70	Temperature	21.3	20.5
March		[°C]		
from		Relative		
6:00 to		Humidity	45.1	41.8
7:00		[%]		
p.m.		CO2 [ppm]	1006.9	1150.9

The temperature and relative humidity values deviated little from the average values measured. Respectively  $0.8^{\circ}$  C less and  $3.3^{\circ}$  more for the realized model. This deviation is probably due to the imposition of the regulatory intake values of 20 °C and 40%. As far as CO<sub>2</sub> concentration is concerned, the deviation is higher. In fact, the model shows 144 ppm more than the measured data. This deviation can be attributed to the fact that the model assumes that each occupant emits the same amount of CO<sub>2</sub> at the same instant.

In addition, a second simulation was implemented as a further verification of the results.

The interval taken into consideration was the time between 4:00 a.m. and 5:00 p.m. on 8 March. During this time, all doors and windows were closed, and the classroom was occupied by 43 people. Table 4 shows the actual values referring to the first half-hour of measurement and the simulation results evaluated at the points already mentioned.

Table 4 – Conditions evaluated in the simulation at the points corresponding to the position of the sensors

Time	Number of people	Type of Measure	Avg (first half- hour)	Comsol point
8th of	43	Temperature	21.4	20.2
March		[°C]		
from		Relative		
4:00 to		Humidity	43.4	40.3
5:00		[%]		
p.m.		CO2 [ppm]	693.4	583.5

In the latter case, the simulated temperature is  $1.2 \,^{\circ}$ C lower, the simulated relative humidity is 3.1% lower and the simulated CO<sub>2</sub> concentration is 109.9 ppm lower.

In general, the percentage deviation between measured and simulated data is 4%-5% for temperature and 7% for relative humidity and 14%-16% for CO<sub>2</sub> concentration.

Nevertheless, the quite good agreement between the measured and computed data highlights the potential of the proposed approach.

## 4. Conclusion

In conclusion, the thorough analyses conducted through in-situ measurements and advanced modeling techniques have yielded valuable insights into indoor environmental quality within educational settings, notably in room A34. The favourable outcomes observed underscore the effectiveness of existing ventilation systems and environmental control measures in upholding conducive learning environments.

Looking ahead, there are exciting opportunities for further advancements in this field. A key focus lies in integrating advanced sensor technologies and real-time monitoring systems to proactively manage indoor environmental conditions. By leveraging transient simulations, educational institutions can enhance precision in optimizing indoor air quality and thermal comfort while concurrently reducing energy consumption.

Furthermore, there is a growing emphasis on sustainable building design and operation, recognizing the intricate relationship between indoor environmental quality, energy efficiency, and occupant well-being. Future endeavors may entail the adoption of energy-efficient ventilation systems, the incorporation of renewable energy sources, and the infusion of biophilic design principles to foster healthier and more productive learning environments.

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# A Comparative Analysis of Simplified Calculation Procedures for Assessing the Energy Losses of Heating Emission Systems

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#### Abstract

In the assessment of energy performance of buildings, the efficiency of technical building systems, especially those related to heating and cooling services, has a significant impact on the overall energy consumption. For this reason, accurately determining the performance of these systems is of utmost relevance.

Current simplified procedures for evaluating technical building systems lack complete validation, potentially leading to undesired inaccuracies in the results.

This paper analyses the existing simplified procedures provided by standards for assessing heat emission and control subsystems. It examines the procedure currently in use in Europe and presents a comparative analysis with more detailed procedures. Through a case study approach, the research explores several configurations of a representative residential space, considering factors such as climatic data, envelope properties, emission terminals, and control strategies. By addressing these aspects, this research contributes to enhancing the understanding of the effectiveness and reliability of simplified procedures for assessing the performance of technical building systems.

## 1. Introduction

One of the key factors influencing building energy performance is the efficiency of the heat emission system. For this reason, precise calculation methods to assess emission losses are required, taking into account their connection with control systems, building thermal inertia, user behaviour, and other boundary conditions. However, complexities in modelling these interconnected systems limit the widespread use of highly accurate procedures. Hence, there is a need for approaches that balance Following the publication of Mandate M/480 EN (European Commission, 2010), efforts were made to enhance the building energy performance assessment by updating the procedures to evaluate the efficiency of the heating and cooling systems. Nevertheless, emission terminals and control subsystems still require systematic revision. Standards like EN 15316-2 (CEN, 2017) and ISO 52031 (ISO, 2020), currently lack comprehensive validation. The application of these procedures is also insufficiently flexible, since they often rely on tabulated values, overlooking the actual emission terminal performance. Other existing calculation methods oversimplify the complexities involved in modelling the emission heat losses, often neglecting some physical phenomena related to the performance of these systems (e.g., non-uniform temperature distribution indoors).

simplicity and accuracy in assessment methods.

Emission losses usually account for spatial temperature variations and component overheating. Stratification arises from different air temperatures across a space, influenced by heat exchanges between air and surrounding objects. Overheating results from excessive heat exchange from internal or external sources, notably affecting long-wave heat transfer. Factors influencing these losses are related to technical building system components and the building itself.

Comprehensive studies on enhancing simplified procedures for evaluating the thermal energy loss of emission and control systems are lacking in more recent research work. Initial efforts by Maivel et al. (2014) were put into the assessment of the hydronic emission system efficiency, revealing significant differences compared to detailed calculation methods, especially in low-temperature systems. Maivel et al. (2015) also validated standard procedures for radiators and floor heating systems, emphasizing the interconnectedness of building, emission, and control systems on efficiency. Further studies by Maivel et al. (2018) explored the influence of stratification on emission efficiency, confirming methodological differences and highlighting the role of control strategies. Seifert et al. (2016) examined simplified procedures for radiators and control valves, assessing efficiency and accuracy through empirical analyses. Võsa et al. (2020) addressed the lack of standardized procedures, proposing an alternative method for analysing parameters in the EN 15316-2 (CEN, 2017) procedure.

#### 1.1 Aim of the Research

This research aims to address existing knowledge gaps through the analysis of simplified calculation procedures for heat emitter losses, with the perspective of complete validation. While previous works, such as Bianco Mauthe Degerfeld et al. (2024), have analysed the effect of different heat emission terminals, this work focuses more on the influence of various control strategies.

The study involves a comparative analysis of energy losses in heating emitters under different control strategies, using simplified methods. A case study approach was employed, analysing a typical residential building in different configurations. Various Italian climates and envelope insulation levels were considered. Two types of emission terminals were analysed: radiators and lowtemperature radiant systems. The effect of different control strategies (i.e., on/off and proportional) was also assessed to study the relevance of the control system in determining heat losses.

The simplified procedures analysed were implemented and simulated in EnergyPlus. The results were compared and evaluated based on the thermal output of the emission system, normalised over the heated floor area. Additionally, the influence of the calculation time-step was considered by performing simulations with both hourly and subhourly time-steps, to assess the relevance of more refined calculation intervals in evaluating the energy losses of the heating emission terminals. Statistical indicators were used to compare the results and present yearly aggregated outputs.

## 2. Methods

In the following sections, the simplified and detailed procedures deployed in this work are presented. The control strategies coupled with the emission systems are described as well.

#### 2.1 Standard Procedure

The analysed simplified procedure is outlined in EN 15316-2 (CEN, 2017) and ISO 52031 (ISO, 2020). The methodology determines the energy loss due to the heat emission and control subsystems by modifying the indoor temperature. The set-point temperature is increased or decreased (in the case of cooling systems), depending on an analysis of the system properties. The consequent variation in heat exchange is considered equal to the heat loss of the analysed subsystems. This procedure is mainly performed through a qualitative assessment of the system properties. If detailed measured system information is available, this step can be performed with a higher level of detail. However, such data are often unavailable, so a tabular approach can be applied. Equations 1 to 3 present the procedure to determine the temperature variation.

$$\Delta \theta_{\rm int,inc} = \Delta \theta_{\rm hydr} + \Delta \theta_{\rm emt,syst} + \Delta \theta_{\rm ctr,syst}$$
(1)

$$\Delta \theta_{\rm emt,syst} = \Delta \theta_{\rm str} + \Delta \theta_{\rm emb} + \Delta \theta_{\rm rad} + \Delta \theta_{\rm im,emt} \quad (2)$$

$$\Delta\theta_{\rm ctr,syst} = \Delta\theta_{\rm ctr} + \Delta\theta_{\rm im,ctr} + \Delta\theta_{\rm roomout} \tag{3}$$

In Equations 1 to 3,  $\Delta \theta_{int,inc}$  is the equivalent internal temperature difference while all the other terms represent temperature variations. Specifically,  $\Delta \theta_{emt,syst}$  for the emission system,  $\Delta \theta_{str}$  for the air stratification,  $\Delta \theta_{emb}$  for embedded emitters,  $\Delta \theta_{rad}$  for the type of emission system,  $\Delta \theta_{im}$  for intermittent operation,  $\Delta \theta_{ctr,syst}$  for the control system,  $\Delta \theta_{ctr}$  for the control variation,  $\Delta \theta_{roomout}$  for the space automation of the system, and  $\Delta \theta_{hydr}$  for the hydraulic system balancing.

## 2.2 Detailed Procedure

Two detailed procedures for energy performance assessment were analysed: one for radiators and another for low-temperature radiant systems. These procedures are commonly integrated into detailed dynamic building energy assessment tools like EnergyPlus.

The first procedure, designed for radiators and convectors, accounts for both the convective and radiative heat transfer. The convective part and the radiative fraction on people and internal items with very low thermal capacity directly affect the air temperature, while the radiative fraction on the building components increases their surface temperature. Although this procedure accurately models the heat transfer between the room and the radiator, it neglects the effects on air stratification and emitter inertia.

The second procedure, designed for low-temperature radiant systems, evaluates the position of the piping within the building component through which the heat transfer fluid flows. The static and dynamic properties of the fluid and piping are assessed to define the temperature inside the component for the energy balance. Consequently, thermal inertia is properly considered in the performance assessment.

## 2.3 Control Strategies

In this work, two control strategies were implemented to analyse their influence on different calculation procedures: on/off control and proportional control.

The on/off control, also known as two-position control, operates in two states: fully open or fully closed. Typically, a deadband is employed. The system switches position when the lower or higher limit of the deadband is crossed. However, due to the system inertia, the latency in response may cause the measured parameter to exceed the deadband limits, causing overshoot and undershoot effects, respectively.

The proportional strategy involves a control deadband applied to a measurable variable. Depending on the measurement, an actuator modulates the control variable through a linear correlation., allowing for more precise control compared to the on/off strategy.

In control strategies applied to heat emission systems, the control variable is usually the flow rate of the heat transfer fluid. For hydronic systems, such as radiators, it involves water flow rate, while air flow rate is the control variable in air systems, such as VAVs.

## 3. Application

## 3.1 Case Study Description

The case study was based on the representative European room outlined in Annex C of ISO 52031 (ISO, 2020). This room is a residential space with a net floor area of 20 m<sup>2</sup> and a net volume of 54 m<sup>3</sup>. Three walls, the floor, and the ceiling are adjacent to internal spaces, and the heat exchange through these components is neglected. The south-oriented wall, adjacent to the external environment, contains two windows with a total area of  $3 \text{ m}^2$ . The opaque enclosure consists of brick walls with plaster finishing, and concrete slabs with parquetry. The envelope's main thermal properties are detailed in section 3.2.

The profiles of internal gains, shown in Fig. 1, are defined according to EN 16798-1:2019 (CEN, 2019).



Fig. 1 – Profile of the internal gains by source type, normalised over the net floor area

Natural ventilation, with an air change rate of 1.4 h<sup>-1</sup>, is considered according to the method based on the perceived air quality for residential spaces (CEN, 2019).

The building includes lighting, domestic hot water, and heating systems. For the purposes of this work, only the heating system is analysed in detail. It comprises a gas-condensing boiler for generation, well-insulated pipes for distribution, and either a radiator or a low-temperature radiant floor for emission. The building is assumed to be heated continuously during winter, with an operative temperature set-point of 20 °C.

## 3.2 Modelling Options

Different options were analysed and compared. As presented in Table 1, five aspects were considered: the calculation procedure, the climatic zone, the period of construction, the emission system, and the control strategy.

Table 1 - Calculation variants and codes

Aspect	Variant	Code	
	Standard	S	
Calculation procedure	Detailed	Е	
	Milan	M1	
Climatic zone	Palermo	M2	
	Old	I1	
Construction period	New	I2	
	Radiator	R	
Heat emission terminal	Radiant floor	L	
	On/Off	C1	
Control strategy	Proportional	C2	

The variants are detailed as follows:

- Calculation procedures: As described in sections 2.1 and 2.2;
- Climatic zones: Typical meteorological years (TMY) were deployed. Two cities, Milan (2404 HDD) and Palermo (751 HDD) were considered;
- Construction periods: The building labelled as "Old" was derived directly from standard values (ISO, 2020). The properties of the building

labelled as "New" were determined from the "Old" building by increasing, if necessary, the thermal performance of the envelope components. The deployed values are presented in Table 2. The maximum thermal transmittance value (labelled as "max") was derived from the current Italian regulations (Italian Republic, 2015);

- Heat emission terminals: As described in sections 2.1 and 2.2;
- Control strategies: On/Off and proportional were considered. For both, a deadband of 1 °C was deployed (±0.5 °C from the temperature set-point).

Table 2 – Envelope properties

Component	Code	<i>U</i> (W m <sup>-2</sup> K <sup>-1</sup> )					
	M1_I1	0.91					
	M1_max	0.26					
	M1_I2	0.26					
External wall	M2_I1	0.91					
	M2_max	0.43					
	M2_I2	0,43					
	M1_I1	2.24					
	M1_max	1.40					
	M1_I2	1.40					
Window	M2_I1	2.24					
	M2_max	3.00					
	M2_I2	2.24					

Some consistency options were applied to the simulations. In particular, for the simplified procedure, only the terms that refer to the type of emission system, the embedded component, and the control variation were analysed, while the others (i.e., the air stratification, the intermittent operation, the space automation, and the hydraulic balancing) were neglected.

## 3.3 Comparison Procedure

The results of the different procedures were analysed in terms of the input thermal energy to the emission system normalised over the net floor area. The 32 simulations are presented in pairs, differing only in the calculation procedure, while the climatic data, construction period, the type of heat emission terminal, and the control strategy are fixed. The 16 pairs are then analysed using two statistical indices, i.e., the mean bias error (*MBE*) and the coefficient of variation of the root mean square error

(cv*RMSE*). The detailed procedure is used as the reference set of data to normalise the *MBE* and the cv*RMSE*.

## 4. Results and Discussion

This section presents the results of the procedures outlined earlier. Fig. 2 to 4 display the monthly actual energy needs absolute differences from the simplified and detailed methods for radiator and radiant floor heating in Milan and Palermo.









Fig. 4 – Monthly actual energy needs normalised over the net floor area for the radiator (a) and the radiant floor (b) in the city of Palermo, ("\*" in case of monthly results close to zero)

The months without heating energy need were excluded from the graphical representation.

For each month and variant, a label with the difference between the simplified and detailed method results normalised over the detailed method result is presented. In the case one or both monthly results are close to or equal to zero, a "\*" is indicated on the label.

An initial analysis of the results of the 16 simulations pairs reveals significant differences between the two methods.

The results for the city of Milan highlight similarities in the trends when the radiator is deployed as the emission terminal, as shown in Fig. 2. On the other hand, the results of the simulations carried out deploying the radiant floor heating system present higher differences, as illustrated in Fig. 3. This may be caused by the inefficacy of the standard procedure in reproducing the energy need fluctuations due to the system inertia.

The results for the city of Palermo, presented in Fig. 4, exhibit a significant variation in the results. The detailed procedure presents in almost all the cases an actual energy need equal to or close to zero. For this reason, the percentage variation of the differences from the detailed procedure results presents values over 300 % in almost every month. This is mainly caused by the differences in the two procedures.

The detailed procedures assess the system efficiency changes, a task that can only be performed in time-steps where the space presents an energy need for heating (or cooling). In contrast, the standard procedure, by increasing the set-point temperature of the building, generates two effects. Firstly, it increases the actual energy needs to assess the effect of the emission and control subsystems, as intended. Secondly, it generates energy needs for time-steps where the energy need should be zero.

While this effect may impact the results when energy needs are not null for most time-steps in an insignificant way, it can significantly affect lowenergy buildings.

The analysis of the calculated statistical indicators, presented in Table 3 further highlights the difference between the two analysed cities and the two emission terminals presented before. The results also show that the cv*RMSE* is lower when the proportional control is applied compared to the cases where the on/off control is used.

This is probably related to the fact that the proportional control gives a more stable output to the emission system, reducing the fluctuations and the errors.

Table 3 – Statistical indicators

Case	MBE [%]	cvRMSE [%]
M1_I1_R_C1	26	36
M1_I1_R_C2	13	16
M1_I1_L_C1	-1	233
M1_I1_L_C2	-17	42
M1_I2_R_C1	29	43
M1_I2_R_C2	13	17
M1_I2_L_C1	-4	151
M1_I2_L_C2	-9	23
M2_I1_R_C1	1596	1124
M2_I1_R_C2	150	400
M2_I1_L_C1	1306	566
M2_I1_L_C2	267	443
M2_I2_R_C1	-	-
M2_I2_R_C2	452	820
M2_I2_L_C1	-	-
M2_I2_L_C2		_

## 5. Conclusion

In this paper, a comparison between different procedures to assess the energy losses of the emission and control subsystems was carried out.

Both simplified and detailed procedures were analysed and implemented in a dynamic simulation tool, EnergyPlus, to standardise the calculation procedure enabling the comparison. A case study approach was adopted, varying climatic data, envelope properties, emission terminals, and heat control strategies within a representative residential space.

The results revealed notable differences between the procedures. In particular, the simplified procedure yielded higher input energy to the emission terminal for radiators, and lower energy consumption for floor heating systems when considering yearly results.

Moreover, the analysis of control systems showed significant monthly differences in energy consumption. Proportional control showed better coherence between the results of the analysed procedures compared to the on/off control.

The results underscored the unreliability of the simplified method in assessing energy consumption for buildings with low energy needs, particularly evident in warm climates. However, this limitation is not limited to warm climates, as there is an increasing number of zero energy buildings across all climates. Mandated by current European Directives, will be impacted.

Future studies will explore phenomena such as air stratification, not addressed in this study, to further enhance understanding of overall building energy performance.

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## Nomenclature

## Symbols

cv <i>RMSE</i>	coefficient of variation of the root									
	mean square error (%)									
MBE	mean bias error (%)									
U	thermal transmittance (W m <sup>-2</sup> K <sup>-1</sup> )									
$\theta$	temperature (°C)									

### Subscripts/Superscripts

ctr	control
emb	embedded
emt	emitter
hydr	hydraulic balancing
im	intermittent
inc	increased
int	initial
rad	radiant
roomout	room automation
str	stratification
syst	system

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# Simplified and Fully Detailed Dynamic Building Energy Simulation Tools Compared to Monitored Data for a Single-Family NZEB House

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#### Abstract

Building energy automation and control strategies have recently been applied to improve the energy performance of the building and to exploit the integration of the building envelope, HVAC and RES. To optimise their application, reliable data on the dynamic energy behaviour of the building should be available possibly from monitoring, but also from simulation at the design stage.

This paper compares the results of two building performance simulation tools: TRNSYS, which implements a fully detailed model and software implementing a simplified model according to the EN ISO 52016-1 standard. We are interested in investigating the potential of the EN ISO 52016-1 model to capture the dynamic behaviour of the building. A NZEB single-family house in Northern Italy, where the thermal loads are met by a domestic air handling unit (AHU) with heat recovery was taken as a case study. The TRNSYS model is calibrated using data available from the 15-minute monitoring of the indoor/outdoor temperatures, the electrical energy consumption and the source/sink temperatures of the heat pump, and then compared with the result of the standard model in terms of both monthly thermal energy demand and hourly heating demand. The simplified model overestimates the annual heating demand compared to the detained model, but is able to capture the daily maximum both in terms of value and temporal cadence.

#### 1. Introduction

Growing global concern about the rising energy consumption and greenhouse gas emissions from buildings has led to increasingly stringent energy efficiency requirements for both residential and commercial buildings (e.g., the Performance of Buildings Directive in the EU), and a wider use of on-site renewable energy generation to achieve the goal of Nearly Zero Energy Buildings (NZEBs) and Zero Emission Buildings (ZEBs).

In response, the building industry has developed innovative technologies that, to be more effective, need to be properly interconnected and integrated into the building system at the different stages: design, construction and operation. In particular, there is scope to improve the control of the interactions between the building envelope and the active systems, such as HVAC and RES. Thus, building energy automation is increasingly being developed and control strategies can be profitably optimised on the basis of reliable data on the dynamic behaviour of the building. This data is provided by monitoring or predicted by simulation tools.

Building Performance Simulation (BPS) tools have been widely used in building design for several decades, providing architects, engineers and researchers with predictions of the energy performance of buildings in accordance with rapidly changing standard and requirements. The simplified steadystate or quasi-steady-state mathematical models are useful in the design process and when the main requirement is the reproducibility of results. However, the use of default values for input parameters means that these models often fail to accurately predict the actual performance of a building during operation. Conversely, the most detailed dynamic models allow for a greater accuracy and flexibility but have the disadvantage of requiring a higher level of user expertise and a time-consuming simulation process, which hinders the adoption among professionals.

An interesting compromise between accuracy and

simplicity is offered by tools that implement the Simplified Hourly Calculation Method (SHCM) for the calculation of the thermal loads and the internal temperatures provided by the EN ISO 52016-1 standard (European Committee for Standardization, 2017). It takes into account the hourly variations in weather conditions, schedules for internal gains and for ventilation loads, while using a RC model with a simplified mass distribution in the building components.

The accuracy of the hourly method has been investigated by several authors by comparing the standard with detailed numerical simulation models, such as TRNSYS (Siva Kamaraj, 2018; Zakula et al., 2019; Magni et al., 2022) or EnergyPlus (Ballarini et al., 2020; De Luca et al., 2019). Furthermore, some works (Mazzarella et al., 2020; De Luca et al., 2023) demonstrate the accuracy improvement provided to the EN ISO 52016-1 standard by the Italian National Annex, which implements a more realistic RC model of the building components based on the detailed description of the wall layers.

The previous studies have focused on the evaluation of the discrepancies caused by the simplifications in the standard method, mainly on the thermal energy demand for different building typologies and climates.

In our research, we aim to use the results of a detailed model in TRNSYS, validated with monitored data, to assess the potential of EN ISO 52016-1 model in capturing the dynamic behaviour of the building in order to use it to define control strategies for optimal integration of the building envelope, HVAC and RES improving the energy performance. In this study, we present the preliminary results of a NZEB single-family house in Northern Italy, where the thermal loads are met by a domestic air handling unit (AHU) with heat recovery. We compare the result of the detailed and standard model in terms of both monthly thermal energy demand and hourly heating demand.

#### 2. Methodology

Two methods have been considered for the dynamic simulation of the building: numerical dynamic simulations carried out with the software TRNSYS 18 (Klein et al., 2010) and the calculation procedure of the EN ISO 52016-1 standard, implemented in a commercial software (EC700).

The *COP* of the heat pump was calculated using manufacturer's data and in compliance to standard UNI/TS 11300-4.

#### 2.1 Detailed Dynamic Model

TRNSYS is a component-based software environment for the simulation of transient systems. In particular, its library includes a multizone building (Type 56) and many components of HVAC and renewable energy systems. The building model is an energy balance model, where the heat balance is set for each zone air node, that is:

$$C\frac{\partial \mathcal{G}_{i}}{\partial \tau} = \dot{Q}_{TRAN} + \dot{Q}_{VENT} + \dot{Q}_{INF} +$$

$$+ \dot{Q}_{SOL} + \dot{Q}_{IG} + \dot{Q}_{HEA} - \dot{Q}_{AC}$$
(1)

where *C* is the effective heat capacity and  $\vartheta_i$  the temperature of the thermal zone; the terms on the right are, in order: the convective heat transfer from the boundary surfaces; the air infiltration and ventilation contributions, including air flow from other air nodes; the fraction of solar gains that is immediately transferred to the air node; the internal convective gains; the convective fraction of the heating load and the cooling load from the HVAC system. Radiative heat fluxes are modelled for the walls and windows of each zone by taking into account the contribution solar gain through the windows and longwave radiation exchange.

The dynamic behaviour of the building is modelled using transfer functions to calculate the transient heat conduction through the capacitive walls. The simulation time step in TRNSYS can be sub-hourly. More detailed mathematical description can be found in the software documentation.

#### 2.2 Simplified Dynamic Model

The simplified hourly method of EN ISO 52016-1 is also based on the heat balance at the air node (Equation 1), but introduces some simplifications, mainly related to the calculation of the transient conduction in the opaque building elements and the solar energy transmission through glazing (Ballarini et al., 2020). Each opaque element is modelled as an equivalent RC-circuit with five nodes, four thermal resistances, whereas the wall heat capacity is concentrated in one, two or five nodes, depending on the typology of mass distribution in the element (according to the classification in Annex B of Standard EN ISO 52016-1).

## 2.3 COP Calculation

The UNI/TS 11300-4 standard specifies the procedure for estimating the performance of electrically driven vapour compression heat pumps at source/sink temperatures other than those specified in the manufacturers' data.

Briefly, for a cold source temperature  $\vartheta_c$  and a hot sink temperature  $\vartheta_h$ , in the operating range of the heat pump, the COP is calculated as:

$$COP(\mathcal{G}_{h},\mathcal{G}_{c}) = COP_{\max}(\mathcal{G}_{h},\mathcal{G}_{c}) \cdot \eta_{II}$$
(1)

where  $COP_{max}$  is the Carnot COP for the same source/sink temperature values and  $\eta u$  is obtained through linear interpolation of the ratios between the full load *COP* declared by the manufacturer at specific temperature conditions (in compliance with UNI EN 14825) and the corresponding Carnot COP. The part load coefficient of performance COP<sub>PL</sub> is calculated as:

$$COP_{PL}(\mathcal{G}_{h},\mathcal{G}_{c}) = F_{p}(CR) \cdot COP(\mathcal{G}_{h},\mathcal{G}_{c})$$
(2)

where the correction factor  $F_p$  as a function of the capacity ratio *CR* has been calculated from the interpolation of the data provided by manufacturer's under at partial load conditions at specific temperature conditions. pump.



Fig. 1 – Case study 3D model in Google SketchUp

Component	<b>U-value</b> [W/m <sup>2</sup> K]	Element Class [ISO 52016-1]				
External wall	0.17	84.6	М			
Ground floor	0.40	61.7	IE			
Upper floor	0.20	32.6	IE			
	U -value	Uglass-valu	ie g-value			
	$[W/m^2K]$	[-]	[-]			
Windows	1.10	1.30	0.5			

# 3. Case Study Description

## 3.1 Description

The case study is a NZEB single-family house in Northern Italy, built in 2020. It consists of a 130 m<sup>2</sup> one floor, the living area is 44.7 m<sup>2</sup> and has a total height of 4.40 m, a large window to the south and a garage on the west side; the sleeping area is 68.3 m<sup>2</sup> and has a total height of 2.4 m, it has an attic above and a bordering house to the east. The 3D model in Google SketchUp is shown in Figure 1.

The building envelope includes concrete walls with EPS panels on both the inner and outer surface, thus it falls under Class M of EN ISO 52016-1 (Annex B) with thermal capacity concentrated in the central node. Windows are double-glazed Low-E ones with roller shutters. Thermal properties of the envelope are shown in Table 1.

The thermal loads are met by a domestic air handling unit (AHU), sketched in Figure 2, which is housed in the false ceiling in a central position, in order to supply four linear diffusers with variable flow rates for a total of 850 m<sup>3</sup>/h as maximum design value. The packaged unit is equipped with hydronic coils for space heating or cooling, an electric heater for occasional reheating, an air-to-air heat recovery exchanger and an economizer with air dumpers to control the recirculation and fresh air flow rates.

The space heating/cooling and DHW demands are supplied by an 8.5 kW monobloc air source heat pump.

The case study is representative of single-family NZEB houses in Northern Italy in terms of square footage and thermal characteristics of the building envelope. On the other hand, low-temperature hydronic heating is much more common than AHUs in residential buildings, although AHU units and mechanical ventilation systems with heat recovery have recently become more widespread. The peculiarity of this heating system, which has a very short response time, is one of the novel features of this case compared to previous studies.



Fig. 2 – Monobloc air source heat pump suppling the domestic AHU and DHW

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Fig. 3 – Electrical appliances and occupancy schedules from family interview

#### 3.2 Model

The building has been modelled in each software with two thermal zones: the living zone and the sleeping zone, according to the temperature data available from monitoring.

The building is occupied by five people and an interview was made to define the occupancy schedules and the use of lighting and electrical appliances. An example is shown in Figure 3.

The rate of heat gain for electric appliances was calculated using 2019 ASHRAE Handbook Fundamental recommended values. The maximum mechanical ventilation rates of 1,8 ach in the living zone and 1,7 ach in the sleeping zone are modulated during the occupied and unoccupied periods and a certified heat recovery efficiency of 0.8 have been applied.

#### 3.3 Monitored Data Processing

The monitoring is carried out in the framework of the installed Building Automation System, which controls the operation of the heat pump, AHU unit, air ventilation dumpers, fan system, heating and cooling coil, etc. through a programmable Direct Digital Control (DDC) unit. Control rules for the actuators are defined as a function of data collected from input sensors (temperature, humidity, CO2, water flow). The system also allows remote monitoring and updating of settings via web. From 20th October 2023 to 31st March 2024, we monitored the internal temperature in the two thermal zones and CO2 concentration, the outdoor temperature, the thermal energy provided by the heat meter installed on the hydronic coil of the AHU (Figure 2), electrical power and supply temperature of the heat pump. Data have been recorded at 15-minute timesteps.

Unfortunately, due to an incorrect installation, the heat counter did not work correctly, and the collected data are not reliable. Thus, the heat pump wattmeter was used to estimate the thermal energy from the COP calculated in accordance to standard UNI TS 11300-4, i.e. for the monitored values of the water temperature  $\vartheta_{w,supply}$  at the outlet of the heat pump (supply temperature) and the outdoor temperature  $\vartheta_e$  (source temperature). The bivalent temperature is -7 °C, and the data interpolated from the manufacturer data given at four source temperature values (-7, -2, 7, 12 °C) for both low temperature (35 °C) and medium temperature (55 °C) applications.

#### 4. Results

The analysis was carried out in the following steps.

 Calibration of the detailed model. The TRNSYS software allows a greater flexibility in the input data (for example, it is possible to set the internal temperature to follow the trend of the monitored data) and the transparency of the results (for example, it is possible to check the single contributions of the heating load for each zone and their variation over time) facilitates the calibration process.

- 2. Updating the simplified model: the input parameters of the simplified model were updated according to the outcomes of the calibration process.
- 3. Comparison of the results between the detailed and simplified models.

The procedure and the intermediate results are described in detail below.

## 4.1 Detailed Model Calibration

In the TRNSYS model, we forced the heating set temperature to assume the values of the air temperature monitored in the two thermal zones and carried out the simulation for an ideal heating system. The first step of the calibration process was to implement the real climatic conditions in the monitored period. As the outdoor temperature sensor is influenced by its location and records higher average temperatures, we preferred to use data available from the nearby meteorological station, including humidity, wind speed and solar radiation on the horizontal plane. The sky model of Perez 1999 with a 0.2 ground reflection was used to split the direct and diffuse radiation for the different wall exposures.

The second step was to calibrate the internal gains (occupancy, equipment and lighting) and solar gains which, during the middle hours of the day, are responsible for the air temperature being higher than the set temperature, ideally requiring space cooling to bring the temperature back to the monitored values. This behaviour is illustrated in Figure 4: in the middle hours of the sample day (from 14:00 to 16:00) and around 21:00 the internal temperature deviates from the setpoint by assuming higher values. Once the internal inputs have been calibrated, the temperature returns to values close to the setpoint throughout the period. At the end of the calibration process, the resulting daily average values for electrical appliances, lighting and occupancy were 5.4 Wm<sup>-2</sup>, 2.5 Wm<sup>-2</sup> and 1.76 Wm<sup>-2</sup> respectively. The Root Mean Square Error RMSE, has been calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\mathcal{G}_i - \mathcal{G}_{i,mon})^2}{N}}$$
(3)

between the indoor air temperature from TRNSYS calculation  $\vartheta_i$  and the monitored air temperature  $\vartheta_{i,mon}$ . The period considered for calibration corresponds to the monitoring period, except for the time interval from 14 to 19 February when a system malfunction occurred and a very few bad data from monitoring (24 measurements at 15-min timesteps). During the calibration period, the RMSE value was lower than 0.28. The thermal energy demand was then calibrated by modulating the fresh air flow rates according to the occupancy schedule.

Figure 5 compares the final results of the simulation, in terms of monthly thermal energy demand for space heating, with the values estimated from the monitored data.



Fig. 4 – Comparison between the set temperature  $\vartheta_{i,mon}$  and the simulated values of the internal temperature pre and post calibration



Fig. 5 – Monthly thermal energy demand from TRNSYS simulation  $(Q_{heat,trmsys})$  of the calibrated model and that estimated from monitored data  $(Q_{heat,\,mon})$ 

In detail, the monthly space heating demand is calculated by subtracting the estimated demand for domestic hot water production from the heat pump heating capacity estimated from the monitored data, as:

$$Q_{HEAT} = \left(\sum_{j=1}^{24 \cdot N_{days}} E_{EL} \cdot COP - N_{days} \cdot Q_{DHW,daily}\right) (4)$$

where the first term on the right is the monthly thermal energy supplied by the heat pump, calculated on an hourly basis from the monitored electrical energy  $E_{EL}$  using the COP calculation procedure described above which takes into account the heat pump water supply temperature and  $Q_{DHW,daily}$  is the thermal energy for an estimated domestic demand of 150 l/day at 40 °C, and  $N_{days}$  is the number of days in the month.

It should be stressed that the October result refers to the last ten days of the month, i.e. since the start of monitoring. The discrepancy seems to be more pronounced in the first two months when the outside temperature was milder. Over the whole period, the simulation result differs by less than 5% from the value estimated by the monitoring. However, it should be pointed out that the discrepancy could be higher as the monthly space heating demand from the monitoring was estimated with several simplifications, such as the rough estimation of the domestic hot water production or neglecting the effect of defrosting. On the other hand, this would not affect the comparison between the simplified and the detailed model.

The annual heating energy need normalized on the conditioned net floor area amounts to 54 and to 52 kWh·m<sup>-2</sup>, assessed by simulation and from monitored data respectively. It is rather high for a NZEB house, due to both the high monitored internal temperatures (which even reaches 24 °C) and the high heat pump supply temperature, which fluctuates between 43 °C and 52 °C over the period, regardless of the DHW demand. The latter trend is shown in Figure 6, over a period of approximatively one month. A marketed change in the temperature control can be seen from 28th March, a few days after the end of the monitoring. This is the effect of the replacement of the actuator supplying the hydronic coil, which restored proper control of the supply temperature to values typical of low temperature applications.



Fig. 6 – Monitored data of the heat pump water supply temperature in the monitored period, before and after the actuator replacement

#### 4.2 Models comparison

The energy model of the building has been implemented in the commercial software taking into account the real climatic conditions and the input parameters such as internal gains and ventilation rates (which includes the heat recovery efficiency) were set to be consistent with the outputs of the calibration process.

The heating setpoint temperature has been set to 20 °C through the day.

The simulation results in terms of monthly thermal energy demand for space heating, from the simplified model (Standard EN ISO 52016-1) and from the detailed model (TRNSYS) are compared in Figure 7. The thermal energy demand of the simplified model differs from a minimum of -4.5 % in January to a maximum of 29 % in March. The simplified method overestimates the yearly heating need of 6.7 % compared to the detained. This result is in line with the results obtained by Ballarini et al. (2020) for the archetype of a two-storey single-family house, although the difference is more pronounced. This is probably due to the fact that the ventilation losses, which are consistent between the two models, are small compared to the other contributions that are model dependent (i.e. transmission losses), thus increasing the discrepancy between the two solutions.



Fig. 7 – Monthly thermal energy demands from simplified dynamic model simulation and from detailed dynamic model simulation



Fig. 8 – Thermal energy demand from simplified dynamic model simulation and from detailed dynamic model simulation on a sample week of November and of January

We are interested in assessing the differences between the two models in capturing the dynamic behaviour of the building. Figure 8 shows the heating flux demand for a sample week of November and January.

The path is similar in terms of the periodicity of the absolute and relative maximum values, and the curve scope changes are well captured by the simplified model. It is particularly interesting that the simplified model is able to capture the daily maximum both in terms of value and temporal cadence. This opens up the possibility of using the simulation with software used by professionals to assess the building energy performance and the design conditions of the heating system, also for predicting demand peaks in the day and heating period. On this basis, control rules can be set to optimize the integration with renewable sources and exploit thermal and electrical storage systems.

On the other hand, the daily heat demand varies within a smaller range in the simplified model, the minimum values are higher than the detailed model thus limiting the flexibility exploitation.

# 5. Conclusion

The case study of a NZEB single-family house in Northern Italy with a residential air handling unit (AHU) and heat recovery exchanger, is used to exploit the potential of the EN ISO 52016-1 model to capture the dynamic behaviour of the building. A fully detailed model and a simplified model according to EN ISO 52016-1 standard were developed. The detailed model was calibrated with the 15-minute monitoring data and the outcomes of the calibration were implemented in the simplified model. The simplified model overestimates the annual heating demand by 6.7% compared to the detailed model, but is equally good at capturing the daily maximum both in terms of value and temporal cadence. It can be profitably used to predict demand peaks over the heating period and over the day, thus allowing control strategies to be defined for optimal integration of the building envelope, HVAC and RES.

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# A Building Renovation Concept Based on a Low-Temperature Geothermal Loop With Decentralized Plug-And-Play Heat Pumps

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#### Abstract

This article proposes a renovation concept for multi-family houses and apartment blocks based on a groundwater loop with heat pumps supplied by groundwater. The study applies the proposed concept to a multi-family building in the province of Milan. The analysis relies on dynamic energy simulations of the building and thermohydraulic simulations of the low-temperature distribution circuit. Energy, economic, and environmental indicators are evaluated to compare the proposed solution against a benchmark retrofit with individual condensing gas boilers. The study demonstrates that the proposed renovation concept leads to increased Energy Efficiency Class compared to the benchmark renovation scenario, as well as to lower operating costs and CO2 emissions. The proposed concept is promising, especially for areas where groundwater is easily available, and no local legal restrictions are present.

## 1. Introduction

Over the past few decades, the utilization of shallow geothermal energy has increased across Europe due to its remarkable energy efficiency potential and encouraged through Renewable Energy policies and European Directives. Groundwater (or water-towater) heat pumps can efficiently supply heating and cooling to buildings on small or large scales (Sezer et al., 2024). In some regions, like the Milan area (Italy), the use of water-to-water heat pumps is extremely interesting, due to the availability of exploitable aquifers next to the ground surface (Città Metropolitana di Milano, 2023). Such systems can be used to further increase the renewable share in the heating and cooling sector and have a potential in the energy retrofit of buildings (Schibuola & Tambani, 2022), as an alternative to conventional, fossilfueled energy plants such as condensing boilers. This paper presents the energy and cost analysis of a retrofit solution for the heating system of an apartment block in the province of Milan, which building envelope was recently retrofitted.

# 2. Building Retrofit Description

This paper presents energy retrofit actions to be performed both on the building envelope and on the heating and cooling system. The latter will be analyzed on a multi-apartment block, described hereafter. This section also includes details about the sizing of the components.

## 2.1 Case Study Building

The building is a five-story (Fig. 1) condominium of 26 apartments located on the outskirts of Milan. Being in the climatic zone "E", according to Italian regulation, the heating period goes from October  $15^{th}$  to April  $15^{th}$ . The annual average air temperature is around 14.7 °C, with 2404 heating degree days. The ground floor houses garages and cellars and is not heated. Each floor has three stairwells (A, B, C). Most apartments have a floor area of about 100 m<sup>2</sup>, except for four with 200 m<sup>2</sup> and five with around 50 m<sup>2</sup>. The net floor area of the building is 2556 m<sup>2</sup>, and the net heated volume is 7305 m<sup>3</sup>.



Fig. 1 – North-West façade (above) and bird's eye view of the case study building (below)

#### 2.2 Retrofit of the Building Envelope

The retrofit of the building envelope consisted of thermally insulating the external walls, the floor slabs towards unheated spaces, and the roof. Table 1 summarizes the stratigraphy of opaque building components pre and post retrofit.

On balcony façades, the width of the insulation layer is 4 cm instead of 8 cm. Similarly, the 10 cm EPS layer below the slab of the first floor is used only above cellars, whereas above the atrium, it is replaced with a 2 cm aerogel layer to save space (height) in the condominium hall.

Table 1 - Building components stratigraphy pre and post retrofit

Building	Original	Additional
component	stratigraphy	layers
Ext. walls	2 cm - Gypsum plaster	Air gap filled with
$U_{\rm pre}$ = 1.03	8 cm - Hollow brick	glass-wool (10 cm)
W/(m <sup>2</sup> K)	10 cm - Airgap	8 cm - Rockwool
$U_{post}$ = 0.17	8 cm - Hollow brick	1 cm - External coat-
$W/(m^2 K)$	2 cm - Gypsum plaster	ing
Floor slab	1 cm - Ceramic tiles	10 cm - Graphite
$U_{\rm pre}$ = 1.04	4 cm - Lean concrete	EPS
W/(m <sup>2</sup> K)	5 cm - Cement	2 cm – Ext. Insula-
$U_{post}$ = 0.24	18 cm - Brick slab	tion
W/(m <sup>2</sup> K)	2 cm - Gypsum plaster	
Roof	3 cm - Clay tiles	14 cm - Rockwool
$U_{\rm pre} = 1.17$	4 cm - Airgap	panel
W/(m <sup>2</sup> K)	4 cm - Lean concrete	
$U_{post}$ = 0.24	5 cm - Cement	
W/(m <sup>2</sup> K)	18 cm - Brick slab	
	2 cm - Gypsum plaster	

In the building, the most common glazed components present wooden frames and a thermal transmittance between 2.74 and 2.91 W/(m<sup>2</sup> K). They were not replaced.

## 2.3 Retrofit of the HVAC System

In the original configuration, each apartment has an independent system for cooling, heating, and domestic hot water (DHW) production. For space heating and DHW production, the apartments have conventional gas boilers, except for one apartment with a condensing gas boiler, and two with electric boilers. Gas boilers are located in the kitchen and all the apartments have radiators. The apartments have direct expansion air conditioning units for cooling. The annual natural gas consumption, simulated using Edilclima, is 34236 Nm<sup>3</sup>, while the annual electrical energy consumption, related to heating, cooling, and DHW production, is 38406 kWh. The proposed retrofit solution consists of distributed waterto-water heat pumps, using groundwater as a heat source during the heating season and as a heat sink during the cooling season. The groundwater does not circulate in the building's hydronic system, but exchanges heat via a heat exchanger. Although less efficient than direct coupling, this solution reduces problems of corrosion and fouling. The hydronic system supplies heat at low temperature to reversible water-to-water heat pumps (one in a balcony of each flat) that extract heat from the network during the heating season and reject heat into the network in the cooling season. During summer, heat can be also extracted to produce DHW. Radiators must be replaced with fan coils to supply cooling during summer. Fig. 2 reports a general scheme of the network. The extraction well that draws the groundwater is placed outside the building. The connection pipes reach a technical room in the basement, where the heat exchanger, the circulation pump, and the manifolds are located. The horizontal pipes run on the ceiling to reach the base of the six risers, which distribute the water to the heat pumps. A reverse return distribution was chosen for the risers to achieve a self-balanced hydronic circuit. The pipes were sized with constant pressure drop (target 30 mmwc/m) and a maximum velocity of 1 m/s to avoid noise issues. The supply and return

temperatures depend on the temperature of the aquifer, assumed equal to the annual average temperature of the outdoor air. For environmental reasons, the difference between the supply and return temperature to the aquifer cannot exceed 5 °C: the return temperature was set to 10 °C in the heating operation (winter) and 20 °C in the cooling operation (summer). A temperature difference of 2 °C was considered in the heat exchanger between the outlet technical water temperature and the inlet groundwater temperature. The heat exchanger was sized to ensure proper heat transfer with these temperatures. The decentralized water-to-water heat pumps were chosen from the catalog of a local heat pump manufacturer (Table 2). The variable-speed multifunctional heat pumps use scroll compressors and R410a as refrigerant. Each unit, including a 200-liter thermal storage for DHW production (at 45 °C), is contained in a box.

Table 2 - Characteristics of the chosen heat pumps

Heat pump	Type 1	Type 2
Heating capacity [kW]	12.4	8.1
Cooling capacity [kW]	9.8	6.3
Rated COP [-]	5.49	5.99
(T <sub>source</sub> =10 °C - T <sub>load</sub> =35 °C)		
COP in operating conditions [-]	4.43	4.83
(T <sub>source</sub> =13 °C - T <sub>load</sub> =45 °C)		
Rated EER [-]	4.69	4.91
(Tsink=15 °C - Tload=7 °C)		
EER in operating conditions [-]	4.49	4.70
(Tsink=17 °C - Tload=7 °C)		

The instantaneous DHW production capacity is 25 l/min. The size of each apartment's heat pump was chosen based on the space heating, cooling, and DHW demand. For the four largest apartments (floor areas from 165 to 209 m<sup>2</sup>), the heat pump Type 1 was chosen. The heat pump of Type 2 was selected for the remaining 22 apartments (floor area below 100 m<sup>2</sup>). The unit's box includes two variable-speed circulators, for the user's and source circuits, which can regulate the water flow according to the apartment's thermal load. The volume flow rate of the source-side circulators is 0.29 l/s for Type 1 and 0.19 l/s for Type 2.

## 3. Method

The proposed retrofit solution with water-to-water heat pumps was analyzed using economic, energy, and environmental indicators and compared with a conventional energy retrofit solution. The latter consists of replacing existing traditional gas boilers with condensing boilers.

#### 3.1 The Building Thermal Loads

The building's dynamic simulations were carried out using Edilclima EC700 (Edilclima, n.d.), a widely used software within the Italian building engineering community to calculate buildings' energy performance. The underlying model is based on the dynamic hourly method of ISO 52016-1 Standard (International Organization for Standardization,



Fig. 2 – Schematic of the proposed system

2017). Domestic hot water load profiles were calculated for each apartment using DHWcalc (Jordan & Vajen, 2005), a software for the generation of stochastic profiles of DHW draw-offs. They were generated by setting a volume of 50 liters/(person day). The heat emission efficiency was set to 95%, while the heat distribution efficiency was set to 99.2%. Ambient temperature control was assumed, with a regulation efficiency of 98%. The emission efficiency for the direct expansion air conditioning units for space cooling was considered equal to 97%, with zone regulation efficiency of 97%.

#### 3.2 Simulations of the Hydronic Network

NeMo is a code written in MATLAB that, given the supply temperatures and users' flow rates, makes it possible to calculate flow rates, pressures, and temperatures in a thermal network.

The network is represented by a set of nodes and oriented branches, and an adjacency matrix determines their mutual connections.

The velocity of the heat carrier fluid is considered uniform in the radial direction (one-dimensional model) and does not depend on the temperature distribution. Therefore, the mass flow rates on the branches and pressures on the nodes of the network can be calculated in a first step, and used as inputs to find temperatures on the nodes. The heat transfer in the radial direction considers the convection between the heat carrier fluid and the inner pipe surface, the pipe's thermal insulation, and the thermal resistance of the surrounding ground. Due to the incompressible nature of the heat carrier fluid, the hydraulic problem can be described using only two equations: the continuity and the momentum equations. NeMo solves these equations using the SIM-PLE method. The heat propagation in the network is then described by the energy balance performed on the water volume of the heat carrier fluid around the network nodes.

NeMo can solve the transient heat propagation problem either with MATLAB's ODE solver or by the Gauss elimination method after linearizing the system of Equations (one for each node). A schematic of the hydronic network simulated with NeMo is shown in Fig. 3.



Fig. 3 – Topology of the supply network

#### 3.3 Economic Parameters

The results of the techno-economic analysis of the proposed building renovation depend on the cost assumptions on the initial investment and the energy prices used to calculate the operating costs. The investment costs were computed considering the costs related to the installation of the thermal insulation layer on the building envelope and the costs associated with the retrofit of the HVAC system. The operating costs depend on the energy carrier used in the installed energy system and its efficiency. The electrical energy cost was assumed to be equal to 0.24 EUR/kWh (ARERA, 2021), while for natural gas, the cost is equal to 0.814 EUR/Nm<sup>3</sup> (ARERA, 2021).

#### 3.4 Key Performance Indicators

To characterize the energy performance of the retrofit solutions, the energy efficiency class of the building was defined using Edilclima. The renewable and non-renewable fractions of the primary energy consumption were calculated for both proposed retrofit scenarios. Concerning electrical energy as the energy carrier, a conversion factor applied to the final electrical energy of 0.47 was assumed to calculate the renewable ratio and 1.95 for the non-renewable part. In addition, the thermal energy extracted from the ground by the heat pump operating in heating mode is considered renewable (groundwater is considered the energy vector). The conversion factor (non-renewable) for natural gas is 1.05. The CO<sub>2</sub> emission factor for natural gas is assumed to be equal to 0.202 kgco2/kWh (IPCC, 2006), while the emission factor for electrical energy is assumed to

be 0.260 kgco2/kWh (ISPRA, 2021).

## 4. Results

This section presents the analysis of the retrofit solutions with water-to-water heat pumps and the solution with condensing boilers and direct expansion air conditioning. Both solutions include external wall insulation.

## 4.1 Building Loads

The annual thermal energy loads per apartment for space heating, cooling, and DHW production are reported in Fig. 4. The yearly overall demand for space heating for the multi-family house is 84.17 MWh, while the heat demand for DHW production is 54.14 MWh, and the cooling demand is 63.2 MWh.



Fig. 4 – Annual thermal energy demand of the insulated building for heating, cooling, and domestic hot water production

The application of the emission, distribution, and regulation efficiency reported in Section 2.1 allows us to calculate the apartments' final thermal energy demand. The total annual final thermal energy is 90.4 MWh for heating and 67.9 MWh for cooling. Concerning the retrofit solution with water-to-water heat pumps, Fig. 5 shows the electrical energy demand related to heating, cooling, DHW production, and the auxiliaries (circulators) per apartment. The annual electricity consumption of the building, calculated considering the heat pumps operating at full load, amounts to 55.4 MWh, 23% of which is related to DHW production, 35% to heating, 26% to cooling, and 16% to the circulators.

On the other hand, concerning the retrofit solution with condensing boilers and direct expansion air conditioning, Fig. 6 shows the estimated electrical and gas consumption per apartment and year. The total gas consumption is 14434 Nm<sup>3</sup>, while the electrical consumption is 15.4 MWh.



Fig. 5 – Annual electrical energy consumption for the water-to-water heat pump solution



Fig. 6 – Annual electrical energy and natural gas consumption for the condensing boiler and direct expansion air conditioning solution

#### 4.2 Hydronic Network

Thanks to the hydronic network model, it is possible to calculate the return temperature and water flow rate to the heat exchanger and, therefore, the total thermal power exchanged with the aquifer. The simulation was carried out for 365 days with a timestep of 10 minutes. Fig. 7 shows the difference between the supply and return water temperature, at the load side, during a cold winter week. The temperature difference at the heat exchanger is around 7°C during the day, when most of the water-to-water heat pumps are on. The minima refer to the timesteps in which the demand for heating or domestic hot water is low, generally occurring at night. In addition, Fig. 7 shows the thermal power supplied to the hydronic circuit: the peaks typically occur during the morning due to the simultaneous demand of space heating and DHW and correspond to
a higher circulating water flow rate. In the same way, Fig. 8 shows the temperature difference between supply and return lines and the corresponding thermal power exchanged at the heat exchanger during a warm summer week. At night, the thermal power related to the DHW demand is close to zero. In the early morning, the DHW demand is higher than the cooling demand: a positive peak in thermal power and temperature difference can be seen because the water temperature in the supply pipe is higher than in the return. During the afternoon, the cooling demand increases, and so does the return water temperature.



Fig. 7 – Temperature difference and thermal power exchanged at the heat exchanger during a winter week



Fig. 8 – Temperature difference and thermal power exchanged at the heat exchanger during a summer week

#### 4.3 Economic Analysis

#### 4.3.1 Investment costs

The estimated investment costs for the solution with water-to-water heat pumps, summarized in Table 3, involve the cost of piping at the source side of the heat exchanger, the heat exchanger, the circulators, the manifolds, the costs related to the installation of the extraction well and the costs associated with the insulation of the envelope.

The overall cost on the source side of the heat exchanger is mainly related to the pipes' length and diameter, as well as the installation costs for the pipes trench and other construction works. Two heat exchangers were considered, installed in parallel for safety reasons, whose costs include the installation costs and the cost of the ancillary components like valves and pipe fittings. The extraction well cost includes drilling, installing piping and filters, cementation, chemical analysis of the groundwater, etc. The costs for the thermal insulation of the envelope include the interventions presented in paragraph 1.2.

Table 3 – Investment costs for the solution with heat pumps.

Intervention	Cost [EUR]
External walls insulation	600,300 (83.6%)
Source side piping	60,384 (8.4%)
Extraction well	22,000 (3.1%)
Heat exchanger	14,750 (2.1%)
Groundwater pump	12,234 (1.7%)
Circulator	7,322 (1.0%)
Manifold	1,000 (0.1%)
Total	717,990

Considering the installation of the water-to-water heat pumps, each apartment owner is supposed to cover the costs for the decentralized heat pump (overall cost of 8,054 EUR for the Type 1 heat pump and 7,952 EUR for the Type 2 heat pump), the substitution of the radiators with fan coils (around 1,000 EUR each), piping (150 EUR/m). The related cost for a single apartment ranges from around 15,000 EUR for the apartments with only three fan coils and a surface of 36 m<sup>2</sup> to around 37,600 EUR for the flats with 14 fan coils and a surface of 218 m<sup>2</sup>. The total cost of the proposed retrofit solution amounts to 1,301,350 EUR, which, considering the apartments' heated floor area, is 521 EUR/m<sup>2</sup>.

On the other hand, the overall cost of replacing the old traditional boiler with the new condensing boiler is estimated to be 4,000 EUR. If the installation of the thermal insulation is considered, the costs of this retrofit scenario amount to 704,300 EUR, i.e., 282 EUR/m<sup>2</sup>.

#### 4.3.2 Operating costs

For the heat pump solution, the total electricity consumption brings the operating costs to 13,289 EUR/year. Therefore, the average operating cost per flat is 511 EUR/year. Considering the total natural gas and electrical energy consumption for the scenario with the condensing boilers, the annual operating costs amount to 15,445 EUR. For each apartment, the mean operating cost is 594 EUR/year. Fig. 9 presents an overview of the operating costs compared to the original case study. Overall, the operating costs are reduced to 40% with the water-towater heat pump solution and 47% with the condensing boiler and direct expansion air conditioning system solution.



Fig. 9 – Operating cost for the original case, retrofit with heat pumps, with condensing boilers and direct expansion air cond

# 4.4 System's Performance

#### 4.4.1 Energy performance class

The analysis performed with Edilclima software showed that the building's efficiency class E and the primary energy consumption was 169 kWh/( $m^2$  y) before the retrofit. If the same energy system (traditional boilers) is considered, combined with the installation of the external wall insulation, the efficiency class is enhanced to B (88 kWh/( $m^2$  y)).

On the other hand, the combination of the external wall insulation and installation of decentralized condensation boilers, with heating capacity ranging from 26 kW to 35 kW and efficiency equal to 94%, leads to an energy efficiency class A1 (72 kWh/(m<sup>2</sup>y)). The retrofit scenario with envelope insulation and water-to-water heat pumps leads to the efficiency class A3, with 47 kWh/(m<sup>2</sup>y).

#### 4.4.2 Primary energy consumption

Table 4 shows the specific primary energy consumption related to the retrofit solutions with water-to-water heat pumps and condensing boilers. Using water-to-water heat pump systems leads to a higher renewable share, up to 55%, compared to the condensing boilers (less than 4%). This is due to the high renewable share in heating and DHW production of the water-to-water heat pump, which reaches 66%.

Table 4 – Specific renewable, non-renewable, and total primary energy (PE)

	PE ren	PE non-ren	PE tot
	kWh/(m² y)	kWh/(m² y)	kWh/(m² y)
W-to-W heat pumps	53.5	43.2	96.7
Heating	30.2	14.9	45.1
Cooling	2.8	11.4	14.1
DHW	18.9	10.1	29.0
Auxiliaries	1.6	6.8	8.4
Condensing boiler	2.9	72.3	75.2
Heating	0.3	43.9	44.2
Cooling	2.5	10.5	13.0
DHW	0.1	17.9	18.0

#### 4.4.3 CO<sub>2</sub> emissions

The retrofit solution with water-to-water heat pumps produces 14.13 tons/year of CO<sub>2</sub>, only 42% compared to the solution with condensing boilers and direct expansion air conditioning which produces 33.07 tons/year of CO<sub>2</sub>.

# 5. Conclusions

This paper investigated a retrofit solution for a multi-family building near Milan, including the installation of a groundwater heat pump coupled with fan coils and thermal insulation of external walls. The hydraulic network was sized and simulated with a dynamic model. The solution with water-towater heat pumps was compared with a benchmark retrofit solution based on individual gas boilers, in terms of investment and operating costs, energy efficiency class, primary energy consumption, and CO<sub>2</sub> emissions. The estimated installation costs for the solution with heat pumps lead to a mean value of 521 EUR/m<sup>2</sup>, including the envelope retrofit, the substitution of the radiators with the fan coils, the extraction wells, the heat pumps and the whole distribution system. The investment cost for the second retrofit scenario is around 282 EUR/m<sup>2</sup>.

Correspondingly, the average annual operating costs for the end users amount to 511 EUR/apartment for the first solution and 594 EUR/apartment for the second one. This means that the solution with water-to-water heat pumps can be competitive if incentives are applied to cut the investment costs for the apartment owners.

The results show that the existing case study (energy efficiency class E) reaches class A3 with the water-to-water heat pumps solution and class A1 with the solution with condensing boilers and direct expansion air conditioning. This achievement is mainly related to the high renewable share in primary energy of the water-to-water heat pump solution (55%) compared to the one with condensing boilers (4%). Overall, the heat pump solution reduces CO<sub>2</sub> emissions to 42% compared to the condensing boilers solution, showing that the ground-water loop can be a valuable technology for multifamily buildings to decrease the environmental impact of the heating and cooling systems.

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# The Urban-Scaled EnergyPlus Simulation Using Korean GIS to Aid Development of Energy Normalization for Shading Effect

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#### Abstract

It is widely recognized that the shading effect between buildings significantly contributes to cooling and heating loads, independent of individual building performance. This necessitates energy normalization for the shading effect to ensure a more objective building performance assessment, requiring an urban database containing the geometric interactions between buildings for analysis. However, in the real world, obtaining data about shade and solar radiation reduced or generated by adjacent buildings is challenging. Such data are crucial for energy normalization concerning the shading effect, and it necessitates the introduction of scientific tools to complement them. With this in mind, the authors suggest the urban-scaled building shading simulation based on the geographic information system (GIS) to address the data acquisition challenge. The GIS serves as an urban database, integrating diverse city information such as buildings, energy, finance, demographics, and transportation, with spatial information as its core, based on a coordinate system. This study utilized the GIS called "Road Name Address System", managed by the Korean government to foster the address-based industry, as the primary input data. EnergyPlus, the whole building energy simulation, was employed as the virtual experiment tool about the geometric interactions between buildings and to quantify the shading and solar radiation on building surfaces. In this paper, the authors discuss how the database of shading and solar irradiation on building surfaces was constructed based on the urban-scaled EnergyPlus simulation and anticipate that the data augmentation with the virtual experiments will contribute to a better explanation of the macroscopic dynamic characteristics of buildings.

#### 1. Introduction

As is widely known, the shading effect significantly impacts the heating and cooling loads of buildings. This effect is independent of the building energy system design, and the energy normalization for the geometric interactions between buildings is reguired to enable objective decision-making in building energy benchmarking. However, currently, the energy benchmarking problems are primarily focused on individual buildings, and there is less discussion on energy normalization for the effects of building groups. Furthermore, the authors believe that the lack of an urban-scaled database available in the development of the energy normalization indicator for the shading effect is one of these barriers. Meanwhile, essential data such as shade and solar irradiation projected on the building surfaces are difficult to collect through measurements in the real world, and virtual experiments can be useful in the acquisition of the inaccessible information. In this context, the authors suggest the construction process of the database of the projected shade and solar irradiation on the building surfaces using EnergyPlus simulation (Crawley et al., 2001) and geographic information system (GIS). The EnergyPlus is the dynamic building energy simulation tool that includes a shading module, which calculates the shade and solar irradiation incident on the building's surfaces considering interactions between buildings. The GIS serves as an urban database, integrating diverse city information with spatial information as its core. In this study, the Road Name Address System, a type of Korean GIS, was utilized, and urban-scaled virtual experiments linked with EnergyPlus were conducted to collect the shading and solar radiation data necessary for the database

construction. Further, the authors wish to discuss that, beyond being a tool for performance evaluation, the urban-scaled building simulation is useful as the data augmentation tool for energy normalization concerning the shading effects in cities. Furthermore, the purpose of this paper is not to discuss the functional advantages of the research findings in comparison with specific packages, but rather to share the data augmentation process from an academic perspective, thereby contributing to the advancement of building energy academia. Fig. 1 illustrates the entire process of this study, and the following items will be addressed in detail: (1) Korean GIS and weather data used in this study, (2) organization of IDF (EnergyPlus model file) generator, (3) database construction.



Fig. 1 - Overall process of this study

# 2. Road Name Address System (GIS)

The Road Name Address System is the GIS developed by the Korean government to promote the address-based industry and adopts the shapefile format (SHP) widely used in the GIS industry. The SHP has a matrix form, where each row and column represents the individual building and the building's attribute, respectively, and has 31 columns (Table 1), including the primary keys of GIS such as 'SIG\_CD' and 'BUL\_MAN\_NO', the spatial attributes including the address, the building polygon (2D), the number of floors. Note that concatenating the address-related items in Table 1 in order yields a 19digit parcel number (PNU) mainly used to identify parcels in Korea, and this study also utilizes it for building identification.

Table 1 - Road Name Address System (\*: primary key of this GIS)

Category	Column (Description)
building geometry	geometry (polygon)
# of floors	GRO_FLO_CO (above-ground), UND_FLO_CO (basement)
serial number	<u>BUL_MAN_NO</u> (building)*, EQB_MAN_SN (building group) RDS_MAN_NO, BSI_INT_SN (road)
building name	POS_BUL_NM, BULD_NM, BULD_NM_DC, EQB_ENG_NM
building type	BDTYP_CD
building address	<u>SIG_CD</u> (district code)*, EMD_CD, LI_CD, MNTN_YN, LNBR_MNNM, LNBR_SLNO
road name address	RN_CD, RDS_SID_CD
postal code	BSI_ZON_NO (state basic dis- trict system),
main building and an- nex classification	BULD_MNNM (main number), BULD_SLNO (sub number) BUL_DPN_SE (indicator)
data history manage- ment	OPERT_DE< MVMN_DE, MVMN_RESN, MVMN_RES_CD, NTFC_DE

In order to perform the 3D modelling through the EnergyPlus scheme, it is necessary to know the coordinate system rules of the GIS, such as the coordinate reference system (CRS) that defines the reference position of the GIS, the ellipsoid (Fig. 2) that approximates the shape of the Earth with a mathematical form, and the projected coordinate system that defines how to transform the 3D coordinate information (XYZ coordinates) into the plane coordinate information (XY coordinates). In case of the Road Name Address System, the International Terrestrial Reference Frame (ITRF) was first adopted as the CRS. This is the 3D coordinate system whose origin, x-axis, and y-axis correspond to the center of mass of the Earth, the direction where the Greenwich meridian intersects with the equator, and the direction of 90 degrees east longitude, respectively.

Second, the ellipsoid is the Geodetic Reference System 1980 corresponding to the global geodesic system. This has a semi-major axis of 6,378 km, and an eccentricity of 0.00818, respectively, and the ellipsoidal coordinates (latitude  $\varphi$ , longitude  $\lambda$ ) can be transformed to the 3D Cartesian coordinates (XYZ coordinates) with the trigonometric functions.



Fig. 2 - Ellipsoidal coordinate system

Third, the universal transverse Mercator (UTM) projection (Fig. 3), a type of cylindrical projection method, was applied as projected coordinate system. For reference, distortion needs to be reduced in the process of projecting coordinates from ellipsoid to cylinder, and for this purpose, the approach of projecting zone-by-zone was adopted instead of projecting the entire ellipsoid at once. And the origin of each zone is usually adopted by the equator, where the higher or lower latitude can increase the degree of projection distortion, so in this GIS, the specific origin (latitude: 38°, longitude: 127.5°, Gapyeonggun, Geongggi.do) adjusted to the Korea was applied. In this study, 547,615 buildings in Seoul (25 districts), Korea, were considered as the subjects of EnergyPlus modeling and simulation, and Fig. 4 shows them with the map.



Fig. 3 – Universal transverse Mercator projection



Fig. 4 – Target buildings in this study

## 3. Weather Data (Solar Radiation)

To perform urban scaled shading simulations, it is required to prepare weather data files with specified format, EnergyPlus Weather format (EPW), in advance. Especially, it is more useful to secure both direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) decomposed results rather than only the global horizontal irradiation (GHI) when calculating the shade and solar radiation introduced to each exterior wall of the building accurately. In this regard, the National Solar Radiation Data Base (NSRDB, Fig. 5) (Sengupta et al, 2018) developed by US National Renewable Energy Laboratory (NREL), which deals with decomposed solar irradiation, was used as raw data. The NSRDB was constructed based on the direct insolation simulation code (DISC) model (Maxwell, 1987) as a theoretical background and provides DNI and DHI data at the international scale, including the United States. In this study, the NSRDB data corresponding to Seoul city (latitude: 37.58°, longitude: 126.97°) were used , and data corresponding to Incheon city (latitude: 37.48°, longitude: 126.63°) were applied only for buildings belonging to Ogok-dong, Gangseo-gu, Seoul in consideration of proximity to the weather station.



Fig. 5 -DNI (blue) and DHI (red) data of NSRDB for Seoul city

# 4. IDF Generator (Python Language Used)

To automatically generate large amounts of EnergyPlus model files (IDFs) from SHP files, the authors made the program for IDF generation (Fig. 6). This program was written based on Python 3 language and contains the extraction of building polygon information, the conversion of geometric information from GIS to EnergyPlus, search for adjacent buildings, and generation of IDF objects. In this program, the following open-source libraries were used for tasks such as SHP file processing, polygon processing, coordinate system, plane modification, and writing the IDF: (1) GeoPandas (Jordahl et al., 2021) for SHP file processing, (2) Shapely (Gillies et al., 2023) for polygon control, (3) Pyproj (Snow et al., 2020) for coordinate system control, (4) tripy (Bolgert, 2024) for pre-processing of concave polygons for EnergyPlus modeling, (5) Eppy (Philip et al., 2024) for IDF writing. The following sections will cover the main functions of the IDF generator.



Fig. 6 - Python program used in this study

## 4.1 Model Configuration

Considering that more than 100,000 dynamic simulations were required in this study, the models were made to reflect only what was necessary to obtain shading data of building surfaces. Firstly, only one zone was placed on each floor, and windows were not placed. Further, internal heat loads (people, lighting, equipment) and the HVAC system were not considered in modeling since this study only focuses on the shades and solar irradiation projected on the building surfaces. The authors set the version of EnergyPlus models to 9.0 for compatibility with higher and lower versions, and the save interval of the simulation results was set to the month. In future work, the authors will discuss the impact of the save interval on the development of the shading indicator, and three output variables related to the solar irradiation and the shade projected to the building surfaces were applied as follows.

- Surface Outside Face Sunlit Fraction (0-1, the fraction of building surface area where beam solar radiation reaches)
- Surface Outside Face Incident Solar Radiation Rate per Area (W/m<sup>2</sup>)
- Surface Outside Face Incident Beam Solar Radiation (W/m<sup>2</sup>)

#### 4.2 Triangulation for Concave Polygons

Based on the EnergyPlus 9.0 version, polygon clipping algorithms such as the Weiler-Atherton (Weiler et al., 1977) and the Sutherland-Hodgman (Sutherland et al., 1974) are utilized to prevent redundant calculations of shades reaching the building surfaces. However, these polygon clipping algorithms only work precisely on convex planes, and consequently, modeling the concave planes is not recommended in the EnergyPlus scheme. For this reason, the authors introduced the process of splitting the original GIS polygon into n triangles so that no concave plane exists. In the realm of computer graphics, a variety of plane triangulation algorithms have been introduced. Among them, this study utilizes the Ear-clipping algorithm (Eberly, 2008; Fig. 7), renowned for its versatile application across diverse plane types. This clipping algorithm sequentially searches the ear (p(i) in Fig. 7), the vertex that makes the polygon concave since the angle between two edges is less than 180 degrees, and every time the ear is found, the polygonal segmentation is carried out.



Fig. 7 – Polygon triangulation by Ear-clipping algorithm

## 4.3 Modelling of Shading Objects

The buffer analysis is often used in GIS work to assess proximity, accessibility, or environmental impact of features such as roads, rivers, or land parcels. The buffer corresponds to a zone (e.g., red colored area in Fig. 8 (a), applied distance: 5 m) of a specified distance around a geographic object such as each node of the polygon or the specific point on the map. Conducting buffer analysis on building footprints allows us to obtain expanded areas while maintaining the shape of the original polygon. According to this context, the buffer analysis with 50 m extension distance (Fig. 8 (b)) was performed in this study to derive the shading area of the target building, and the buildings located within the generated area were regarded as shading objects (i.e. neighborhood buildings). And the shading objects were reflected in the EnergyPlus model by applying the shading related class (shading:building:detailed, Fig. 8 (c)).



Fig. 8 - Buffer analysis (upper) shading modeling (middle & lower)

#### 4.4 IDF Generation and Simulation

The GeoPandas library was used to read the SHP file for Seoul city, and the whole GIS data was divided into 25 subsets based on district of Seoul city. In addition, each separate GIS data was exported as a binary file (Parquet file), and the program was organized to convert the buildings' information within the binarized SHP file into IDFs based on the

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   | Radiation Rate per   | Area [W/m2]  | Monthly)   | 18.687   | 24.478  | 32.245  
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  | 309   | 19.375   | 16.702  | 30.65   
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   | ((Monthly)   |  |  | 0.004  | 0.013   | 0.026   
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   | 266.85   | W.   |
| 04 1156013200100970  | JUAW DOR  | 2  | 1 Surface Outsid   
   
  | e Face Incident Solar  
   
   | Radiation Rate per-  | Area (W/m2)  | Monthly)   | 14.313   | 19.679  | 27.118  
  | 33.5   |   
  | 785   | 15,548   | 13.283  | 65.09   
   | 266.85   | w  |
| 04 1156013200100970  | WALL DO   | 2  | 1 Surface Outsid   
   
  | r Face Incident Beam   
   
   | Solar Radiation Rel  | te per Area [V   | //m2](Monthly)   | 0.069  | 0.564   | 1.957   
  | 22   |   
  | 120   | 0,014  | 0.542   | 65.09   
   | 266.85   | W.   |
| 04 1156013200100970  | JIAW DOD  | 3  | 1 Surface Outsid   
   
  | Face Sunlit Fraction   
   
   | (Monthly)  |  |  | 0.039  | 0.069   | 0.136   
  | 0.1  |   
  | 690   | 0.054  | 0.033   | 13.69   
   | 174  | 5  |
| 04 1156013200100970  | MALL 00   | 3  | 1 Surface Outsid   
   
  | Face Incident Solar  
   
   | Radiation Rate per   | Area (W/m2)  | Monthly)   | 33,451   | \$1.828   | 80.638  
  | 88.5   |   
  | 677   | 41.128   | 27.369  | 13.69   
   | 174  | S  |
| 04 1156013200100970  | JIAW DO   | 3  | 1 Surface Outsid   
   
  | P Face incident Beam   
   
   | Solar Radiation Rat  | te per Anea (V   | (/m2)(Monshiy)   | 14.893   | 25.771  | 42.511  
  | -64.3  |   
  | 721   | 20.968   | 11.232  | t3.69   
   | 174  | 5  |
| 04 1156013200100970  | NOO WALL  | 4  | 1 Surface Outsid   
   
  | e Face Sunlit Fraction   
   
   | (Monthly)  |  |  | 0.001  | 0.010   | 0.053   
  | 0.0  |   
  | 021   | 0.000  | 0.000   | 3.92  
   | 268.26   | W  |
| 04 1156013200100970  | JIAW DO   | 4  | 1 Surface Outsid   
   
  | e Face Incident Solar  
   
   | Radiation Rate per   | Area (W/m2)  | Monthly)   | 15.585   | 23.697  | 45.497  
  | 69.1   |   
  | 352   | 16.510   | 13.580  | 3.92  
   | 268.26   | W  |
| 04 1156013200100970  | JUAW 000  | -4   | 1 Surface Outsid   
   
  | P Face Incident Beam   
   
   | Solar Radiation Rat  | te per Area (V   | I/m2](Monthly)   | 0.227  | 2.688   | 15.426  
  | 29.4   |   
  | 175   | 0.149  | 0.000   | 3.92  
   | 268.26   | w  |
| 04 1156013200100970  | MALL DOG  | 5  | 1 Surface Outsid   
   
  | e Face Sunlit Fraction   
   
   | ([(Monthly)  |  |  | 0.008  | 0.022   | 0.077   
  | 0.1  |   
  | 032   | 0.013  | 0.005   | 22.85   
   | 160.21   | 5  |
| 04 1156013200100970  | WALL OD   | 5  | 1 Surface Outsid   
   
  | Face Incident Solar  
   
   | Radiation Rate per   | Area [W/m2]  | Monthly)   | 20.510   | 33.856  | 54.661  
  | 80.7   |   
  | 784   | 24.925   | 16.682  | 22.85   
   | 180.21   | 5  |
| 04 1156013200100970  | JJAW DOG  | 5  | 1 Surface Outsid   
   
  | e Face Incident Beam   
   
   | Solar Radiation Rat  | te per Area (V   | (/m21(Monthly)   | 4.925  | .11.991   | 23.058  
  | 39.5   | 1   
  | 187   | 7.984  | 3.105   | 22.85   
   | 180.21   | 5  |
| 04 1156013200100970  | WALL 00   | 6  | 1 Surface Outsid   
   
  | Face Sunlit Fraction   
   
   | n (Monthly)  |  |  | 0.000  | 0.000   | 0.001   
  | 0.0  | $\sim$  
  | 100   | 0.000  | 0.000   | 4.21  
   | 84,76  | E  |
| 04 1156013200100970  | WALL      | -6   | 1 Surface Outsid   
   
  | e Face Incident Solar  
   
   | Radiation Rate per   | Area (W/m2)  | Monthly)   | 13.464   | 17.999  | 23.574  
  | 35.6   |   
  | 62.1  | 14.679   | 11.878  | A.71  
   | 84.76  | 1  |
| 04 1156013200100970  | JIAW DO   | 6  | 1 Surface Outsid   
   
  | Face Incident Beam   
   
   | Solar Radiation Rat  | te per Area [V   | (/m2)(Monthly)   | 0.000  | 0.000   | 0,169   
  | 5,0  |   
  | 101   | 0.000  | 0.000   | 4,71  
   | 84,76  | £.   |
| 04 1156013200100970  | MALL 000  | 7  | 1 Surface Outsid   
   
  | e Face Sunlit Fraction   
   
   | n El(Monthly)  |  |  | 0.000  | 0.005   | 0.035   
  | 0.0  |   
  | .020  | 0.000  | 0.000   | 6.03  
   | 177.81   | 5  |
| 04 1156013200100970  | WALL 00   | 7  | T Surface Outsid   
   
  | e Face Incident Solar  
   
   | Radiation Rate per   | Acea [W/m2]  | Monthly)   | 13.805   | 20.300  | 35.127  
  | 54.1   |   
  | 674   | 15,037   | 12.193  | 6.03  
   | 177.31   | 5  |
| 04 1156013200100970  | JJAW WALL | 7  | 1 Surface Outsid   
   
  | e Face Incident Beam   
   
   | Solar Radiation Rat  | te per Azea (V   | I/m2][Monthly]   | 0.000  | 1.514   | 8.636   
  | .19.1  |   
  | .415  | 0.045  | 0.000   | 6.03  
   | 177.31   | 5  |
| 04 1156013200100970  | MALL OOK  | 8  | 1 Surface Outsid   
   
  | e Face Sunlit Fraction   
   
   | h [[(Monthly)  |  |  | 0.001  | 0.007   | 0.029   
  | 0.0  |   
  | 020   | 0.005  | 0.000   | 19.08   
   | 83.99  | E  |
| 04 1156013200100970  | WALL:     | 8  | 1 Surface Outsid   
   
  | e Face Incident Solar  
   
   | Radiation Rate per   | Area [W/m2]  | Monithly)  | 13.414   | 19.441  | 30.192  
  | 40.5   |   
  | 789   | 15.617   | .11.710   | 19.08   
   | 83.99  | E  |
| 04 1156013200100970  | WALL OD   | 8  | 1 Surface Outsid   
   
  | Face Incident Beam   
   
   | Solar Radiation Rat  | te per Area (V   | (7m2](Monshly)   | 0.161  | 1.444   | 5,771   
  | 97   |   
  | 668   | 1.017  | 0.043   | 19.08   
   | 83.99  | E  |
| 04 1156013200100970  | MALL DO   | 9  | 1 Surface Outsid   
   
  | e Face Sunlit Fractice   
   
   | 1 E(Monthly)   |  |  | 0.000  | 0.000   | 0.000   
  | 0.0  |   
  | 000   | 0.000  | 0.000   | 5   
   | 359.5  | N  |
| 04 1156013200100970  | NDO WALL  | 9  | 1 Surface Outsid   
   
  | e Face Incident Solar  
   
   | Radiation Rate per   | Area [W/m2]  | Monthly)   | 14.900   | 19.783  | 25,778  
  | 10   |   
  | 143   | 15,995   | 13.201  | 5   
   | 359.5  | N  |
| 04 1156013200100970  | NDQ WALL  | 9  | 1 Surface Outsid   
   
  | e Face Incident Beam   
   
   | Solar Radiation Rat  | ie per Area (V   | i/m23(Monthly)   | 0.000  | 0.000   | 0,000   
  | 0.0  |   
  | 000   | 0.000  | 0.000   | .5  
   | 359.5  | N  |
| 04 1156013200100970  | NDO WALL  | 10   | 1 Surface Outsid   
   
  | e Face Suniit Fraction   
   
   | (Monthly)  |  |  | 0.033  | 0.025   | 0.016   
  | 0,0  |   
  | 039   | 0.041  | 0.037   | 49.7  
   | 80,09  | E  |
| 04 1156013200100970  | NOO TWALL | 10   | 1 Surface Outsid   
   
  | P Face Incident Solar  
   
   | Radiation Rate per   | Area (W/m2)  | Monthly)   | 18.876   | 23.588  | 28.087  
  | 34.5   |   
  | 200   | 19.039   | 16:157  | 49.7  
   | 80.09  | 1  |
| 04 1156013200100970  | ADO TWALL | 10   | 1 Surface Outsid   
   
  | e Face Incident Beam   
   
   | Solar Radiation Rat  | te per Area [V   | (/m2)(Monthly)   | 3.587  | 3.475   | 2189  
  | 2.1  |   
  | 833   | 2.845  | 2.703   | 49.7  
   | 80.09  | 1  |
| 05 1156013200100970  | LIAWI 008 | 1  | 1 Surface Outsid   
   
  | e Face Sunlit Fraction   
   
   | (Monthly)  |  |  | 0.058  | 0.063   | 0.054   
  | 0.0  |   
  | .068  | 0.059  | 0.035   | 27.28   
   | 69.09  | E  |
| 051 1156013200100970 | ALL WALL  | 1  | 1 Surface Outsid   
   
  | e Face Incident Solar  
   
   | Radiation Rate per   | Area [W/m2]  | Monthly)   | 31,437   | 40.905  | 43.175  
  | - 52.5   |   
  | 484   | 35,404   | 23.096  | 27.28   
   | 69,09  | 1  |
|                      |           | Image: sector | 1160-1260/097000         WAL         1           1160-1260/097000         WAL         2           1160-1260/097000         WAL         2 <th>11160         <td< th=""><th>01         1550112000099000         MAL         1         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission</th><th>011000112000007000         WALL         01         Index Counter Face Summer Face Summer Summers           01100012000070000         WALL         01         Index Counter Face Summer Summers           01100012000070000         WALL         01         Index Counter Face Summers           01100012000070000         WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           011000120000700         WALL         01         Index Counter Face Summers           011000120007000         WALL         01         Index Counter Face Summers           011000120007000         WALL         01         Index Counter Face Summers           01100012001007000         WALL</th><th>01         11660 10000000000         Nut.         1         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         1         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south rate information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south rate information large and south)           01         11660 1000000000         Nut.         2         5         5         5         5         5         7         5         5         5         5         5         5         5         7         5</th><th>11460112000007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         2         Suffer Quarks Fraz Transmit Transmit Transmit Monthly           1146011200007000         WALL         2         Suffer Quarks Fraz Transmit Tr</th><th>01         114601/2010/097000         Weil,         01         115601/2010/097000         Weil,         01         115601/2010/207000         Weil,         01         115601/2010/207000</th><th>01         11660/30100000000         Walk         1         0         0.000         <td< th=""><th>01         1160/1200/097000         WALL         01         150/070         0000         0.000</th><th>01         11460 12000097000         Will,         01         050000         050000         050000         050000         050000         050000         050000         0500000         0500000         0500000         0500000         0500000         05000000         050000000000         0500000000000000000000000000000000000</th><th>Normality         Open Control         Open Contro         Open Control         Open Control</th><th>M1         M1         L         Suffic Conduct Frag South Real Display         0.000         6.000         <th< th=""><th>01         11460 12000070000         Mul.L         11         11         11460 1200007000         Mul.L         11         11460 1200070700         Mul.L</th><th>M         THEOD DECOMPOSITION         Mul.         1         Subscription         Subscr</th><th>01         11461/1200007000         Mull.         11         11         11461/120007000         0100         6.000</th><th>01         11460 12000000000         VAL         1         0 Sume Output         0.000</th></th<></th></td<></th></td<></th> | 11160         11160 <td< th=""><th>01         1550112000099000         MAL         1         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000  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     WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           011000120000700         WALL         01         Index Counter Face Summers           011000120007000         WALL         01         Index Counter Face Summers           011000120007000         WALL         01         Index Counter Face Summers           01100012001007000         WALL</th><th>01         11660 10000000000         Nut.         1         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         1         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south rate information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south rate information large and south)           01         11660 1000000000         Nut.         2         5         5         5         5         5         7         5         5         5         5         5         5         5         7         5</th><th>11460112000007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         2         Suffer Quarks Fraz Transmit Transmit Transmit Monthly           1146011200007000         WALL         2         Suffer Quarks Fraz Transmit Tr</th><th>01         114601/2010/097000         Weil,         01         115601/2010/097000         Weil,         01         115601/2010/207000         Weil,         01         115601/2010/207000</th><th>01         11660/30100000000         Walk         1         0         0.000         <td< th=""><th>01         1160/1200/097000         WALL         01         150/070         0000         0.000</th><th>01         11460 12000097000         Will,         01         050000         050000         050000         050000         050000         050000         050000         0500000         0500000         0500000         0500000         0500000         05000000         050000000000         0500000000000000000000000000000000000</th><th>Normality         Open Control         Open Contro         Open Control         Open Control</th><th>M1         M1         L         Suffic Conduct Frag South Real Display         0.000         6.000         <th< th=""><th>01         11460 12000070000         Mul.L         11         11         11460 1200007000         Mul.L         11         11460 1200070700         Mul.L</th><th>M         THEOD DECOMPOSITION         Mul.         1         Subscription         Subscr</th><th>01         11461/1200007000         Mull.         11         11         11461/120007000         0100         6.000</th><th>01         11460 12000000000         VAL         1         0 Sume Output         0.000</th></th<></th></td<></th></td<> | 01         1550112000099000         MAL         1         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         2         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission           01         155011200099000         MAL         1         Suffee Double Face Social Transmission | 011000112000007000         WALL         01         Index Counter Face Summer Face Summer Summers           01100012000070000         WALL         01         Index Counter Face Summer Summers           01100012000070000         WALL         01         Index Counter Face Summers           01100012000070000         WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           0110001200007000         WALL         01         Index Counter Face Summers           011000120000700         WALL         01         Index Counter Face Summers           011000120007000         WALL         01         Index Counter Face Summers           011000120007000         WALL         01         Index Counter Face Summers           01100012001007000         WALL | 01         11660 10000000000         Nut.         1         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         1         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south tracture (information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south rate information large and south)           01         11660 1000000000         Nut.         2         15667 Context rate south rate information large and south)           01         11660 1000000000         Nut.         2         5         5         5         5         5         7         5         5         5         5         5         5         5         7         5 | 11460112000007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         1         Suffer Quarks Fraz Suff Transmit Transmit Monthly           1146011200007000         WALL         2         Suffer Quarks Fraz Transmit Transmit Transmit Monthly           1146011200007000         WALL         2         Suffer Quarks Fraz Transmit Tr | 01         114601/2010/097000         Weil,         01         115601/2010/097000         Weil,         01         115601/2010/207000         Weil,         01         115601/2010/207000 | 01         11660/30100000000         Walk         1         0         0.000 <td< th=""><th>01         1160/1200/097000         WALL         01         150/070         0000         0.000</th><th>01         11460 12000097000         Will,         01         050000         050000         050000         050000         050000         050000         050000         0500000         0500000         0500000         0500000         0500000         05000000         050000000000         0500000000000000000000000000000000000</th><th>Normality         Open Control         Open Contro         Open Control         Open Control</th><th>M1         M1         L         Suffic Conduct Frag South Real Display         0.000         6.000         <th< th=""><th>01         11460 12000070000         Mul.L         11         11         11460 1200007000         Mul.L         11         11460 1200070700         Mul.L</th><th>M         THEOD DECOMPOSITION         Mul.         1         Subscription         Subscr</th><th>01         11461/1200007000         Mull.         11         11         11461/120007000         0100         6.000</th><th>01         11460 12000000000         VAL         1         0 Sume Output         0.000</th></th<></th></td<> | 01         1160/1200/097000         WALL         01         150/070         0000         0.000 | 01         11460 12000097000         Will,         01         050000         050000         050000         050000         050000         050000         050000         0500000         0500000         0500000         0500000         0500000         05000000         050000000000         0500000000000000000000000000000000000 | Normality         Open Control         Open Contro         Open Control         Open Control | M1         M1         L         Suffic Conduct Frag South Real Display         0.000         6.000 <th< th=""><th>01         11460 12000070000         Mul.L         11         11         11460 1200007000         Mul.L         11         11460 1200070700         Mul.L</th><th>M         THEOD DECOMPOSITION         Mul.         1         Subscription         Subscr</th><th>01         11461/1200007000         Mull.         11         11         11461/120007000         0100         6.000</th><th>01         11460 12000000000         VAL         1         0 Sume Output         0.000</th></th<> | 01         11460 12000070000         Mul.L         11         11         11460 1200007000         Mul.L         11         11460 1200070700         Mul.L | M         THEOD DECOMPOSITION         Mul.         1         Subscription         Subscr | 01         11461/1200007000         Mull.         11         11         11461/120007000         0100         6.000 | 01         11460 12000000000         VAL         1         0 Sume Output         0.000 |

Fig. 9 - Database for shading and incident solar irradiation of building surfaces based on urban-scaled EnergyPlus simulation

Eppy library, script based IDF editing tool. And the coordinates of each building surface were placed to rotate counterclockwise when the plane was viewed from the outside according to the geometry rule of the EnergyPlus. Generating IDFs and EnergyPlus simulations were carried out by the district and the batch file (RunDirMulti.bat) provided by EnergyPlus was utilized for parallel simulations. It should be noted that the run period of the EnergyPlus simulation was from January 2018 to December 2019 (24 months) and the additional parser was used to extract the values of three output variables from the output files (csv format) and the information for the building surfaces' area and orientation from the summary reports file. The simulation computation time took approximately 1 day per district under the following hardware conditions, and in this study, the multi-processing was considered at the district level: AMD Ryzen Threadripper PRO 5975WX (CPU) & 128Gb RAM

## 5. Database Construction

Fig. 9 shows the database constructed in this study. Considering that it will be used to develop energy normalization index for shading caused by geometric relationships with adjacent buildings, the database was designed to integrate the following information: (1) the building identification (two primary keys of GIS, PNU), (2) the building surface identification (surface type, index and floor), (3) the simulation output type (three variables), (4) the monthly simulation result (Jan(2018) to Dec(2019), 24 months), (5) the figure information of the building surface (area and orientation). The Pandas Data-Frame, the widely used database structure in data science, was applied and the database was exported as the binary file (Parquet file), considering deployment and information reuse. Moreover, utilizing this database enables easy retrieval of ingress the shading and the solar irradiation information for buildings at specific time points, and allows the construction of building-level indicators by combining the area and the orientation information of the building surfaces. Furthermore, by utilizing the SIG CD and the BUL MAN NO, which correspond to the primary keys in the original GIS, it is possible to trace the raw data, and by using PNU, integration with other urban databases in Korea (such as building energy, social factors) is enabled. Fig. 10 visualizes the data of July 2019 for three variables using the database of Fig. 9. It illustrates the case where the indicators at the building level were calculated by taking the weighted average of the building surface areas. The brighter the color (indigo color to yellow color), the less shading occurs due to surrounding buildings. It indicates that the values of the three output variables can vary depending on the density of buildings in the area.

## 6. Conclusion

The shading and insolation entering the facade serve as fundamental information for developing shading indicators, but obtaining this through on-site measurements is challenging from the economic perspective. To overcome this, the authors suggest GIS-based virtual experiments (urban-scale shading simulations) and explain the process of information conversion between heterogeneous information (GIS, EnergyPlus). Finally, the authors show the case study that analyzes the shading effects of buildings using the shading/solar irradiation database, demonstrating that geometric interactions between buildings are appropriately reflected in the database. This study corresponds to the foundational phase for establishing shared knowledge assets regarding the shading effect, and the authors will develop the energy normalization index for buildings consideration of the following items: (1) climate change, (2) terrain geometry, (3) impact of seasons (4) correlation analysis between the shading indicator and the building energy use, (5) urban factors such as urban heat island and microclimate.



Surface Outside Face Sunlit Fraction (surface area weighted average)



Surface Outside Face Incident Solar Radiation Rate per Area (surface area weighted average)



Surface Outside Face Incident Beam Solar Radiation (surface area weighted average)

Fig. 10 – Visualization example of the constructed database

# Acknowledgement

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# Thermal Comfort and Environmental Impact in the Heating System Refurbishment of a Victorian Hall With Infrared Ceiling Panels

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#### Abstract

This study presents a holistic approach to evaluating the heating refurbishment of a historic Victorian hall in Brighton, UK, using infrared ceiling panels. While field studies have explored radiant heating ceiling panels in new constructions, limited research has investigated their application in renovating historic buildings with highly dissipative envelopes. The methodology addresses this gap and integrates perceived thermal comfort, financial feasibility, and environmental impact. The study involved a two-phase method: a thermal comfort analysis and Building Energy Simulations (BES). Results revealed that while infrared panels are easy to install, their environmental impact outweighs alternatives requiring more complex installations but offering economic returns and user satisfaction. The study provides valuable guidelines for designing and installing ceiling radiant systems in large community spaces, emphasizing comprehensive planning to achieve user comfort, energy savings, and environmental sustainability.

#### 1. Introduction

The extent of building energy consumption is widely recognized. The task of decreasing building carbon footprints is becoming increasingly urgent, while people are raising their expectations for the perceived comfort and well-being of their living spaces (Nicol & Humphreys, 2002).

Field studies have tested the efficacy of radiant heating ceiling panels in new construction (R. Li et al., 2015), but few studies tested their applicability in the renovation of historic buildings with highly dissipative envelopes, despite being identified as suitable candidates for their refurbishment (Safizadeh et al., 2018). Conventional energy efficiency technologies in new buildings can decrease energy consumption by 20-30% on average, and reduce the carbon footprint by about 16%, just by installing a smaller or cheaper HVAC system (Kneifel, 2010). Moreover, in office buildings, the radiant ceiling panel system can create a more comfortable environment than conventional systems (Imanari et al., 1999; Bojić et al., 2013).

The study advocates for innovative methodologies in assessing both building-integrated and individual-oriented renovations. It introduces a holistic approach to evaluate the refurbishment of a spacious environment with infrared ceiling panels in terms of perceived thermal comfort, financial feasibility, and environmental impact. The distinctive case study of a historic Victorian hall (Brighton, UK) allows for addressing the integration challenge while preserving architectural integrity (Nair et al., 2022).

#### 2. Method

This study aimed to evaluate the effectiveness of electric radiant panels in improving thermal comfort and reducing energy consumption in the Brighton Victorian Hall.

As part of the hall's renovation project, which involves upgrading the heating systems, two ceiling electric radiant heating systems were strategically installed in one room, the community hall, for testing before potential application throughout the entire building. The study employed a three-phase approach, including:

 Simulation phase utilizing Building Energy dynamic Simulation (BES) to consider the environmental impact

- Objective thermal measurement phase with probes and a microclimatic monitoring station
- Subjective field study analysis assessing users' perceived thermal comfort through questionnaires

This paper discusses the study's first two phases.

#### 2.1 Case Study

The "Exeter Street Hall" is a historical building located in Brighton, UK, built during the Victorian Age, in 1884. It was a Sunday School for St. Luke's Church, Prestonville, in Brighton.

Exeter Street Hall exhibits distinct architectural characteristics indicative of the Victorian era, allowing for its identification within the predominant construction style of that period. Victorian-era architecture is marked by its unapologetic devotion to ornament and flourish and its ornate maximalist interior design (X. Li & Densley Tingley, 2021).

The structure comprises a spacious central hall spanning approximately 135 square meters, flanked by two smaller rooms, each measuring around 25 square meters, positioned on opposite sides of the main facade facing the street (Fig. 1). Fig. 2 shows the architectural drawing of the building.

The building's energy efficiency is low, featuring walls primarily made of double layers of bricks and plaster (U-values 1.86 W/m<sup>2</sup>K). Interior walls are plastered on both sides, while exterior walls have plaster only on the inside, exposing the brick facade. The structure sits on brick wall foundations directly on clay ground, with a wooden plank floor raised about half a meter above, creating space for cables and equipment. Insulation is limited, with only the Main Hall's flooring insulated. The kitchen and Community Room's exterior wall is the sole insulated wall, positioned between two brick layers. Roofs are insulated in select areas, using a double layer between and above/below rafters (U-values 0.30 W/m<sup>2</sup>K). The windows are historically significant, featuring single-pane glass and wooden frames (U-values 5.8 W/m<sup>2</sup>K, SHGC 0.82). Chimneys are internally insulated, and false ceilings consist of plasterboard.



Fig. 1 - Picture of the Exeter Street Hall from the frontal street



Fig. 2 - Architectural plan of the Exeter Street Hall

The building employs an air conditioning heating system, featuring gas heaters located in both the Main Hall and the Community Room. Given the considerable height of the rooms, the warm air generated by the air conditioning systems tends to rise to the ceiling, leaving the lower spaces uncomfortable for occupants.

The current heating system's performance has prompted an evaluation of electric infrared radiant ceiling panels to eliminate convective heat loss and air stratification. Among radiant systems, suspended panels offer advantages as they integrate into drop ceilings of existing and new buildings, allowing for design flexibility, reconfiguration, and easy maintenance access.

Two panels, each with a power of 1 kW, were installed in the Community Room, resulting in a total power of 2 kW (superficial T of 100  $^{\circ}$ C). Each panel is 1.6 m wide and 0.63 m high (Fig. 3, Fig. 4).



Fig. 3 - Architectural plan of the community hall with panel position



Fig. 4 – Picture of the community room with the two infrared panels installed on the sloped ceilings.

## 2.2 BES Model

While the panels have been physically installed only in the community room, the EnergyPlus simulation encompassed the entire building (Fig. 5), considering the interrelationship between rooms to ensure accurate results and evaluating the feasibility of implementing the heating system throughout the Hall.



Fig. 5 – 3D pictures of the EnergyPlus thermal model

Two Typical Meteorological Year (TMY) weather files were selected and downloaded from two databases:

- Meteonorm, based on 19-year observations (2000-2019)
- JRC (Huld, Müller, and Gambardella 2012), based on 16-year observations (2005-2020)

The typical year is composed of 12 typical months of the full-time period available. Fig. 6 shows the output temperature trends of the climatic files used for the simulations.

Despite both being TMY files, the trends depicted by the variables show some differences. For instance, the temperature trends are very similar, as evidenced by an R<sup>2</sup> value of 0.57. However, the JRC weather file is much more flattened, lacking the peaks found in the Meteonorm weather file. Specifically, using Meteonorm as the statistical baseline, the JRC has a Mean Absolute Error (MAE) of 3.1°C and a Root Mean Square Error (RMSE) of 3.9°C. Construction stratigraphies were modeled using a survey and documentation of the building.



Fig. 6 – Annual evolution of daily temperatures in the TMY of Meteonorm and JRC. The solid lines represent the daily averages, while the opaque colored areas indicate the hourly minimum and maximum values observed throughout the day

It was not possible to create a personalized weather file with measured climate data and subsequently validate the model simulating the building with the Actual Meteorological Year (AMY). However, internal temperature and humidity monitoring was conducted throughout the winter season of 2021/2022. The internal temperature data obtained was compared with the simulated ones to evaluate the accuracy of the EnergyPlus model.

Internal loads and occupancy profiles were then modeled based on the actual usage of the building.

#### 2.3 Energy/Economic Impact Evaluation

The study conducted an energy and economic comparative analysis to evaluate the new system against other suitable options for the historic building.

An ideal heating system was modeled in EnergyPlus to obtain the energy needs of the building envelope. Various scenarios for heating were then identified, and the energy consumed by the systems was calculated based on the yields of each specific case.

Various scenarios were evaluated, from the least to the most efficient, all compatible with the historic building involved (Table 1).

Scenarios H\_7 and H\_8 pertain to the evaluation of infrared panels. Scenario H\_8 differs from the others in temperature control. As the panels operate with radiant input, the EnergyPlus simulation was configured with the system setpoint based on the operative temperature rather than the air dry-bulb temperature. This led to varying energy consumption and, consequently, differences in the results of the proposed scenario. To be realistic, scenario H\_8 would require a thermostat capable of measuring the mean radiant temperature and thus calculating the operative temperature.

Table 1 – Heating scenarios evaluating for the hall refurbishment

Scena.	Generator	Source	Terminal
H_1	Traditional boiler	Natural gas	Radiators
H_2	Condensing boiler	Natural gas	Fan coil
H_3	Gas heater	Natural gas	Internal unit
H_4	HP (air-air)	Electricity	Internal unit
H_5	HP (air-water)	Electricity	Radiant pan.
H_6	Electric radiators	Electricity	Radiators
H_7	Infrared panels	Electricity	Radiant pan.
H_8	Infrared panels	Electricity	Radiant pan.

The analytical framework unfolded through a comprehensive process encompassing various stages. Firstly, EnergyPlus was employed to assess the Heating envelope needs. Subsequently, an exploration of systems efficiencies informed the determination of energy source consumption. The subsequent steps involved the integration of energy cost conversion factors for detailed financial analysis in pounds (£). Therefore, the calculation process unfolded as follows:

- EnergyPlus -> Heating envelope needs (Q<sub>H</sub>) [kWh]
- Systems Efficiencies (distribution, production, regulation, and emission) -> energy source consumption (Q<sub>5,H</sub>) [kWh]
  - Primary Energy conversion factor (gas, electricity) -> Primary energy analysis (Q<sub>P,H</sub>) [kWh]
  - Energy cost conversion factor -> Financial analysis [£]

The primary energy conversion factors were set at 1.50 for electricity and 1.13 for natural gas (UK Department for Energy Security and Net Zero 2023).

The Energy costs for England were set at 0.27 £/kWh for electricity and 0.07 £/kWh for natural gas (Nimble Fins, 2023). Since the costs are subject to rapid variations, simulations were conducted by applying variation factors of  $\pm$  20% to evaluate the impact of potential changes over the years.

## 2.4 Thermal Comfort Evaluation

A thermal comfort analysis with objective measures, including real-time thermal data from strategically placed probes, was conducted to compare the new radiant panels with the previous heating systems. A Deltaohm HD32.3 data logger was used to measure air temperature, globe temperature, air velocity, and air relative humidity at face height (1.10 m). The probes were placed in 3 locations (next to the windows, at the center of the room, and next to the internal wall) and measured 2 conditions: the heating panel switched off and on. These are single-day measurements that complement the temperature and humidity monitoring conducted throughout the winter season of 2021/2022. It was then verified that the measurement day fell within the typical winter range and did not deviate from the average conditions.

The model developed by Fanger (Fanger, 1970) was used to assess thermal comfort based on the ambient measured data, which calculates as output the Predicted Mean Vote (PMV). The inputs of the models are four environmental parameters (air temperature, mean radiant temperature, relative humidity, and air velocity), obtained with the Deltaohm probes, and two individual parameters (clothing insulation and metabolic rate). Clothing insulation data ( $I_{clu,i}$ ) and activity (MET) were collected through a survey held in the community hall between February and March 2022, with a total of 59 participants.

All participants were asked to dress as they would normally for a workday. The clothing insulation ( $I_{clo}$ ) was calculated using equation [1] (ASHRAE, 2021):

$$I_{cl} = 0.835 \cdot \sum_{i} I_{clu,i} + 0.161$$
<sup>[1]</sup>

where  $I_{clu,i}$  is the effective insulation of garment i, and  $I_{cl}$  is the insulation for the entire ensemble. The median clo value was  $0.87 \pm 0.23$ . Most participants were seated, with a MET set at 1.1. However, some were standing or moving, with a MET set at 1.9. PMV results will be variable depending on the specific participants'  $I_{clo}$ , MET, and positions inside the room.

## 3. Results

Fig. 7 displays the primary energy consumption results for the building across the 8 heating scenarios, utilizing simulations performed with two different weather files in EnergyPlus. While Fig. 6 suggests that the two weather files exhibit similar trends but with varying magnitudes and significantly different daily peaks, the building envelope heating requirements were found to be 19% lower for the JRC weather file compared to those of Meteonorm. Consequently, for the additional scenario, H\_8 (opera-



Fig. 7 – Building Primary Energy consumption according to the weather file and the Heating system scenarios. The scenarios marked with an asterisk (\*) pertain to the solution installed in the Community Room, which involves the installation of infrared radiant pan els.



Fig. 8 – Absolute energy cost according to the weather file and the Heating system scenarios. The scenarios marked with an asterisk (\*) pertain to the installation of infrared radiant panels. The interval bars show the result in the case of a  $\pm 20\%$  change in input energy cost.

tive temperature setpoint), only the Meteonorm climatic file (more realistic and featuring more peaks) was used for simulation.

The values presented below refer to the entire building and not just the community room, thus highlighting a comprehensive solution for the entire Victorian hall.

Among the simulated heating, gas systems showed about a significant 28,000 kWh more primary energy requirement on average (with a total of 33,000/47,000 kWh) compared to electric systems with heat pumps (with a total of 12,000/16,000 kWh). Electric infrared panels, more in line with gas systems, exhibited a higher primary energy consumption of approximately 40,000/51,000 kWh per year. The simulation with an operative temperature setpoint reduced electric panels' primary consumption to 33,000 kWh annually, positioning it between heat pump and gas scenarios. heating scenarios. Electric radiators and infrared panels incurred higher energy costs, reaching up to 9 k£. The operative temperature setpoint lowered costs to 6 k£, still more than double compared to the first five scenarios: H\_1 to H\_3 (gas scenarios) all hover around 2,100 and 3,000 £, while H\_4 and H\_5 (heat pump) around 2,300 and 3,000 £. The higher cost was attributed to the significant price difference between electric and gas energy (0.27 vs. 0.07  $\pounds/kWh$ ) and the efficiency of the systems.

Fig. 9 shows the PMV results divided for scenarios with heating panels switched on and off and for positions inside the room: next to the window, in the center of the room (with greater exposure to panels), and next to the internal wall. The PMV results pertain solely to the community room, unlike the previous ones presented for the entire building. This is because the panels were installed only in the community room, where measurements with the microclimatic monitoring station were feasible.



Fig. 8 shows the annual energy cost of the simulated

Fig. 9 – Predicted Mean Vote (PMV). Results divided by panels switched on/off and position in the room. The top box represents the number of surveys for the specific sub-category.

Overall, the situation slightly improves with the presence of the panels, but still falls within the range of a slightly cool sensation (from  $-0.8 \pm 0.5$  to  $-0.4 \pm 0.4$ ). Significant improvements are not noticeable even in terms of position within the room. The most neutral condition appears near the windows; indeed, the panels moved the PMV from  $-0.4 \pm 0.2$  to  $-0.2 \pm 0.2$ . The contribution is greater in the center of the room, moving from  $-0.8 \pm 0.5$  to  $-0.3 \pm 0.4$ .

## 4. Discussions

Proper planning is essential ahead of applying innovative technologies to ensure user comfort and energy savings in certain environments.

The room, primarily used for one-hour teaching activities, does not always have continuous use throughout the day, making the panels unsuitable. Radiant systems perform best when installed over large surfaces with a clear view factor to users and operating at low temperatures. However, their current position prevents optimal radiant contribution, leading to overall dissatisfaction with the thermal environment. PMV predictions indicate a slightly cool thermal sensation (-0.4  $\pm$  0.4). The most comfortable area seems to be near the windows, likely due to the sunny winter day providing radiative benefits. While the panels offer some comfort in the room's center, where occupants are more exposed to radiation, the improvement does not significantly reach a neutral sensation.

Although PMV is not recommended for predicting thermal sensation in non-uniform environments, such as those created by Personal Comfort Systems (PCS) (Rugani et al., 2023; Cheung et al., 2019), it remains widely used in uniform settings. While the studied radiant panels are not strictly PCS, they also do not create a completely homogeneous environment. With caution regarding the obtained results and planning to analyze the detailed outputs provided by studies in real environments using questionnaires, it can be preliminarily concluded that the panels do not seem to provide the desired contribution.

The two panels installed in the community room adhere to some principles of PCS, offering localized warmth, quick activation, and easy installation.

However, they deviate from fundamental PCS principles: high consumption (1 kW per panel), delayed response (panels needed to be switched on 2 hours before room use), and high operating temperatures (100 °C). Essentially, radiators were mounted on the sloped ceiling, causing heat stratification at the top of the room and insufficient radiant heat for users. Installing even larger panels in the main hall would have exacerbated these issues, increasing the distance between users and panels, and potentially amplifying consumption and energy expenditure. Although they are the easiest solution to install, as they involve a simple connection to the power line, their environmental impact is higher than other possible scenarios that would require a more complex installation, but a winning economic return and a reduction in energy consumption.

# 5. Conclusions

While radiant heating ceiling panels have proven effective in building refurbishments, their application in the renovation of historic structures presents unique challenges. The research conducted within a Victorian hall in Brighton underscores the importance of a holistic approach, considering perceived thermal comfort, financial feasibility, and environmental impact.

In the specific community room, where two panels were installed, suboptimal functioning and slightly cool sensation were obtained due to installation issues and operational practices.

BES simulation revealed significant primary energy consumption gaps, with electric infrared panels showing low efficiency compared to electric heat pumps and reaching similar consumption as the gas systems. The high cost of electricity and the low efficiency of systems result in scenarios with electric radiant ceiling panels reaching energy costs up to three times higher compared to all other scenarios.

The PMV results obtained from measurements conducted with the probes show consistent findings in the slightly cool sensation scenario, without significantly improving comfort levels.

Despite the ease of installation, the cost and environmental impact of simple solutions prompt a reconsideration in favor of more complex scenarios. LCC and LCA analyses are necessary to evaluate the entire lifecycle of these systems, particularly the installation costs, which will be assessed in future phases of this study.

The findings provide valuable guidelines for designing and installing radiant systems in large community spaces, stressing the importance of comprehensive planning for user comfort, energy savings, and environmental sustainability.

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# Personal Comfort Systems (PCSs) in Offices: Efficient Utilization Threshold Based on Energy Consumption

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#### Abstract

Personal Comfort Systems (PCSs) have emerged as a solution to customize thermal conditions at individual workstations, potentially reducing overall energy consumption. This study investigates the optimal utilization of PCSs in office environments extending beyond their thermal comfort provision to delve into their overall energy performance, considering various HVAC systems, building insulation levels, and occupancy patterns. Building dynamic Energy Simulations (BES) were conducted for an openplan office in London, utilizing heating desks. The evaluation method involves comparing scenarios with and without PCSs across various indices, including energy cost and Primary Energy consumption. Results highlight the year-round adaptability of PCSs, offering insights into their efficacy, efficiency, and potential impacts in both new and existing buildings. The absolute savings vary between non-insulated and highly insulated buildings and the study suggests integrating PCSs into building design for optimized energy efficiency and cost-effectiveness.

#### 1. Introduction

Addressing the well-being and comfort of individuals has emerged as a central concern for researchers. The assessment of the thermal environment holds particular significance, given its substantial impact on both the comfort of occupants and the energy efficiency of the building (Veselý & Zeiler, 2014). Thermal comfort is the most influential Indoor Environmental Quality (IEQ) factor in space perception and the predominant one regarding energy consumption (Bluyssen, 2020). Ensuring thermal comfort holds utmost significance in work environments, playing a dual role in enhancing personal well-being and boosting productivity (Antoniadou & Papadopoulos, 2017; Kim et al., 2019) while also being a primary contributor to overall dissatisfaction within a space (Frontczak et al., 2012).

In this context, numerous researchers have developed models and systems designed to meet individual needs, such as Personal Comfort Systems (PCSs). PCSs are defined as systems that heat and cool individuals without affecting the environments of surrounding occupants (Arens et al., 2006). Unlike traditional HVAC systems that condition the entire building volume, PCSs focus solely on creating a "personal" microclimate. Moreover, neutral sensation in a uniform environment reaches the rating of "comfortable" but cannot reach the rating of 'very comfortable', which can only be achieved in asymmetric or transient environment conditions (Arens et al., 2006), often created by PCSs.

This targeted approach allows for the customization of thermal conditions at individual workstations, enabling the primary HVAC system to operate within a broader setpoint range and leading to a significant reduction in overall energy consumption (Kalaimani et al., 2020; Toftum, 2010). This is based on the premise that individuals will primarily occupy the individually conditioned workstations, with limited time spent in other areas within the building (Zhao et al., 2014).

Given the insights above, the question arises: how many PCSs can be used simultaneously in a less conditioned environment while maintaining energy convenience?

This study aims to test a new methodology for defining the threshold for PCS usage in terms of energy efficiency within an office setting. Specifically, the research aims to identify when these systems can be efficiently applied in conjunction with various types of primary HVAC systems, taking into account the number of occupants and the building insulation quality in which they are utilized.

## 2. Method

The study aims to investigate how many PCSs can be used simultaneously in an office maintained at a less conditioned level to achieve both energy and cost gains. In this initial phase, Building dynamic Energy Simulations (BES) of an open-plan office during the heating period are employed. The office is situated in the city of London and utilizes heating desks, which have already proven efficient in recreating thermal comfort conditions in previous studies (Rugani et al., 2023). Although this is an initial exploratory phase of the methodology for assessing the overall impact of PCSs on energy consumption, the approach is general and can be adapted to any other type of PCS, for both heating and cooling.

#### 2.1 BES Model

EnergyPlus was employed to investigate the PCS impacts. A three-floor standard landscape office building type was chosen, having a 27.6 x 28.0 m plan dimension (770 m<sup>2</sup>) and 9 m height (3 m per floor). The building is north-south oriented and the window area ratio is 1/8 of the floor area, equally distributed on the four sides. Fig. 1 shows the architectural plan of the typical building floor.

The building simulation model was conceived according to the simplified definition developed in previous studies, named FREDS (Picco & Marengo, 2019). The building is conceived as a simplified geometric shape, with glazed areas equivalent to the sum of the individual glazed surfaces on each wall. For this geometric simplification, Fig. 1 does not include the windows drawn in the typical floor plan. The building was divided into three thermal zones, one for each floor.



Fig. 1 – Architectural plan of a typical floor of the simulated building (measures in meters)

Two distinct building constructions were applied, one representing a typical heavyweight hollow brick, non-insulated structure, and the other exemplifying the same structure, but with insulation to meet nearly zero energy building (nZEB) standards (European Parliament, 2024) (Table 1).

Table 1 - Design features of the selected building

	nZEB config.	Common config.
Walls transmittance	0.256 W/m <sup>2</sup> K	1.019 W/m <sup>2</sup> K
Ground floor transmittance	0.26 W/m <sup>2</sup> K	1.236 W/m <sup>2</sup> K
Roof transmittance	0.224 W/m <sup>2</sup> K	1.745 W/m <sup>2</sup> K
Windows transmittance	1.323 W/m <sup>2</sup> K	2.718 W/m <sup>2</sup> K
Windows SHGC	0.416	0.737

The Office was simulated in London, which has a rainy climate in which temperatures remain fairly low throughout the year. TMY (Typical Meteorological year) weather files suitable for use with BES programs were chosen and downloaded from the Meteonorm database, statistically based on 19-year observations (2000-2019). Fig. 2 shows the output temperature trends of the climatic file.



Fig. 2 – Annual evolution of daily temperatures in the TMY from Meteonorm. The solid lines represent the daily averages, while the opaque colored areas indicate the hourly minimum and maximum values observed throughout the day

Two distinct operational conditions of the building were simulated: one with PCSs (less conditioned state, 17 °C) and one without (regular setpoint, 21 °C). Specifically, the selected PCS for heating is a warming desk with 40W of power input. The desk has two distinct electric heating surfaces: a narrower one on top that heats upward and is concentrated towards the user (working primarily by conduction), and a larger one underneath that heats downward (working primarily by radiation).

The study utilized internal loads data from the FREDS database, adjusting people's time schedules to align with the analysis objectives. The office layout, based on a FREDS "people index" of 18.8 m<sup>2</sup>/person, accommodated 40 people per floor in the case study.

The simulation considered four office occupancy scenarios: 25 %, 50 %, 75 %, and 100 % capacity. The purpose of the people loads configuration is to conduct a sensitivity analysis of PCS's benefit, considering the simultaneous presence load of individuals in offices and the electrical load generated by PCSs. The EnergyPlus simulations consider the heat load produced by the occupants and the corresponding activation of personal systems, depending on the specific combination of scenarios. In practice, the number of activated PCSs depends on the number of people present in each scenario, each of whom has their own PCS.

Therefore, the activation of PCSs is contingent on two distinct factors: temperature conditions and the presence of individuals. Thanks to the "Energy Management System" of EnergyPlus, it was feasible to correlate the activation of PCSs with the indoor air temperature attained by the case study in the simulated location. The code utilized in EnergyPlus is as follows:

EnergyManagementSystem:Program, DESK, IF T1 >= 21, SET Desk\_PT\_power = 0, ELSEIF (T1<21) && (DayOfWeek>=2) && (DayOfWeek <=6) && (Hour >= 9) && (Hour <=19), SET Desk\_PT\_power = [XXX], ELSE, SET Desk\_PT\_power = 0, ENDIF;

The simulation encompassed different occupancy levels, and in the less conditioned scenario, during the heating phase, PCSs activated as the room temperature dropped below 21 °C. Additionally, the main heating system was triggered when the temperature fell below 17 °C during working hours.

## 2.2 Energy/Economic Impact Evaluation

The study compares the different conditions created by the scenarios with and without PCSs examining primary energy consumption and energy costs. An ideal heating system was modeled in EnergyPlus to obtain the energy requirements of the building envelope. Various heating scenarios for heating were then identified, and the energy consumed by the heating systems was calculated based on the yields of each specific case. This helped evaluate how PCSs interact with various heating scenarios, providing insights for optimizing energy efficiency and sustainability in different operational conditions. Table 2 shows the three simulated combination scenarios for heating.

Table 2 - Building main heating scenarios

Scena.	Generator	Source	Terminal
H_1	Condensing boiler	Natural gas	Radiant pan.
H_2	HP (air-air)	Electricity	Internal unit
H_3	HP (air-water)	Electricity	Fan coil

The analytical framework unfolded through a comprehensive process encompassing various stages. Firstly, EnergyPlus was employed to assess the heating envelope needs. Subsequently, an exploration of systems efficiencies informed the determination of energy source needs. This was followed by the incorporation of Primary Energy conversion factors for gas and electricity, contributing to the Primary Energy analysis. The subsequent steps involved the integration of energy cost conversion factors for detailed financial analysis in euros [€]. Therefore, the calculation process unfolded as follows:

- EnergyPlus -> Heating envelope needs (Q<sub>H</sub>) [kWh]
- Systems Efficiencies (distribution, production, regulation, and emission) -> energy source consumption (Q<sub>5,H</sub>) [kWh]
  - Primary Energy conversion factor (gas, electricity) -> Primary energy analysis (Q<sub>p,H</sub>) [kWh]
  - Energy cost conversion factor -> Financial analysis [€]

In each scenario, the cumulative electricity consumption of the PCSs was added, calculated based on their actual usage throughout the year, as an effect of the previously explained EnergyPlus EMS.

The Energy costs for England were set at 0.27 £/kWh for electricity (Nimble Fins, 2023) and 0.07 £/kWh for natural gas (Nimble Fins, 2023). To standardize the results, all prices with foreign currency were converted to Euros (€) using the exchange rates applicable in October 2023 (resulting in 0.31 €/kWh for electricity and 0.08 €/kWh for natural gas). Since the costs are subject to rapid variations, simulations were conducted by applying variation factors of  $\pm$  20 % to evaluate the impact of potential changes over the years.

The primary energy factor is 1.50 for electricity and 1.13 for natural gas (UK Department for Energy Security and Net Zero, 2023).

#### 2.3 Scenarios Summary

The earlier detailed scenarios are described here to provide a comprehensive overview of the conducted study. Fig. 3 shows a schematic plot of the 49 combinations, which can be summarized as:

- 2 operational setups of PCSs
- 1 location
- 2 stratigraphy configurations
- 4 occupancy patterns
- 3 HVAC configurations



Fig. 3 – Schematic summary of the combinations (49) with which the simulations were performed

## 3. Results

The EnergyPlus EMS script facilitated the simulation of the practical utilization of PCSs. Fig. 4 shows the usage hours of PCSs, drawing also a comparison between non-insulated (common) and insulated (nZEB) buildings.



Fig. 4 – Usage hours of the heated desks, divided by months, based on the occupational profile, for the common non-insulated and the nZEB insulated building



Fig. 5 – Absolute and percentage energy cost reduction according to the heating system scenario and the occupational profile, for the common non-insulated and the nZEB insulated buildings. The interval bars show the result in the case of a  $\pm$  20 % change in input energy cost



Fig. 6 – Absolute and percentage Primary Energy consumption reduction according to the heating system scenario and the occupational profile, for the common non-insulated and the nZEB insulated buildings

Usage hours peak around 240/260 in January and December in the non-insulated building, while they are lower in the nZEB (160 in January and 60 in December). The desk sees substantial use until April, with some hours in May, and resumes in October for the non-insulated building, while it has more limited use (from December to February) in the nZEB building. The results highlight the effectiveness of enabling year-round usage of PCSs, emphasizing the dynamic adaptability of PCS strategies to various building structures.

Energy and cost results are shown as differences between the standard conditioned state (21 °C) and the less conditioned state (17 °C) with PCSs. Every positive outcome signifies a benefit derived from the operational state with PCSs. Primary energy (Fig. 6) and costs (Fig. 5) are investigated.

The scenarios with condensing boilers show a greater absolute reduction in primary energy, with values of up to 40 MWh for the non-insulated building and 6 MWh for the nZEB. Meanwhile, other scenarios with heat pumps hover around 15 MWh and 2 MWh. The percentage reduction follows a consistent trend, approximately 40-60 % for the non-insulated building and 50-80 % for the nZEB.

Annual cost savings range from about 40 % to 60 % for the non-insulated building, with absolute values ranging from €1400 to €3300, while they range from 40 % to 75 % for the nZEB, equivalent to values between €250 and €550. In terms of costs, scenarios with heat pumps experience greater savings due to the higher cost of electricity.

## 4. Discussions

The use of heated desks as a PCS in the simulation of the case study office, coupled with a reduction in the office's winter setpoint, consistently yielded positive effects in London. Full scenarios, where everyone has their PCS turned on, were explored to establish thresholds, even though they don't align with the logic and objective of PCS usage.

In the worst-case scenario, where 40 people per floor have 40 W desks powered on, the minimum primary energy savings amount to 39 %, and the minimum cost savings to 34 %. The advantage of PCSs depended on factors like occupancy rates, building insulation, and heating system configurations. The reduction in primary energy consumption demonstrated the environmental benefits of heated desks, especially in scenarios powered by natural gas. However, the influence of occupancy rates and building insulation on these reductions highlighted the need for a tailored approach to maximize environmental gains.

While the percentage savings are very high, the absolute savings between the non-insulated building and the nZEB building are vastly different. This study does not consider the installation cost of PCSs, which, if taken into account, would change the equation. From these initial results, it can be argued that PCSs would yield good results in retrofitting an existing system of a non-performing building, bringing both economic benefits and high thermal comfort, justifying the expenditure and return on the investment cost. The same might not apply to the installation of these PCSs in a newly constructed nZEB building whose system has already been designed. However, looking at it from a different perspective, if the PCSs had been designed alongside the building's system, allowing for downsizing of the main HVAC components to operate with lower thermal loads associated with reduced working setpoints, it would have led to cost and environmental impact reductions. In this scenario, the PCSs would have delivered advantages to the nZEB building in terms of personal comfort, control, as well as environmental and energy consumption.

#### 5. Conclusions

In conclusion, the study delves into the intricate landscape of PCSs and their impacts on building energy dynamics. Utilizing a comprehensive evaluation framework that incorporates energy considerations, the study offers actionable insights for the effective deployment of PCSs in real-world scenarios. The approach is general and can be used to evaluate any type of PCS, not limited to the specific heating desk in this study. The examination focused on a three-floor standard landscape office building, taking into account diverse building stratigraphy, occupancy patterns, and heating configurations.

Key findings include:

- The energy benefits and savings resulting from the use of a 40 W heated desk combined with less-conditioned operation of the main heating are consistently positive.
- In these scenarios, there are no usage thresholds; even if the entire office were to utilize a 40
   W desk, disadvantageous situations would never arise.
- Great potential has emerged in the application of PCSs to complement the improvement of existing underperforming buildings.
- The study recommends conscious PCS use in highly insulated buildings and their integration into new building projects to optimize energy efficiency and costs.

Overall, the findings provide valuable insights for deploying PCSs as effective, adaptable, and sustainable solutions in various operational scenarios. Future developments of this work will involve expanding the combinations of analysis, including the cooling season, other climatic locations, and various PCS power levels. This aims to create an informative usage map and more general thresholds to be considered during the economic and environmental assessment of the applicability of PCSs with different power inputs.

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# Integration of Rooftop Photovoltaics and Roof Retrofitting Strategies for Enhanced Energy Efficiency in Warm Climates

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#### Abstract

To forward renewable energy as a self-reliant option of energy production, the Government of India is promoting the extensive adoption of Rooftop Solar Photovoltaic (PV) in domestic buildings. Rooftop solar PV systems offer the dual benefit of being a clean energy source and serving as shading devices for roofs, reducing the impact of incident solar radiation. However, the effectiveness of PV shading in minimizing incident solar radiation on mounting surfaces depends on the urban context such as neighbouring building heights and distances between buildings, as well as on the mounting angle and geometry of the PV panels. This study investigates the potential of a roof-mounted PV as a shading element for a typical and retrofitted roof of a low-rise building in a warm and humid climate in Kharagpur, West Bengal. To identify the geometry of PV panels, a grid-connected PV system was first designed for the selected residential unit using PVSyst. The identified PV structure (with dimensions 5.5 m (l) X 4 m (w)) has been considered, mounted over the building at a height of 1.9 m with a tilt of 22° facing south (true azimuth). DesignBuilder, integrated with the EnergyPlus building energy simulation engine, is used to simulate the model to predict the heat transfer through the roofing structure and evaluate the change in the cooling demand associated with it. Three types of roofing structures were studied: an uninsulated roof, a cool roof retrofit, and a roof with mounted PV structure. The results show that the PV structure can provide additional shade to the roof, decreasing the conductive heat gained by incident solar radiation through the roofing assembly by 13.7 % and 9 % for the uninsulated and cool roof cases, respectively. Considering this study observes the Solar PV as a detached and mounted structure, focussing solely on its shading, the reduction in heat gain also resulted in a decrease in the annual cooling demand of the building, demonstrating the effectiveness of PV panels not only as an energy generation solution but also as a thermal management strategy for buildings in warm and humid climates.

#### 1. Introduction

With one of the world's fastest-growing economies, India stands at a critical juncture with increasing urbanization and industrialization rates accompanied with increasing energy demand. According to reports, India is at present the third-largest global energy consumer in the world (U.S. Department of Commerce, 2024). India currently contributes to 3.4 % of the global energy consumption, with the energy demand expected to increase by 25 % by the year 2040 (International Energy Agency, 2021). Policy and technological transformations in the country have nearly electrified 97 % of households in the country, thus increasing the per household energy consumption (CEEW, 2020). The residential sector in India is responsible for 24 % of the total energy consumption (Ramapragada et al., 2022). Recognising this, India has embarked on various initiatives to integrate energy efficiency and sustainability in both the existing and up-coming building stock of the country.

India's goal to achieve 500 GW of non-fossil energy capacity by 2030 strengthens its aims to generate 50 % of its energy requirement through renewable sources and reduce the total projected carbon emissions by one billion tons by the year 2030 (PIB, 2023). India's geographical location endows it with significant solar potential, with most regions receiving between 4 to 7 kWh/m<sup>2</sup>/day of solar radiation. Currently solar energy constitutes 37 % of the 179 GW installed renewable energy in the country (U.S. Department of Commerce, 2024). While solar photovoltaics represent an active strategy to provide alternative energy, reducing reliance on conventional fuels, it is equally important to investigate passive strategies to enhance the efficiency of buildings. Heat transfer through a building envelope has been cited as one of the main factors influencing buildings' cooling and heating loads (Lubis, 2018). Moreover, the heat gain through a roof is one of the major components of the building envelope that affects the thermal performance of buildings. The vast research on this subject has highlighted that the direct and diffuse solar radiations falling on the roof can raise the temperature of the roofs significantly, thus increasing the indoor temperature, causing discomfort and increased usage of cooling equipment (Bozonnet & Allard, 2011; Farhan et al., 2021). Thus, energy efficient roofs serve as a key factor in reducing building cooling loads whilst imparting thermal comfort, with daily peak roof surface temperature showing reductions of 10 to 20 °C in green roofs and 15 to 25 °C in cool roofs (Cavadini & Cook, 2021). While recent studies have focused on roof insulation technologies and retrofitting techniques based on concepts such as green roofs or cool roofs, the combined effect of building-applied photovoltaics and roof retrofitting strategies are also being investigated. Various studies have deliberated the differences in solar panel yield for different type of sustainable roofs by investigating the relationship between the roof surface temperature, albedo and the PV panel power output (Altan et al., 2019; Witmer & Brownson, 2011; Shafique et al., 2020; Lamnatou & Chemisana, 2015). Along with the analysis of the PV yield, a few studies have examined the shading effect of Rooftop Solar PV structure on indoor thermal conditions of the building (Dominguez et al., 2011; Pandiaraj et al., 2022; Wang et al., 2020; Ma et al., 2023; Albatayneh et al., 2022; Vakilinezhad & Ziaee, 2024). Given this context, the objective of this study is to investigate the impact of the indirect shading of Rooftop Solar PV on the conductive roof heat gain for a residential building in a warm and humid climate for an uninsulated and retrofitted cool roof. The essential aim of the research is to investigate the passive role of the Solar PV in lowering the heat transfer from roof to indoors in the summer months, thus lowering the cooling load.

## 2. Methodology

This study employs field study and numerical simulations for data gathering and analysing purposes. A residential complex in Kharagpur is selected for the study. A field study was conducted to collect building envelope, occupancy, and household data. Next, a thermal simulation model of the building was constructed to run the analysis. A rooftop Solar PV that adequately serves the demand of the household is designed for the building using a solar simulator, which was then integrated into the whole-building simulation model. Cool roof retrofitting strategy integrated with Solar PV shading was studied to understand its effect on roof heat transfer into the building. The subsequent sections outline the research tools and techniques employed in this investigation.

#### 2.1 Simulation Software and Engine

The simulations are performed using the whole-building simulation software DesignBuilder (Designbuilder Version v7), which incorporates the EnergyPlus engine used extensively for doing energy studies (Zhang, 2014; Bharath et al., 2016; Blanco et al., 2016; Choi et al., 2017; Bahri et al., 2024). To understand the structure and sizing of the PV system, a grid-connected roof mounted PV system (as described in Section 1.1) is constructed in PVSyst (PVSyst SA, Version v7), a solar simulation software used in scientific studies (Panicker et al., 2023; Alnoosani et al., 2019; Kandasamy et al., 2013). This PV system is integrated into the DesignBuilder environment for further analysis.

## 2.2 Specifications of Building Analysed in Study

The building chosen for the study is a typical singlefamily residence located in Kharagpur, West Bengal. Kharagpur (22°19′49″N 87°19′25″E) is a town located in West Bengal, in the eastern part of India. It is situated at an elevation of 49 m above mean sea level, exhibiting a tropical wet and dry climate, as classified under the Köppen climate classification. The mean annual temperature recorded in Kharagpur is 30.6 °C. The region accumulates an annual precipitation of roughly 157 mm and experiences an average of 144 rainy days per annum. Assumed climatic data for the region is extracted from Meteonorm database in PVSyst.

The building is a single storey residence with a floor area of  $115 \text{ m}^2$ . The entire roof area of  $106.2 \text{ m}^2$  has been considered for the study. The window to wall ra-

tio is calculated as 0.36. The building has 2 bedrooms, a living room, kitchen, a semi-open porch area, and a common bathroom and toilet as seen in Figure 1. The floor-to-floor height is of 3.3 m, the window sill height is 1 m, and the lintel level is 2.2 m. A field study was conducted on site to assess the construction assemblies and materials of the building components of the existing building. The building has standard construction, with plaster finished 230 mm exterior brick masonry wall, 150 mm thick interior walls, 150 mm flat RCC concrete roof, polished concrete floor and wooden framed single glazed (multiple paned) windows with grilles.



Fig. 1 – Floor Plan (Ground Floor) of the residential unit

It is found that the house did not utilise any heating systems. The bedroom in the northern side is the only conditioned space (18.5 m<sup>2</sup>) in the house with a split AC system. Information on appliance purchase, ownership, usage and bi-monthly electricity bills for one year was collected from the household.

#### 2.3 Building Simulation Model

#### 2.3.1 Solar Simulation

To understand the sizing of the roof-mounted Solar PV, a grid-connected Photovoltaic plant connected to a power inverter has been designed for the analysed building with inputs presented in Table 1 fed into the PVSyst interface.

Table 1 – Inputs for design of Rooftop Solar PV on PVSyst

Parameter	Details
Module Technology Used	Monocrystalline Silicon
Module Dimension	2 m X 1.1 m X 0.035 m
(l X w X d)	
Cells	72
Nominal Operating Cell	45 °C
Temperature	
Modules in Series	5
Modules in Parallel	2
Module Peak Power (Pmax)	530 Wp
Open Circuit Voltage	49.32 V
Optimum Operating Voltage	41.36 V
Module Efficiency	20.54 %

Studies have shown that panels placed at tilt angles corresponding to the latitude of the location towards South (for northern hemisphere) perform well for the location being studied (Panicker et al., 2023). Thus, the panels are placed at a tilt of 22° facing South (true Azimuth).

#### 2.3.2 Solar PV as a shading element

This study investigates the influence of the shading provided by solar structure on roof, and its impact on the conductive heat gain through the roof and thermal loads of the building. To evaluate the indirect effect of shading by installing PV panels on rooftop of buildings, factors such as the ideal tilt angle, design of the mounting structure for the PV, and the roof assembly need to be analysed (Albatayneh et al., 2022). Different methodologies to examine the same have been explored - Experimental (Dominguez et al., 2011; Pandiaraj et al., 2022), Numeric Model (Wang et al., 2020; Ma et al., 2023) and simulation-based studies (Albatayneh et al., 2022; Vakilinezhad & Ziaee, 2024) showcase the improved thermal comfort in the studied spaces through the shading effect of Solar PVs on the rooftop. In contrast to the above-mentioned studies, Zonato et al. (2021) states that parallelly placed photovoltaic panels on the roof help in reducing the roof temperatures during daytime by acting as a shield but cause warmer roof temperature during nighttime causing a positive heat flux into the building.

In an urban context, studies have also shown that the employment of large-scale cool roofs and photovoltaic deployment can lead to local cooling effect on the environment (Millstein et al., 2011). Various studies have reiterated that the deployment of solar panels reduce the near-surface air temperature as well as the citywide cooling energy demand (Salamanca et al., 2016; Masson et al., 2014). Another study (Tan et al., 2023) states that employment of city-wide solar panel roofs can reduce the cooling energy consumption. This is in contrast with studies stating that use of photovoltaic panels may lead to decreased thermal comfort and increase in local temperature (Gafford et al., 2016; Broadbent et al., 2019). These studies have been conducted for large scale PV systems, deployed on citywide rooftops or on large fields.

Keeping these studies in mind, the current research presents a case of a small rooftop PV analyzed at building level, a schematic (side) section of which is shown in Fig. 2.



Fig. 2 - PV panel placed on a mounted structure on the roof

Each module measures 1.1 m x 2 m x 0.035 m (length, width, depth), with the entire PV structure with 10 modules covering an area of  $22.5 \text{ m}^2$ . The PV is kept detached from the roof, mounted on a steel MS frame, placed at an angle of  $22^\circ$  facing South, at a height of 1.9 m from the roof floor. Further, the PV panels are placed on the part of the roof that encases the non-sleeping areas (living, porch) where night-time cooling is not used, and no occupancy is recorded during the nighttime. Due to the significant space left between the PV structure and roof, this study does not discuss the heat flux exchanges in the zone between

the PV panel and roof and focusses on the passive shading of the PV on the roof.

#### 2.4 Roofing Assemblies as Cases

To select the most efficient roofing system, the existing roof structure is tested against two roofing options, cool roof and roof shaded by PV.

Cool roofing is a technique that offers better solar reflectance and thermal emittance compared to standard roofing materials (Coutts et al., 2013). Cool roofs specifically focus on the outer layer of the exterior roof surface being a highly reflective surface (BEE, 2018). Its adoption in the built environment is rapidly expanding as it presents itself as a viable resolution in mitigating the urban heat island effect, as well as improving indoor thermal comfort (Altan et al., 2019; Baik et al., 2022). A cool roof is designed to reflect more sunlight and absorb less heat compared to a standard roof, that may lead to lowering of indoor surface temperatures (Salamanca et al., 2016; Rawat & Singh, 2022) as well as near-surface air temperature (Song et al., 2016; Baik et al., 2022). As a result, the lower surface temperatures contribute to decreased heat transfer between the roof and the building, aiding in the management of cooling load (Rahmani et al., 2021).

The three parameters used to measure the efficiency of these roofs are 1) Albedo or solar reflectance (SR), 2) Thermal emittance (IE), and 3) solar reflectance index (SRI). Table 2 indicates the SR, IE and SRI for different roofing materials (Shakti Foundation, 2020). ECBC recommends materials for cool roofs like shingles, membranes, high albedo coating, broken glazed tiles, regular white paint, given a prescriptive requirement of minimum initial solar reflectance of 0.60, and an initial emittance no less than 0.90 (BEE, 2018). Integration of Rooftop Photovoltaics and Roof Retrofitting Strategies for Enhanced Energy Efficiency in Warm Climates

Material	Solar Reflectance (SR)	Thermal Emittance (IE)	Solar Reflectance Index (SRI)
White	0.73	0.91	90
Cement tile			
White EPDM	0.69	0.87	84
White	0.80	0.91	100
Coating 8			
mm (1 coat)			
PVC White	0.83	0.92	104
White	0.85	0.91	107
coating 20			
mm (1 coat)			

Here albedo refers to the ratio of the reflected solar energy to the incident solar energy and, emissivity points to the fraction of the absorbed solar energy that is radiated back to the sky as invisible infrared radiation. A cool roof can minimise the solar heat gain of a building by reflecting a significant amount of the incoming radiation and re-radiating a portion of the absorbed radiation before it is transferred through conduction. The third factor - Solar Reflectance Index (SRI) is calculated from the solar reflectance and the thermal emittance (ASTM, 2011). The SRI of a standard black surface is taken as 0 and for a standard white surface is taken as 100 (BEE, 2018).

For the current study, the RCC roof has been retrofitted with white coated cement tiles possessing an SRI of 90. This was assumed to be directly applied to the existing roof without addition of any insulation to the existing roof. Studies have shown that the application of cool roof in poorly or non-insulated residential buildings shows more energy savings than installations in well-insulated buildings (Synnefa et al., 2007). Four scenarios were created for comparison: R1 – Existing Uninsulated Roof, R1.1 – Uninsulated Roof with Rooftop PV, R2- Cool Roof, R2.1 – Cool Roof integrated with Rooftop PV. The details of the roof are given in Table 3 with thermophysical and surface properties of the roofing material guided from ECBC (BEE, 2017 and 2018). Table 3 - Roof Assembly details

Parameters	Uninsulated Existing Roof	Cool Roof		
	(R1)	(R2)		
Roof Area (m <sup>2</sup> )	106	106		
Albedo	0.4	0.8		
Emissivity	0.85	0.91		
U Value (W/(m <sup>2</sup> ·K))	3.8	3.2		
	Top La	yer		
		White		
	Cement	Coated		
	Screed	Cement		
		Tiles*		
Thickness (mm)	20	10		
Density (kg/m³)	1648	2100		
Thermal Conductivity (W/(m.K))	0.72	1.1		
Specific Heat Capacity (kJ/(kg.K))	0.92	0.83		
	Bottom Layer			
	RCC Slab			
Thickness (mm)	150			
Density (kg/m <sup>3</sup> )	2288	3		
Thermal Conductivity (W/(m.K))	1.58			
Specific Heat Capacity (kJ/(kg.K))	0.88	1		

\* New material created (Khan et al., 2016, EnergyPlus 24.1.0, IESVE, 2014)

#### 3. Results and Discussion

This section first discusses the simulated performance of the designed rooftop PV that is integrated into the building simulation model. Next, for the four roofing cases the predicted value of roof surface heat conduction, surface temperature, and implications on the cooling demand are analysed and compared.

#### 3.1 Rooftop Solar PV Generation

A 5.3 kW Rooftop PV consisting of 10 panels of 530 Wp (5 in series, 2 strings) is designed. PVSyst software expresses the simulation results as yield energies displayed as [kWh/kWp/day]. Here kWh represents the mean produced electrical energy, and kWp represents the array nominal installed power at Standard Test Conditions (STC). The reference System Yield (Yr) refers to the ideal array yield without considering for any loss, numerically equal to the incident energy in the array plane [kWh/m<sup>2</sup>/day]. The System Yield (Yf) representing the system daily useful energy or the

nominal power [kwh/kWp/day]. The Performance Ratio (PR) is the system efficiency with respect to the system yield and the incident energy [Yf/Yr]. The predicted monthly system yield, along with array and system losses for the designed PV system can be observed in Figure 3.



Fig. 3 - Predicted monthly System yield for the designed Solar PV

PVSyst accounts for array losses including shading, irradiance and thermal loss, as well as Inverter loss (PVSyst SA, Version v7). For this study, three parameters – the annual system production, the System Yield (Yf), and the Performance Ratio (PR) have been examined. The simulated on-site electricity production from the designed Solar PV after accounting for losses is calculated as 6158 kWh annually. The average system yield is 3.92 kWh/kWp/day, with a performance ratio of 0.8.

## 3.2 Surface Heat Conduction for Different Roofing Strategies

In the context of the study, the "Surface Inside Face Conduction Heat Transfer Rate" as defined by EnergyPlus quantifies the heat flow rate as measured by a heat flow meter. This includes the heat flow by conduction at the inside face of an opaque heat transfer surface. A positive value indicates net heat gain through the analysed opaque surface through conduction, and a negative value indicates the net heat loss from the building through conduction (Passerini et al., 2018). Figure 4 represents the roof surface inside face conduction heat transfer rate (in kWh) for a period of one year for the roofing assemblies.



Fig. 4 — Simulated Roof surface inside face conduction heat transfer rate for the different roof strategies

The existing uninsulated roof (R1) demonstrates the highest annual heat gain at 1615 kWh, suggesting significant heat flow into the building. Introducing shade with solar panels (R1.1) reduces this to 1392.6 kWh, indicating that passive shading by solar panels can have a significant effect on heat intake in a building. A negative value of – 283.2 kWh for the Cool Roof (R2) indicates that over the year the cool roofs lead to net heat loss through conduction. Cool Roof with PV shading (R2.1) shows that this heat loss is amplified by PV shading by 9.5 %.

#### 3.3 Indoor Roof Surface Temperature

As observed in Fig. 5, the predicted indoor surface temperature of the analysed roof surfaces was analysed through simulations for each day of the analysed year. Roof R1, the existing uninsulated variant, consistently showed the highest temperature readings, peaking at around 42 °C. This demonstrates the limited thermal resistance of a roof lacking insulation. Due to the absence of insulation, there is a significant temperature fluctuation, showing that the indoor surface temperature follows the external temperature variations.



Fig. 5 — Predicted Indoor Roof Surface Temperature (Daily) for the different cases over a year

Both the Cool Roof (R2) and the Cool Roof with PV (R2.1) exhibit lower temperatures compared to the uninsulated roof. The Cool Roof maintains temperatures that generally remain below approximately 35 °C, even in the hottest months. During the peak of summer, the temperature differences between the roofing types are most pronounced, with the Cool Roof and Cool Roof with PV displaying better performance in reducing heat. During winter months, the inside surface temperature of the cool roof significantly decreases showing that cool roof is less effective at insulating and retaining heat during colder periods, especially when applied without insulation. For the PV installed roof variants, the uninsulated roof displays a temperature difference of 1 to 1.5 K, whereas a marginal change of 0.5 to 0.9 K is observed for the cool roof when compared with the cases without shading.

#### 3.4 Implication on Cooling Demand

Fig. 6 shows the simulated cooling demand for the different roofing configurations annually. Here the generation from the PV has not been considered when estimating the cooling demand. The results only highlight the impact of the roofing retrofit and the shadowing effect of the PV on the cooling demand of the modelled residential building. The existing uninsulated roof (R1) registered the highest annual cooling demand at 4560 kWh, while the Cool roof (R2) retrofit by itself marked a substantial decrease in cooling demand to 3511 kWh, denoting a decrease of 23 % relative to the uninsulated roof. The integration of photovoltaic (PV) panels further reduces the roof affected cooling demand. The results show that the annual cooling demand is reduced from 4560 kWh to 4120 kWh for the uninsulated roof, and from 3511 kWh to 3396 kWh for the cool roof when the shading effect of PV is added. If the generation of the PV is added, then the PV production will be able to offset the cooling demand of the facility in addition to reducing the thermal loads for both the uninsulated and cool roof scenarios. However, this may require additional considerations of the heat flux calculations between the PV modules and the roof to estimate the energy benefits.



Fig. 6 - Predicted annual Cooling Demand for the Roof Variants

#### 4. Future Work

The current study analyses a Rooftop Solar PV mounted at a height of 1.9 m in a building scale and does not detail out the convective and radiant heat transfer between the PV panel and the roof surface. Both the power generation of the PV and the energy balance of the entire roofing structure needs to be studied to evaluate the overall energy performance. Additionally, studies can benefit from the performance investigation of different types of Rooftop Solar PV (horizontal, attached, tilted) on roof coatings of different albedo values to identify the best performance for both, PV yield and building thermal load reduction. Furthermore, the possible heat island effect of large utility PV arrays in or close to urban settings (Gafford et al., 2016; Garshasbi et al., 2023) needs to be investigated further. Future studies can also be aided by experimental analysis to measure the actual effect of Solar PV to the building indoor environment, as well as changes to the urban micro-climate for building configurations in different climatic conditions.

# 5. Conclusion

The study described in this paper suggests that, for a single-storey residential building in a warm and humid climate, roof mounted Solar PV systems not only provides on-site renewable energy generation but also impart passive rooftop cooling due to roof shading thus enhancing indoor comfort as well as energy efficiency in buildings. The study concludes the following:

- The roof-mounted tilted Solar PV shading reduces the conductive roof heat gain of the uninsulated roof by 13.7 % when compared to the uninsulated roof alone for the single storeyed residence.
- By adding the mounted Solar PV to the cool roof, the conductive solar heat gain is reduced by 9 % compared to the cool roof alone.
- The predicted indoor surface temperatures of the roof show that during summer months shading by Solar PV can create a 1 to 2 K drop in indoor roof surface temperature for uninsulated roofs, while cool roofs show close to 0.5 to 1 K variation in temperature due to shading by the Solar PV.
- The shading effect of mounted and tilted Solar PV structures on uninsulated roof create more comfortable conditions indoors, reducing the cooling energy load by 440 kWh annually.
- Integration of Solar PV with cool roof further reduces the energy consumption of the building by providing shading effect to the roof, but this effect is greater for the uninsulated roof with no cool coating.
- The ease of retrofitting cool roofs, along with their complementary performance with Solar PV structures render them as a viable retrofitting option towards lowering the indoor temperature, proving more comfortable conditions indoor and thus reducing the cooling demand.
- For future studies in this area, the impact of the PV system's diurnal heat storage and release on local temperature variations, and subsequently on the building's cooling load, needs to be evaluated by considering a holistic heat balance of the PV system and building envelope. Additionally, the changes in microclimatic conditions resulting from large-scale deployment of PV systems over building surfaces must be examined to understand the broader implications on urban thermal environments and energy demands.

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# Effects of an Indoor Living Wall on Room Lighting Conditions: Comparison Between Measured and Simulated Data

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#### Abstract

In recent years, vertical greening systems have been progressively used not only on the external side of the building but also within indoor spaces. In parallel to other IEQ domains as thermal comfort, air and acoustic quality, an Indoor Living Wall (ILW) impacts lighting quality. In lighting design with specific simulation software, it is fundamental set the most appropriate colouration and reflectance coefficients (Qs) of the surfaces. Otherwise, plants' reflectance coefficients are difficult to estimate since they do not have any of the following characteristics: planarity, colour and texture uniformity. In addition, each plant's essence is characterized by peculiar lighting and growing properties. These factors make the design process quite tricky because the unknown distance between simulated lighting conditions and real lighting performances is difficult to be evaluated in advance. This research describes a case study where a room containing an ILW is simulated with DialuxEVO and then compared and validated with in situ monitored data. An empirical procedure for estimating os of the ILW in situ is used. The aim is to assess the level of precision of the previous procedure by comparing measured and simulated lighting data in order to carry out useful hints for ILW lighting simulations for designers.

#### 1. Introduction

After the Coronavirus disease in 2019 (COVID-19), the design of a comfortable indoor space is even more urgent, considering also that people spent from 80 % to 90 % of their time indoors (Kaushik et al., 2020) and considering all the implications that the indoor environment has on productivity and physiological and psychological aspects (Li et al., 2022). The building design is becoming human-centred, oriented to satisfy, at the same time, resource savings optimizing human health, comfort, and productivity in a holistic approach (Lassen et al.,

2021). There is a strong connection between Indoor Environmental Quality (IEQ), such as thermal comfort, acoustic comfort, air quality and visual comfort (Salamone et al., 2022; Mujan et al., 2021) and health and productivity, with a connection between perception and energy consumption (Pisello et al., 2021). In recent years, scientific research has been paying increasing attention to the positive effects produced by the presence of Vertical Greenery Solutions (VGS) in indoor environments in terms of users' satisfaction, control of air quality, temperature and relative humidity (Salamone et al., 2020). In literature, green walls are commonly divided into two categories: "green facades (GF)", ground-based, usually with climbing plants along the wall, and "living walls (LW)", which include planted technologies to be applied directly on the wall without connection to the ground and a uniform growth along the surface (Gunawardena & Steemers, 2019). In interior environments, living walls (ILW from now on) are the widely used solutions and their indoor application is becoming more frequent with benefits in relation to particles and VOC retention and CO2 concentration (Torpy et al., 2017), temperature and humidity control (Fernández-Cañero et al., 2012) (Egea et al., 2014), acoustic (Scamoni et al., 2022) and well-being (Gunawardena & Steemers, 2019). Since VGS are living elements, their performances are influenced by their health/stress status: it has been demonstrated for years that the health level of these elements is related to chlorophyll activity and content (Gitelson & Merzlyak, 1996), but daylight is not sufficient for the correct growth of the ILW and the integration of an artificial lighting system may be necessary (Tan et al., 2017). Good lighting is by definition human-centric, as suggested by Houser et al. (2021), but the assessment of the visual environment through human perception is often complicated and needs, during the design phase, the maximum accuracy of the main parameters and indicators which influence the lighting environment (Bellazzi et al., 2022). Most used lighting indicators are related to illuminance level (EN 12464) and glare (UNI 11165), (EN 17037). The calculation of these indicators, especially in the design phase, needs a detailed knowledge of the building morphology, lighting facilities and of their optical properties. Among the factors, the reflection coefficient of surfaces (0) is both one of the most influential (Makaremi et al., 2017) and difficult to estimate correctly, mainly in real environments (Peña-García & Salata, 2020). The assessment of these indicators is complex since indicators and variables often change dynamically but current models can analyse them in a predictable way. Another complex issue is the ILW modelling for lighting analysis. ILW, with respect to a usual indoor wall material, is not homogeneous in different aspects such as roughness, colour and placement/planarity of its leaves. In addition, light spectrum characteristics strongly affect plant growth leading to an unpredictable change of previous properties (Wu et al., 2019).

The paper aims to investigate ILW impacts on indoor lighting environments comparing monitoring campaign data of an ILW installed within a test cell and lit by a dedicated lighting system with the simulated data provided by the correspondent model made up with DialuxEVO 9.2 software (DIAL GmbH 2021). The most important lighting variables are evaluated: illuminance on the horizontal plane, vertical illuminance (on ILW, room wall surfaces and at eye level of the seated users), ILW and room walls surface luminance. Finally, a simplified and empirical estimation of the ILW reflectance coefficient is performed useful for lighting design purposes.

#### 2. Methodology

The experimentation is conducted in a Test Room of the Construction Technologies Institute of the National Research Council of Italy (ITC-CNR, Milan) with no transparent openings with inner dimension of 4.95x2.8x2.8 meters (L x W x H). The ILW, installed on the room wall facing South (South wall), is lit by 4 spotlights with different light cones aperture of 38° and 60°. All lamps are LED based with the same colour temperature and power. The ILW is divided into 4 quadrants of 1x1 m, each characterized by a different planted essence as reported in Fig. 1 and fed throughout the test period by a dedicated irrigation system. Spotlights are aligned to quadrant centres: spotlights L1 and L4 lights (60° aperture angle) to upper quadrants UL and UD, spotlights L2 and L3 (38° aperture angle) to lower quadrants BL and BR. The experimentation is divided in two phases: T<sub>0</sub> and T<sub>1</sub>, respectively before and after the ILW installation. During both phases, Illuminance and Luminance are measured on the same grid-points. Specifically, the following measurement points are considered: 25-points of a vertical grid on ILW (Fig. 2 b), 10-points of a vertical grid on the side walls (Fig. 2 c-d) and 15-points of a horizontal grid placed 0.80 meters above floor level (Fig. 2 a).



Fig. 1 – View of the ILW within the test cell in T0 (a) and T1 (b) through videophotometer



Fig. 2 - Position of the measurements points on horizontal plane (a), ILW surface (b), West side wall (c) and East side wall (d)

Vertical (E<sub>v</sub>) and horizontal (E<sub>h</sub>) Illuminance measurements are manually collected with a portable luxmeter (Konica Minolta T10) in order to avoid shadows on the receptor due to operator presence and waiting 30 seconds after luxmeter placement before recording the illuminance measure. The luxmeter is always placed on a fixed support so that it is always perpendicular to the surface to be measured and is not tilted: a support 80 cm high in the case of Eh and directly towards the wall at heights 80 and 120 in the case of Ev. Luminance measurements are collected only for vertical walls (Ls) through High Dynamic Range (HDR) images taken with a LMK videophotometer equipped with a 180° fisheye lens. Data measured in-situ during the phase To were used to validate the geometric model of the Test Room in DialuxEVO with the following steps: a) calculation of os values of the walls according to Lambert Cosine law using L<sub>s,situ</sub> and E<sub>vsitu</sub> values; b) application of the previous reflectance values to the DialuxEVO model surfaces; c) calculation of the illuminance (Ev,calc) and luminance (Ls,calc) values over the same grid points; d) validation of the lighting conditions of the empty room. After ILW installation ( $T_1$ ) reflection coefficients  $o_s$  are estimated using in situ data of surface luminance and illuminance

values. In order to test the feasibility of an on-field method of reflectance estimation, two methods are tested. The first (method I) uses both the in-situ data, surface luminance L<sub>s</sub> and surface illuminance E<sub>s</sub>, according to Lambert cosine law:

$$\rho_{s,ILW} = \frac{L_{s,situ}}{E_{s,situ}} \cdot \pi \tag{1}$$

In the second method (method II), ILW reflectance is retrieved only from in-situ surface luminance values starting from a known  $Q_s$  value (South wall in this case –  $\rho_{s,south}$ ) and by adjusting it proportionally to the South wall / ILW luminance (L<sub>s</sub>) ratio and considering also the variation of the distance between lights and surface centres of south wall (d<sub>south</sub>) and ILW (d<sub>ILW</sub>) using the inverse square law:

$$\rho_{s,ILW} = \frac{L_{s,situ,ILW}}{L_{s,situ,South}} \cdot \left(\frac{d_{ILW}}{d_{South}}\right)^2 \cdot \rho_{s,South}$$
(2)

In both cases, ILW quadrants are assumed to be homogeneous and planar. Subsequently, ILW reflection values are transferred in the DialuxEVO model (Fig. 3) for the calculation of the Luminance and Illuminance values and their comparison with in situ measurements.



Fig. 3 - View of the DialuxEVO model of the test room

#### 3. Results

In the first step, Luminance and Illuminance values are recorded in situ at  $T_0$  in order to define  $\rho_s$  values. Results are showed in Table 1, Table 2 and Table 3.

Table  $1-T_0-\mbox{test}$  room – measured luminance, illuminance and reflectance values on West wall

Point	A4	A5	B4	B5	C4	C5	D4	D5	E4	E5
Ls,situ	21	24	31	34	45	48	73	81	131	168
Ev,situ	80	90	108	120	160	170	240	275	390	565
Qs	0.82	0.84	0.89	0.88	0.89	0.89	0.95	0.93	1.05*	0.94

Table 2  $-T_0$  – test room – measured luminance, illuminance and reflectance values on East wall

Point	A6	A7	B6	<b>B</b> 7	C6	C7	D6	D7	E6	E7
Ls,situ	25	27	29	32	45	49	80	90	151	186
Ev,situ	80	95	110	116	160	175	285	325	500	625
Qs	0.96	0.88	0.83	0.86	0.87	0.88	0.88	0.87	0.95	0.93

Table  $3 - T_0$  – test room – measured luminance, illuminance and reflectance values on South/ILW wall

Point	G1	G2	G3	G4	G5	I1	I2	13	I4	15
Ls,situ	176	245	245	187	119	191	248	254	206	123
$E_{v,situ}$	1210	1723	1685	1310	895	1318	1755	1800	1400	860
Qs	0.46	0.45	0.46	0.45	0.42	0.46	0.44	0.44	0.46	0.45

The followed approach allows, in absence of the ILW, to estimate the  $\rho_s$  values of the south wall and

side walls respectively to 0.45 and 0.89 with a correspondent standard deviation of 0.01 and 0.04. Within the calculation process, measurement points giving unrealistic reflectance values were discarded (i.e. E4) as well as for measurement points placed on ILW frame (points belonging to F, H and L columns). Previous  $Q_S$  values were used in DialuxEVO in order to calibrate the room model without the ILW installed (T<sub>0</sub>). In this sense, Table 4 reported the main calculated values with DialuxEVO model and the comparison with the correspondent measured data.

Table 4  $-T_{0}-$  Comparison of measured/simulated data for East, West and South/ILW wall

Wall	Ls,max	Ls,min	Ev med	Ev Max	Ev min	$\Delta L_{s,m}$	$\Delta E_{v,m}$
West situ	168	21	220	565	80		
West calc	166	34	243	593	121	6	26
East situ	186	25	247	625	80		
East calc	156	34	240	583	117	14	33
South/ILW	248	119	1271	2180	645		
South/ILW	247	117	1261	2039	669	4	38

Observing the results, calculated mean Illuminance values differ from real ones by 3 % of the mean  $E_v$ on the south wall and up to 14 % of the East/West wall mean value. At the same time the comparison between Luminance values collected by HDR images and DialuxEVO model prediction shows a minimum difference ranging from 4 cd/m<sup>2</sup> on South-ILW wall to 14 cd/m<sup>2</sup> on West wall corresponding respectively to 2 % and 15 % of the mean measured value. Luminance maximum values are similar in ILW and the West wall, while lowest values are higher when simulated on DialuxEVO. Focusing on DialuxEVO side wall Luminance and Illuminance data, an overestimation of values on farthest points from ILW can be noted, receiving only reflected light. In relation to scenario T<sub>1</sub>, the measured Illuminance values on ILW grid points are reported in Table 5.

Table 5 - T1 - test room - measured illuminance on ILW wall

Point/ Ev,situ	F	G	Н	I	L
1	1240	1900	2470	2070	1230
2	1290	2160	2720	2270	1325
3	1265	2035	2210	2370	1230
4	1050	1290	1220	1000	750
5	540	630	620	670	510

ILW  $L_{s,situ}$  values are determined for each quadrant by averaging the luminance values of the belonging pixels. Subsequently, the  $E_m$  value of each ILW quadrant is determined from belonging measurement points (one placed on the quadrant centre and eight on the quadrant edge) and, finally, the reflection coefficients are calculated according to method I (Table 6).

Table 6 – Method I – Summary of the calculation of reflection coefficient

Q	$\mathbf{E}_{\mathbf{v},\mathrm{situ}}$	Ls,situ	<b>ρ</b> ilw
Qul	1921	37	0.06
Qur	1988	39	0.06
$Q_{BL}$	1206	43	0.11
QBR	1175	15	0.04

In order to apply method II, the measured distances between reference spotlight and correspondent ILW quadrant are 1.66 m for  $Q_{UL}$  and  $S_{UR}$  and 2.27 m for  $Q_{BL}$  and  $Q_{BR}$ . Since the ILW plane is 30 cm nearer to spotlights, the dILW/dsouth factors are respectively 0.85 for  $S_{UL}$  and  $S_{UR}$  and 0.90 for  $Q_{BL}$  and  $Q_{BR}$ . Table 7 summarizes the calculation of ILW reflection coefficient according to method II.

Table 7 – Method II – summary of the calculation of the ILW reflection coefficient

	Sout	h wall		ILW				
Q	Ref. point	Ls,situ	Ls,situ	$d_{ILW}/d_{South}$	QILW			
$Q_{\text{UL}}$	G2	245	37	0.85	0.11			
Qur	I2	248	39	0.85	0.11			
$Q_{\text{BL}}$	G4	187	43	0.90	0.19			
$Q_{BR}$	I4	206	15	0.90	0.06			

By a quick comparison, method II leads to higher reflection coefficients for all the ILW quadrants. Previous reflectance values are then alternatively assigned to ILW within the DialuxEVO model and the obtained results are reported in Table 8.

Table 8 –  $T_{\rm 1}$  - Summary of results obtained with DialuxEVO using method I and method II

Wall	Ls max	Ls min	Ev med	Ev max	Ev min	ΔLs,m	$\Delta E_{v,m}$
ILW situ	43	15	1443	2720	510		
ILW(I)	38	14	1252	2619	353	1	154
ILW(II)	69	22	1264	2632	365	10	154
East situ	131	12	151	460	35		
East (I)	100	15	123	375	48	13	62
East (II)	105	17	136	385	57	12	61
West situ	131	12	122	370	35		
West(I)	107	13	125	401	57	10	22
West (II)	111	17	137	410	57	10	18

The comparison of results carried out by method I and method II with real measurements shows, in most of cases, similar performances. Simulated maximum luminance values (L<sub>s,max</sub>) are generally lower compared to those measured while L<sub>s,min</sub> are in line or slightly higher than measured. In this sense method II on ILW represents an exception with high luminance values up 50 % above measured. Focusing on illuminance analysis, calculated mean values were about 20 % lower than those measured, while E<sub>v,max</sub> tend to be similar and E<sub>v,min</sub> were significantly higher in the DialuxEVO model, especially on side walls with an overestimation of about 60 %. In order to validate the results obtained by applying the proposed methodology, the difference between simulated and measured values of luminance and illuminance are assessed and the correspondent standard deviation are calculated ( $\Delta L_{s,m}$  and  $\Delta E_{v,m}$  respectively). Calculated errors are similar for both methods. The main difference between the two methods regards ILW Luminance error because with method I the results are close to measured values (1) while method II calculation carries out a significant higher standard deviation value (10).

## 4. Discussion

The research described in the previous chapters shows significant differences between measured and simulated values of Luminance and Illuminance. In particular, it could be noted that values calculated with DialuxEVO tend to be closer to reality in direct lighting conditions while in diffuse or indirect lighting they deviate more with respect to measured data.

However, such data must be contextualized in relation to the visual well-being issue, by comparing specific indicators as the mean illuminance ( $E_m$ ) and the illuminance uniformity ( $U_{x/y}$ ), considered in technical standards (i.e. EN 12464-1 technical standard). Focusing on  $E_m$  indicator, calculated values with both methods are often lower than measured ones with a range of difference of 1 to 18 % according to the surface typology. For lighting design, the analysis over the horizontal plane is very important, where task illuminance and uniformity requirements must be satisfied (or achieved). Table 9 reports the comparison of results of all the considered scenario related to the horizontal plane.

Table 9 – Overview of the indoor lighting indicators values measured/calculated on the horizontal plane

	Eh,m	Eh,max	Eh,min	$U_{min/m}$	Umax/min
T0,situ	440	1470	100	0.23	0.07
$T_{0,calc}$	392	1439	130	0.33	0.09
T1,situ	298	980	50	0.17	0.05
T1,1	268	1151	55	0.21	0.05
Т1,П	286	1195	65	0.22	0.05

The calculated  $E_{h,m}$  values are lower (up to 11 %) with respect to the measured ones even on the horizontal plane. The overestimation of lower values in calculation influences the uniformity ratio  $U_{min/m}$ : the difference is lower when ILW is installed. On the contrary, the  $U_{min/max}$  is substantially the same. Focusing on T<sub>1</sub> scenario, method I gives better uniformity results than method II.

Considering the implications of the previous results on lighting design, two aspects are to be pointed out. Firstly, the test room conditions are intentionally unusual (no openings, only directional lights towards ILW, no diffuse light) in order to emphasize the ILW contribution on the lighting environment. This fact implies that the results provided with the DialuxEVO model are very sensitive to the position of the grid of measurement, especially in points characterized by extreme lighting conditions (with very high or very low Illuminance). Secondly, despite the different Em values, no subjective difference in lighting perception was expected. In fact, according to the EN 12464-1 standard, a 1.5 multiplication factor between subsequent levels of illuminance is the minimum threshold for the detection of changes in the lighting environment for a user. Both in T<sub>0</sub> and T<sub>1</sub>, the E<sub>m</sub> difference respects that threshold. And the fulfilment of the illuminance perception threshold reported by a previous standard has been verified in T1 scenario, for 59/60 measurement points with method I, and for 57/60 measurement points with method II.

#### 5. Conclusion

The experimentation demonstrated the differences of Illuminance and Luminance values in a room with an ILW, comparing measured data and simulation models outputs. However, the difference between measured and simulated data does not influence the overall lighting comfort and keeps the lighting design performance previsions valid. Both the proposed empirical assessments of the Qs value represent a good compromise between the precision of results and the ease of assessment of the reflectance coefficient of ILW by spot measurements of surface Illuminance and Luminance with portable instruments like luxmeters and luminance meters. Investigating the results, method I, using both insitu luminance and illuminance input data with the Lambert cosine law, ensures a slightly better precision than method II, that only uses in-situ luminance data, especially on luminance assessment. According to obtained results, the modelling of ILW elements could be reasonably simplified reducing the time and the effort of the design process. However, the presented results compare real data of a particular lighting scenario that is not common in current building rooms and spaces. Even if the absence of natural light allows for a better control of the internal parameters, in the next step a different lighting scenario will be considered. Another limit of this research is that the monitored data have been compared with a unique software. Despite its wide diffusion between professionals (DialuxEVO), the next step will be to compare monitored data with different software output. In this sense, future research activities could deepen the proposed methodology by a results comparison with other modelling software/engines such as Blender or Radiance and considering standard artificial lighting configurations that allows also a deep customization of surface lighting properties.

## Nomenclature

#### Symbols

Δ	Deviation (measure units, -)
E	Illuminance (lux)
L	Luminance (cd/m <sup>2</sup> )
Q	Quadrant (-)
ρ	Optical reflectance coefficient (-)
Т	Moment of measurement (-)
U	Uniformity ratio (-)

#### Subscripts

0	Before the installation of the Indoor
	Living Wall
1	After the installation of the indoor
	living wall
В	Bottom
ILW	Indoor Living Wall
Ι	Method I
II	Method II
L	Left
h	Measured on horizontal plane
m	The mean value
max	The maximum value
min	The minimum value
R	Right
U	Up
v	Measured on vertical plane
VGS	Vertical Greenery Solutions
Calc	calculated with DialuxEVO software
Situ	Measured in test room

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# Mold Growth Affecting the Achievement of NZEB in the Long Term in Tropical Climates

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#### Abstract

The net-zero energy concept significantly impacts global goals regarding energy accessibility (SDG 7) and responsible consumption (SDG 12), particularly in the building sector, which accounts for substantial energy use and greenhouse gas emissions. While extensive research on Net Zero Energy Buildings (NZEB) has focused on the global north, tropical regions require further study, where high solar radiation, temperatures, and humidity challenge building performance throughout the year. Addressing problems like mold growth caused by these tropical climate aspects can undermine NZEB's performance. This study aims to evaluate the impact of mold growth on a representative building under the tropical climate of Panama City (high temperatures and humidity) and Boquete (low temperatures and high humidity). Long-term hygrothermal and energy performance analyses are conducted using simulation software to assess when and how mold growth affects building performance. Mold can harm the health of occupants and increase energy consumption, as additional humidity control devices may be required after the building's design phase.

#### 1. Introduction

Reducing building energy consumption is among the actions outlined to address the 2030 Agenda Sustainable Development Goals and cut global emissions. Current energy policies encourage airtight and highly insulated building envelopes to achieve Net Zero Energy Buildings (NZEB). As a result, NZEB often has insufficient indoor air exchanges, which reduce air quality and produce higher latent loads. High indoor humidity and the increasing tendency to use organic building materials facilitate the growth and spread of mold in indoor environments (Brambilla & Sangiorgio, 2020). The combination of factors such as humidity, temperature, exposure time, and nutrient availability leads to the growth of fungi on internal surfaces (Di Giuseppe, 2013). Prolonged exposure to relative humidity above 80% and temperature between 15 and 30 °C indicates a high risk of mold growth. The risk is also intensified by increased capillary water absorption (Parracha et al., 2024). In particular, moisture condensation is more likely to occur at wall corners, vertical wall connections, and ceiling joints (You et al., 2017) and depends on the wall orientation (Xue et al., 2022). Mold growth can cause degradation of construction materials and poor indoor air quality, impacting respiratory health with respiratory problems such as asthma or allergic rhinitis and occupant discomfort (Hall et al., 2013). It is recognized that fungal colonization in indoor environments is an important public health problem, and currently, no regulation or threshold value for the intensity of fungal colonization has been agreed upon internationally, partly due to the lack of quantitative studies that connect intensities directly to adverse health effects (Perez et al., 2024). The rise in temperature and humidity due to climate change even exacerbates the problem (Zhao et al., 2024). The renovation of buildings with the addition of thermal insulation can promote the growth of fungi. (Recart & Sturts Dossick, 2022) observed that postretrofit of buildings' envelopes may experience higher levels of moisture and dampness, increased condensation risk, and more rapid structural deterioration due to higher humidity levels. (Liu et al., 2024) and (Hall et al., 2013) also reported an increased occurrence of mold growth conditions following thermal insulation, particularly in humid climates (Silveira et al., 2019). The phenomenon is more pronounced in low-energy buildings (Carpino et al., 2023), in which high levels of Volatile Organic Compounds have been found (De Jonge & Laverge, 2021) (Yang et al., 2020) and in near-zero energy, where internal microbial contamination was detected (Kang & Nagano, 2016) (Sharpe et al., 2016). Considering NZEB characteristics, humidity control is essential to prevent health hazards associated with moisture and mold growth (Tang et al., 2020). (Qiao et al., 2024) proved that relative humidity lower than 75 % at a temperature of 25 °C represents safe conditions for mold formation in all the ten different building materials analyzed. Therefore, moisture safety should be included in the commissioning process for renovation in nearly zero-energy buildings to ensure sustainability and high-quality interventions (Pihelo & Kalamees, 2021). Effective measures to prevent moisture-related risks include predicting the mold index (Aggarwal et al., 2024), monitoring thermo-hygrometric conditions during the building's operation (Fedorik et al., 2021) (Shaw et al., 2024), using moisture-regulating materials (Verma, et al., 2022) (Kumar et al., 2023) and bio-based materials (Tlaiji et al., 2022) (Jirgensone et al., 2024).

Furthermore, ventilation is essential in maintaining appropriate indoor conditions (Niculita-Hirzel et al., 2020), as well as the filter efficiency when using mechanical ventilation (Pavard et al., 2022).

Few studies have been conducted on the risk of fungal growth in Zero Energy Buildings in tropical climates. (Strang et al., 2021) investigated the durability of envelopes made with mass timber in the hot and humid climate of Australia, emphasizing the best practice of informing the design process with hygrothermal risk and mold growth assessments. (Udawattha et al., 2018) have studied the growth of moss and mold on walls of different materials in tropical climate, showing that high porosity and high organic content promote the colonization and proliferation of fungi.

Therefore, the objective of the present study is to assess the risk of mold growth in an NZEB building in a tropical climate and evaluate how the need to dehumidify spaces to reduce the risk of condensation and, thus, fungal growth can impact energy consumption and the maintenance of NZEB performance during the building's operation.

# 2. Simulation

# 2.1 Methodology

The study is based on analyzing a building renovated to become NZEB in a tropical climate following conventional methodology, according to the energy efficiency measures explained in the previous study (Carpino et al., 2024). The renovation of the building, which required energy upgrading of the building envelope, increased cooling system efficiency, and integration of renewable sources, resulted in a Net Site energy balance close to zero, thus achieving an NZEB. The next phase, addressed in the present study, involves investigating the behavior of the building during its operation. Specifically, indoor temperature and relative humidity levels are analyzed in order to detect the occurrence of conditions favorable to mold growth. The need to control humidity could lead to an increase in energy demand, shifting the building away from the NZEB target. The methodology was developed in three phases. First, the entire building model was created in DesignBuilder to simulate the indoor climate (air temperature and relative humidity) of each room. In the second phase, using the WUFI Pro software, a dynamic hygrothermal analysis was conducted for the external walls of two different rooms, representative of two indoor conditions (air-conditioned and not air-conditioned rooms). Finally, the WUFI Bio postprocessor was launched directly, acquiring the dynamic thermohygrometric analysis results to assess the mold formation risk. The influence of climate was considered by simulating the building in two different locations: Panama City, which is characterized by high temperatures and humidity, and Boquete, which has low temperatures and high humidity, both in Panama.

# 2.2 Description of the Case Study

The case study consists of a single-family residential building with a total enclosed area of 65.80 m<sup>2</sup>. The dwelling is single-story and includes ten zones. The image in Fig. 1 depicts the floor plan of the house.



Fig. 1 - Floor plan of the analyzed single-family house

Following the renovation, the building was converted into a NZEB. Table 1 shows the characteristics of the building elements after refurbishment. Fixed solar shading consisting of horizontal overhangs is applied to windows. Only three rooms are equipped with a cooling system. The latter corresponds to split units with an average seasonal efficiency (CoP) of 3.0 and operating on a schedule from 11 p.m. to 7 a.m., with a set-point temperature of 28 °C. This operation was defined as the NZEB's optimum point, identified through a multi-objective optimization procedure, shown in the paper (Carpino et al., 2024), which also complies with national regulations.

Table 1 – Optimal U-values for the building elements

Building elements	Optimal U-value [W/m²K]
External walls	2.2
Roof	0.4
Ground floor slab	3.8
Semi-exposed ceiling	4.0
Windows	3.0

Air dehumidification is active in the rooms with a cooling system, with a set-point of 60 %. No air exchange between rooms is modeled. A 3 kWp photovoltaic system is installed on the roof of the building. The building, as renovated, has an energy demand of 52.80 kWh/m<sup>2</sup>y in Panama City and 40.46 kWh/m<sup>2</sup>y in Boquete. Considering the PV producibility, the building shows an energy surplus of 936.64 kWh/y if located in Panama City and 1984.38 kWh/y if located in Boquete, thus performing as an NZEB.

#### 2.3 Mould Growth Risk Assessment

Considering the building during the operation phase, hourly simulations were conducted in DesignBuilder in both locations to investigate the evolution of indoor conditions. The graph in Fig. 2 shows the air temperature and relative humidity of the living room, which was not equipped with cooling and dehumidification, for Panama City for one year. It can be seen that the relative humidity often reaches high values (over 80 %).



Fig. 2 – Hourly trend of indoor air temperature and relative humidity of the living room (no cooling and dehumidification) for Panama City

Subsequently, using WUFI Pro, dynamic thermohygrometric analysis was conducted for the external walls of two rooms: Bedroom 2, equipped with air conditioning, and the Living Room, without air conditioning. WUFI Pro allows for the calculation of heat and moisture fluxes through a building component exposed to certain outdoor and indoor climatic conditions. Specifically, the following climatic conditions were adopted. The same ".epw" file used in DesignBuilder was provided for the outdoor climate. For indoor climate, the "sinusoidal" modeling option was selected. This allows the indoor climate to be modeled as a sine wave of an annual period based on user-defined data. Specifically, by providing the average values of room temperature and relative humidity (obtained from the DesignBuilder simulation) and the amplitude of the quantities, thus the variability between the minimum and maximum values, the software outlines a sinusoidal trend for the indoor climate in terms of indoor temperature and relative humidity. Based on the ambient data, the program performs transient thermohygrometric simulations through the various layers of the building component.

As shown in Fig. 3, the south wall of the living room is affected by surface condensation because the sur-

face temperature reaches the dew point. This seems to create suitable conditions for mold development. Therefore, the risk of mold growth was assessed using the WUFI Bio software. This post processor can be launched directly from inside the WUFI Pro, being integrated into it, and is able to acquire the results of the simulation carried out by WUFI Pro (computed hourly temperatures and relative humidity at the interior surface of the component).



Fig. 3 – Trend of the surface temperature and dew temperature for the south wall of the living room (Panama City)

WUFI Bio uses the biohygrothermal model to assess the risk of mold growth under transient ambient conditions. This method is based on comparing the simulated (or measured) transient ambient conditions and the growth conditions needed by the fungi usually encountered in buildings. The moisture content of the mold spores is simulated and compared with the critical content required for spore germination. Once germination has occurred, growth curves are used to estimate the subsequent spread of the infestation. The results regarding mold growth rate (mm/year) are provided and associated with different occupant exposure classes. Moreover, according to the approach developed by (Viitanen et al., 2015), the software allows the conversion of the "mold growth" determined by WUFI Bio's biohygrothermal model into the "mold index" used by the Viitanen model. The model provides three classes of occupant exposure and different levels of severity of mold infestation if present on indoor air contact surfaces. A class labeled "green traffic light," indicates mold growth < 129 mm/year and a mold index  $\leq$  1. A class labeled with the "yellow traffic light" has mold growth between 129 and 176 mm/year and a mold index between 1 and 2. Finally, a class labeled "red traffic light" is obtained for mold growth > 176 mm/year and mold index > 2. The analysis conducted for the south wall of the living room returns the "red light signal" for mold risk for both locations analyzed. Specifically, the mold index equals 6, and the mold growth rate is greater than 176 mm/year in both cases. This level is usually considered unacceptable. The graphs in Fig. 4 and Fig. 5 show the critical water content and the spore's water content evaluated for the south wall of the living room in Panama City and Boquete, respectively.



Fig. 4 – Critical water content and water content in the spore evaluated for the south wall of the living room (Panama City)



Fig. 5 - Critical water content and water content in the spore evaluated for the south wall of the living room (Boquete)

The analysis conducted for the north wall of Bedroom 2, equipped with a cooling and dehumidification system, returns the "green light signal" for both locations. The water content in the spore decreases, as illustrated in Fig. 6 and Fig. 7, corresponding to the two different locations. The mold index is 0.87 for Panama City and 0.056 for Boquete. This level is usually considered "acceptable."



Fig. 6 – Critical water content and water content in the spore evaluated for the north wall of the bedroom (Panama City)



Fig. 7 – Critical water content and water content in the spore evaluated for the north wall of the bedroom (Boquete)

However, when the water content in the spore exceeds the critical water content, it is assumed that the spore can germinate, and fungal growth can develop. In the long run, this can damage surfaces and pose a threat to the health of occupants. Fig. 8 shows the mold growth rate over three years for the north wall of bedroom 2 for the building located in Boquete. Although the mold risk classification returns a green light, which is considered an acceptable level, in the long period, with the interior conditions remaining unchanged, mold progressively grows.



Fig. 8 – Mold growth rate for the north wall of the bedroom (Boquete)

## 3. Discussion and Result Analysis

The findings presented underscore the crucial role of mold risk prevention measures and their impact on energy consumption. The ideal condition necessitates that mold does not grow on interior surfaces. Therefore, to mitigate the risk of mold, humidity control and cooling must be extended to all rooms in the house. In the case of the Panama City building, to eliminate the mold risk, in addition to extending cooling to the whole house, the cooling setpoint temperature must also be lowered from 28 °C to 26 °C.

Under these conditions, the simulations showed zero risk of mold formation. It is worth noting that although lowering the temperature leads to an increase in relative humidity, the extension of humidity control in all areas ensures safety from mold risk. However, this results in an increase in energy consumption by about 46 %. The total energy demand rises from 52.80 kWh/m<sup>2</sup>y to 77.30 kWh/m<sup>2</sup>y, and the Net Site energy balance passes from -936.64 kWh/y (surplus of renewable) to 674.75 kWh/y (withdrawn from the grid). This means that the building designed to be an NZEB, under operating conditions, with the intent to ensure mold safety and the well-being and health of the occupants, will have higher energy consumption. Consequently, the NZEB target is nullified.

Regarding the building located in Boquete, it is sufficient to extend the humidity control to 60 % for the whole house, maintaining a set-point temperature of 28 °C. Simulations conducted under these conditions have shown the absence of mold formation. However, an increase in energy consumption is also recorded in this case. The energy demand increases from 40.50 kWh/m<sup>2</sup>y to 42.50 kWh/m<sup>2</sup>y. The Net Site energy balance passes from -1984.38 kWh/y to -1849.80 kWh/y. In this case, even after implementing mold risk prevention measures, the building remains an NZEB, albeit with an increase in energy demand of about 5 %. This tradeoff between mold prevention and energy consumption highlights the challenges of maintaining a balance between occupant health and energy efficiency. The graphs in Figures 9, 10, and 11 display monthly energy consumption trends and Net Site energy balance under design conditions and operating conditions to prevent fungal growth in the two locations.



Fig. 9 – Monthly energy consumption under design and operating conditions with preventive measures for mold safety, Panama City



Fig. 10 – Monthly energy consumption under design and operating conditions with preventive measures for mold safety, Boquete



Fig. 11 – Annual Net Site energy balance under design conditions and operating conditions with mold safety for the two locations

# 4. Conclusion

The present study analyzed the performance of a renovated NZEB building in a tropical climate. A single-family house was considered, located alternately in Panama City and Boquete (Panama). The results of simulations conducted in DesignBuilder and WUFI showed that there is a mold growth risk during building operation. In particular, an occupant exposure Class III (red light) was found for non-air-conditioned areas, in which high indoor humidity is achieved along with high temperature. Under these conditions, mold growth and proliferation become a severe risk for occupants.

In order to prevent microbiological contamination, it is necessary to dehumidify the indoor environment. Dehumidification comes as the only effective measure since ventilation is not useful in lowering humidity levels in hot and humid climates. The application of dehumidification and, therefore, cooling to all the rooms of the house and for the whole day results in significant increases in energy consumption. The increase in energy demand is such that the NZEB behavior is nullified for the building located in Panama City, while for the building located in Boquete, the NZEB target is maintained despite an increase of 5 % recorded. The obtained results, therefore, suggest that special attention should be paid to indoor mold risk assessments when designing NZEB in tropical climates.

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# Mitigating Summer Overheating of a Primary School Building Based on Dynamic Simulations

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#### Abstract

Overheating in buildings is a prevalent issue during summer, especially in school buildings due to their design and use. Despite schools being mostly closed during peak summer months, warmer temperatures in May, June, and September exacerbate the situation. We analyzed a primary school building in Budapest, conducting dynamic simulations to evaluate interventions such as flat roof renovations, window shading techniques, passive ventilation strategies, and a comprehensive 'nearly zero' energy retrofit. Systematic night-time ventilation proved an effective tool for summer cooling, offering a sustainable, cost-effective solution. The simulations revealed that the current state of the primary school leads to significant overheating. However, the cases revealed that systematic nighttime ventilation of the buildings is an effective tool for summer cooling. Additionally, installing shades proved beneficial, installing external overhangs or shades offers practical retrofit options. Conversely, flat roof insulation and energy renovation resulted in slightly worse summer overheating values. Among the solutions, light-colored reflective surface waterproofing performed the best, but further studies with green roof layering are still worthwhile. The study also revealed that a 'nearly zero' energy efficiency retrofit focusing solely on thermal insulation and airtightness led to higher indoor temperatures without altering ventilation patterns. This highlights the need for a balanced approach that includes both insulation and ventilation. Combining night-time ventilation with window shading was the most effective strategy to mitigate overheating in schools. These findings can guide energy renovations in educational facilities to enhance comfort and sustainability, ultimately creating a healthier learning environment for students and reducing energy consumption.

#### 1. Introduction

Investigating the summer overheating of school buildings is crucial due to children's increased vulnerability to overheating effects (Hyndman et al., 2023). Additionally, classrooms are often designed with large windows facing east or south to allow natural light, which can lead to increased overheating during peak occupancy hours (Grassie et al., 2022). Classroom conditions are mainly influenced by teachers' preferences, and research indicates that the comfort needs of adults can differ significantly from those of children (Korsavi et al., 2020; De Giuli et al., 2012; Hellwig et al., 2022).

Examining indoor air conditions in primary schools is a complex task, considering factors such as temperature, humidity, natural ventilation, natural light, acoustics, air quality, and children's satisfaction. It is important to ensure good air quality to create a conducive learning environment. Air cooling systems can alleviate thermal conditions, but inadequate ventilation can cause compromised air quality. In poorly ventilated classrooms the amount of carbon dioxide (CO<sub>2</sub>) can rapidly increase over 1200-1500 ppm and reach a level where it can adversely affect the performance of children (Teli et al., 2016; Clements-Croome et al., 2012), and with closed windows and air tightness, this value can rise above 3000 ppm (Bakó-Biró et al., 2008). It has also been found that students can become accustomed to the air conditions in the classroom, making it difficult for them to notice when the air quality worsens (Teli et al., 2016).

On the other hand, open windows and proper natural ventilation during classes lead to increased inner temperatures. Demozzi et al. in their study found a significant, 16-22 % performance loss caused by thermal discomfort (Demozzi et al., 2022).

A great emphasis has to be placed on the design of the division of windowpanes to achieve effective natural ventilation. Hellwig shows that classroom air change rates can be improved by separating the opening for supply air and exhaust air horizontally, 2 rows of tilt windows work best (Hellwig, 2010).

The other important factor of the indoor environment is natural light. Children need an adequate amount of natural light, 500 lux (EN 16798-1:2019) for studying so it is important to find the proper shading methods to let enough diffuse sunlight in but blocking solar radiation as much as possible. This standard also specifies requirements for indoor environmental parameters. The mentioned standard specifies four categories for the classification of expectations, with different, progressively lighter threshold values for each category in terms of expected temperature, air quality, and comfort expectations. Retrofits belong to category III. The thermal comfort level of an examined building can be evaluated by the satisfaction levels of the users. Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) values reflect the human comfort level and the percentage of dissatisfied users. These values can aid in calibrating simulation settings more accurately.

In the Hungarian practice, energy renovations typically focused on winter conditions only: achieving air tightness and applying thermal insulations on walls and roofs, choosing windows with good insulating parameters, and installing modern heating systems according to the National regulations that follow the EU directive of nearly zero energy consumption (2010/31/EU 2010). Summer overheating is not considered in most of the cases. Eight schools in the district of the examined school in Budapest have been retrofitted in the past 10 years, but the issue of solar protection or ventilation after school hours has not been taken into account in either case. Cooling, shading, and water-retention potential of vegetation and green roofs have not been considered in retrofitting policy either, despite studies showing their potential (Gómez et al., 2021).

This study investigates and suggests passive solutions to prevent schools from overheating during warmer months.

#### 2. Methodology

#### 2.1 Introduction and Modeling of the Building

The subject of the investigation is a 2-storey primary school building with 16 classrooms located in Budapest suburbs. The building was originally built in 1960 with brick walls, reinforced concrete frames, and reinforced concrete beam/block slabs. Fig. 1 and Fig. 2 show the 3D model and floor plans of the building.



Fig. 1 - BIM model of the building using Archicad 26



Fig. 2 – Floor plans of the building, from left to right: ground floor, first floor, second floor. The subject of this investigation: eastern classrooms, southern classrooms, and the corridor with the service areas are highlighted in different shades of blue

We chose this building for our examination because the layout is typical for Hungarian schools: 2 blocks of classrooms facing east and south connected by a corridor on one side. The service areas and stairs are located at the end of the corridors which connect the classroom area to the offices, teachers' rooms, and the gym.

We used WUFI Plus software for the hygrothermal dynamic simulation of the building. First, the BIM model of the school building was modeled in Archicad and then converted into a Sketchup file. In Sketchup, we used a WUFI plugin and arranged the main settings. We divided the school building into 10 zones and defined their relation to each other and the outside air and ground. The Sketchup file then was saved in a WUFI-compatible format and was ready to use. Fig. 3 shows the model of the block of classrooms in WUFI.



Fig. 3 – Model of the building in WUFI

#### 2.2 Setting up the Model in WUFI

The building's location was determined using coordinates, and data from a weather station based in Budapest was utilized. The weather file contained complex weather data for 2020, such as temperature, relative humidity, solar radiation, driving rain, and wind.

The simulation was set for a whole year but only the data from 01.05. to 24.06., the last few weeks of the school year were analyzed in this research.

We divided the building into 10 zones. There are 3 main zones on each floor, (ground floor, 1<sup>st</sup> and 2<sup>nd</sup> floor):

- eastern classrooms (zone 1, 4, 7),
- southern classrooms (zone 2, 5, 8)
- corridor (zone 3, 6, 9)
- zone 10 is the basement.

We set the materials of building structures from the WUFI database according to the architectural documentation not only on the outside structures but on the inside as well, because the heat storage capacity is an important factor in overheating calculations.

Flat roof layers were set according to the present state, with 2 possible retrofit options – a minor and a complete renovation. A preset green roof layering was chosen from the WUFI database. Green roofs can retain water, which plays a key role in night cooling and can be calculated in WUFI but the material properties need to be carefully selected (Baniassadi et al., 2018).

A wide range of window parameters can be set manually or from the WUFI database. For shading, we can choose window overhang or sunscreen devices with 3 options. In sunscreen settings, both the closing factor and shading factor can be determined. The shading effect of the surroundings, in this case, a few trees near the eastern façade, was not considered. The trees only impact the ground-floor classrooms, which are not the most affected areas of this study.

The window blinds in some scenarios were selected with actual products in mind such as light fabric roller blinds and Venetian blinds. These blinds block direct sunlight while allowing natural lighting to filter through. The shading factor was set to 0.2 in each case, (1 - no shading, 0 total shade). Closing factor was set differently in each of the 3 cases keeping in mind that a fully closed shade can block natural ventilation. The software limitations prevent an accurate calculation of reduced natural ventilation, potentially impacting results during school hours.

At present, the building lacks external shading, so the 2005 scenario is calculated accordingly.

The internal load was calculated based on the ISO 7730:2005 standard, preset in the WUFI database, in which heat, moisture, and CO2 emissions are assigned to a given action, and a given age (child or adult). In this case: sitting activity during the classes and standing or a light walk during the breaks (child sitting activity, moisture: 33 g/h; convective heat: 56 W; radiant heat: 28 W; CO<sub>2</sub>: 40 g/h; human activity: 1.2 met).

The calculation was based on an average school day with 45-minute lessons and 15-minute breaks from 8.00 to 13.00, a lunch break, and then afternoon classes until 17.00, from Monday to Friday. After school hours the internal loads and ventilation were set to zero. The values were set as accurately as possible to model the actual usage.

Setting the amount of natural ventilation was a difficult task. We assumed that the windows are mostly open in summer to maintain fresh air and keep CO<sub>2</sub> levels low, so after a few trial simulations we set natural ventilation to 3 ACH or 4 ACH during classes.

The settings for summer internal air velocity (here: a light draught, 0.4 m/s) and summer clothing (clo=0.5) were also considered. (1 Clo is a fully dressed person, 1 clo =  $0.155 \text{ m}^2\text{K/W}$  for adults). These settings affect satisfactory values (PMV and PPD).

All simulation scenarios had the same settings for the internal loads and occupancy.

#### 2.3 Scenarios of the Research

We examined the following scenarios and combinations within the current research:

- Original building (1960) as reference
- Present case (2005)
- Flat roof renovation
  - light surface
  - dark surface
  - · green roof
- External shading
  - window overhang
  - schedule
  - reduce overheating
  - radiation limit
- Night ventilation
  - 2 ACH
  - 6 ACH
- Nearly zero retrofit
  - nearly zero
  - nearly zero + night ventilation
  - nearly zero + window overhang
  - nearly zero + night ventilation + shade

#### 2.3.1 Present case scenario (2005)

The first scenario was run with the basic settings of the building in its present state. In 2005 the building underwent a basic renovation focusing on increasing energy efficiency according to the regulations of that time. The walls were insulated with 5 cm of EPS and the windows were replaced with PVC windows with 2-layer insulating glazing ( $U_w = 1.4 \text{ W/m}^2\text{K}$ ). We have named this scenario '2005' after the year of the most recent renovation.

We generated a simulation of the original, 1960 building as a reference to make the effects of the 2005 minor renovation more visible.

For data comparison, we used the ODH<sub>26</sub> indicator (Overheating Degree Hours over 26 °C [Kh/a]) which sums up the parts of the operative temperatures above 26 °C. This is a simple method for analyzing the received data set and detecting trends. In each of the simulations, we aggregated these values by zone so we got a series of values that can be easily compared (Fürtön et al., 2022).

#### 2.3.2 Cases of flat roof renovation

We examined three possible cases of flat roof renovation. If the waterproofing of the roof is in good condition the layers in the roof and the slab might be dry, so there is a possibility to keep the old layers and add new layers of thermal insulation and waterproofing. The present bituminous layers have dark surfaces, so in the three cases, we examined a dark surface and a light surface, reflective waterproofing as a closing layer, and also calculated for an extensive green roof. WUFI has options for setting the value of the absorption coefficient of shortwave radiation on surfaces (0-1), so we set those to 0.8 for dark surfaces; 0.2 for light surfaces; and 0.6 for green roofs.

#### 2.3.3 Cases of external shading

In the 'window overhang' scenario, the dimensions of the shades were determined by a solar exposure test to maximize efficiency in both summer and winter. Solar heat gain can be advantageous during the winter months but has negative effects during the summer.

In the 'schedule' setting scenario, the schedule of the blinds was based on the hours exposed to direct sunlight and was considered pulled down to varying degrees hour-by-hour. The solar transmittance of the shade fabric and the percentage of closedness can be determined in a daily profile setting. The downside of this setting is that it does not take into account the solar radiation values, i.e. it considers the shade closed even if the sun is not shining.

In the 'reduce overheating' setting scenario the shade is considered pulled down when the maximum temperature set for the zone (27 °C) is exceeded. We set this simulation with a light-surfaced reflective textile blind in mind.

With the 'radiation limit' setting we set the solar radiation threshold value to 400 W/m<sup>2</sup> after which the shades are closed and block direct sunshine.

#### 2.3.4 Cases of night ventilation

In these scenarios, we examined the effect of night ventilation. Lower temperature outside air cools the building's inner structures in the night, which helps regulate indoor temperatures. Using the building's heat storage capacity is an effective passive cooling method. The division of the windowpanes is the key to natural ventilation in classrooms. A row of tilt windows in the uppermost section seems to be a feasible solution for security concerns. Setting the amount of the exact air change rate is difficult in a simulation of natural ventilation. We set 2 ACH and 6 ACH air change rates in our scenarios from 21.00 to 6.00 at night. Night cooling must be monitored daily or must be completely automated because, with unexpected drops in night temperatures, overcooling can occur. (Pellegrini et al., 2012).

In our simulation, we found that with a 6 ACH air change rate in some cases, the inner temperatures fall below 20 °C in the morning hours, but as the children arrive it quickly rises to 23-24 °C. Also, strong winds, rain, or storms can cause problems. With monitored temperature data and motorized control, it is possible to determine the number of windows needed in each room for night ventilation, and thus optimal night cooling is achieved.

We should note that during heatwaves, the temperature of the air at night is much higher in densely populated urban areas, so night ventilation might not be as effective during those periods.

# 2.3.5 Cases of 'nearly zero' energy renovation

To reach the nearly zero energy efficiency goals we added additional subsequent thermal insulation on the walls and on the flat roof. We also replaced the existing windows with new, triple glazed thermal insulating low-e coated glazing and insulating frames and thermally insulated the basement slab of the ground floor from the basement side. We set the U value of the structures to safely meet the current Hungarian regulations which entered into force in autumn 2023, shown in Table 1. (176/2008. Gov. decree 2023).

Table 1 – Thermal transmittances (U; W/m <sup>2</sup> K) for structures in	
present, planned, and for 'nearly zero' regulation conditions	

	U pre- sent (W/m²K)	U planned (W/m²K)	U regulation (W/m²K)
exterior walls	0.465	0.194	0.24
flat roof	0.349	0.139	0.17
unheated basement slab	0.782	0.159	0.26
windows	1.4	0.8	1.1

#### 3. Results

# 3.1 Results of Present Case Scenario (2005)

According to the first two simulations of models 1960 and 2005, a 60 % reduction in the heating energy demand can be observed, but in addition, the results show a significant, 210-420 % increase in the ODH<sub>26</sub> indicator. The results of the ODH<sub>26</sub> for the zones and the average ODH<sub>26</sub> value for the overall building are shown in Fig. 4.

Observing the results by zones, it is visible that the zones representing the Eastern classrooms, especially on the first and second floors (zones 4 and 7), experienced the highest temperatures and overheating due to intense morning solar radiation. These are followed by the classrooms of the southern block (zones 8 and 5). Shading these zones' windows to limit the incident solar radiation would be certainly necessary to avoid overheating in summer conditions.

In contrast, the ground floor areas benefitted from the cooling effect of the basement, showing lower temperatures and ODH<sub>26</sub> values. This tendency showed in every further simulation, so we concentrated our investigations mainly on the two most affected eastern zones: 4 and 7.

Interestingly, in the 2005 scenario, zone 4 was the most affected, while in the 1960 case zone 7 had the worst results in the case of the  $ODH_{26}$  indicator, the effect of the previous renovation is visible on the results.



Fig. 4 – ODH $_{26}$  values of zones in 1960 and 2005 case scenario

WUFI generates diagrams of operative temperatures as a function of the exponentially weighted running mean of the outdoor temperature according to EN 16798-1:2019 standard. The diagram shows that the majority of operative temperatures in zone 4 in the current, 2005 scenario are above the acceptable boundaries, shown in a red continuous line (see Fig. 5). Compared to the reference building, thermal insulation prevents building heat loss in winter but can result in overheating in summer.



Fig. 5 – Zone 4 operative temperatures in 1960 (left) and 2005 (right) scenarios from 01.05. – 09.01. in the adaptive temperature range according to EN 16798-1:2019 standard

#### 3.2 Results of Flat Roof Renovation Scenarios

In all flat roof renovation scenarios, a slight rise in temperatures can be observed. Understandably, the temperatures in the  $2^{nd}$  floor zones (7, 8, 9) rise the most, because the thicker thermal insulation prevents heat loss through the flat roof. The simulation indicates that choosing a light, reflective material for the flat roof reduces the heating of the surface, thus decreasing overheating (see Fig. 6).



Fig. 6 –  $ODH_{26}$  in 3 different flat roof renovation scenarios compared to the present state in zones 1–9, and overall performance of the building

Temperature data of Table 2 of the external surfaces of the roof also show a significant, 24 °C difference in the best and worst cases. The internal surfaces have slightly different values in maximum temperature, as the result of the building's heat storage capacity and the lack of night ventilation. This issue will be discussed in the night ventilation scenarios. The cooling effect of green roofs was not considered in the present study; therefore, further investigations are needed. The results indicate that selecting reflective or light-colored materials for roof surfaces can significantly reduce heat absorption and improve indoor thermal conditions. Green roofs offer additional benefits and should be considered for their cooling potential and water retention capabilities.

Table 2 - Max. temperatures of the surfaces of the flat roof

	inner surface temp (max).	outer surface temp (max.)
2005	38 °C	67 °C
green roof	38.4 °C	54.4 °C
dark surface	38.3 °C	64.8 °C
light surface	37.5 °C	43 °C

#### 3.3 Results of Shading Scenarios

The effect of external window overhangs reduced the value of the ODH<sub>26</sub> indicator notably to 45-71 % in the zones, and 60 %. in zone 7. The scheduled shading scenario also showed positive results, but its effectiveness depends on accurately predicting solar radiation patterns. The "reduce overheating" setting, where shades close based on indoor temperatures, provided the best results, balancing natural light and thermal comfort. Every shading solution were effective in reducing overheating, but it is difficult to say which setting depicts the actual operation best (see Fig. 7), our research shows that any kind of external shading can be beneficial as it effectively reduces internal temperatures by blocking direct sunlight and should be integrated into the building design. When selecting window shades, it is important to consider both the amount of natural light and the natural ventilation of rooms.



Fig. 7 – ODH $_{26}$  of shading scenarios compared to the 2005 phase in zones 1–9, and overall performance of the building

#### 3.4 Results of Night Ventilation

Night ventilation proved to be a highly effective passive cooling method. Both 2 ACH and 6 ACH scenarios showed significant reductions in ODH<sub>26</sub> values. The 6 ACH scenario, although more effective, sometimes resulted in overcooling, indicating the need for monitored or automated control systems to optimize ventilation rates and prevent discomfort. Implementing night ventilation systems with automated controls can optimize indoor temperatures without compromising comfort. This method is cost-effective and sustainable, reducing reliance on active cooling systems. Further research is needed to optimize night cooling in schools, but the potential of this kind of passive cooling is promising.



Fig 8 – ODH  $_{26}$  of night ventilation compared to the 2005 phase in zones 1-9, and overall performance of the building

#### 3.5 Results of Nearly Zero Scenario

In each zone of the building, we can see a jump in the ODH<sub>26</sub> indicator values (Fig. 8). Unlike before, the temperature of the rooms on the ground floor increased most dynamically, due to the insulation of the basement slab. The nearly zero energy retrofit, focusing on enhanced thermal insulation and airtightness, led to higher indoor temperatures across all zones. This retrofit, while improving winter energy efficiency, exacerbated summer overheating issues. The results underscore the necessity of incorporating ventilation strategies alongside insulation to maintain thermal comfort year-round.



Fig. 8 – ODH $_{26}$  of nearly zero renovation compared to 2005 and 1960 in zones 1–9, and overall performance of the building

Based on the results presented in Fig. 9, the worstperforming eastern zone 4 is already in the temperature range of 33 - 37 °C by June and does not follow the external temperature fluctuations. The building cannot cool down and will become unusable during warmer months without shading and unchanged ventilation habits. Increasing the thickness of thermal insulation changed the trend: the zones positioned in the middle of the building became the most affected by overheating. This phenomenon has been observed in other studies too (Szagri et al., 2019).



Fig. 9 – Hourly temperatures of zone 4 in nearly zero scenario (05.01-06.24)

We examined the effect of the formerly presented scenarios with the 'nearly zero' settings. Based on the ODH<sub>26</sub> results, by blocking solar radiation in summer, indoor temperatures are more favorable than without shading. With night ventilation, we can achieve results similar to the previous scenarios. By combining the two solutions, we can create very favorable conditions in the classrooms (see Fig. 10).



Fig. 10 – ODH<sub>26</sub> of scenarios for possible nearly zero solutions

## 4. Conclusion

Due to global warming, children's school environment needs to be revived nationwide. This study demonstrated the effectiveness of various interventions to mitigate summer overheating in a primary school building in Budapest. Our findings align with research indicating buildings should be protected against summer overheating. Designers must prioritize this in energy renovations.

The examined school is prone to overheating in its present state and this tendency is likely to worsen. In each simulation, the eastern classroom block on the 1<sup>st</sup> and 2<sup>nd</sup> floor consistently experienced the highest levels of overheating. This is due to the combination of high internal loads in the classrooms and the intense morning solar radiation on the eastern façade. The dynamics of overheating depend on the thickness of the thermal insulation applied to the walls and flat roofs.

The degree of warming slightly increases in all cases. of flat roof renovation scenarios. Of the solutions listed, waterproofing with a light-colored, reflective surface proved to be the best. Further studies of the cooling effect of green roofs need to be conducted. There was a significant improvement in every case when applying external shades. The best results came with the reduce overheating setting, where the screen closes to a given percentage when the defined maximum temperature is reached in the classroom. Also, a more affordable but effective solution can be achieved with the combination of window overhangs and internal curtains.

The results of the 2005 energy renovations do not meet the current 'nearly zero' energy expectations. The calculations showed that by refurbishing the thermal envelope to meet the 2024 requirements the warming indicators deteriorate very significantly.

Nighttime ventilation proved to be the best solution in all scenarios. Even the smallest amount of air change rate can be used as a powerful tool in mitigating overheating. It can be combined with any of the examined scenarios.

In 'nearly zero' energy cases it is impossible to cool down buildings without nighttime ventilation.

In our calculations we proved that the current design and operation of the school is not sustainable. Installing air conditioning in classrooms may effectively cool the temperature, but it can lead to poor air quality and high CO<sub>2</sub> levels due to the lack of ventilation.

Currently, the windows of school buildings are closed during non-school hours for security reasons. of night ventilation offers a long-term profitable solution. The maintainers must be informed of its potential so that solutions can be found at the system level. The results of this study can also provide a basis for the modernization of similar school buildings.

Buildings cannot be always cooled to a comfortable level by passive means during heatwaves. The solution can be found by developing hybrid systems. It is recommended to prioritize passive solutions or renewable energies even in systems with mechanical cooling.

These findings can guide future energy renovations in educational facilities to enhance comfort, sustainability, and the overall learning environment for students.

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# Analysis of Energy Consumption of a Building Placed in Milan by Adopting Common Building Insulation Materials and Recycled Surgical Masks

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#### Abstract

The paper analyses using recycled materials for insulation panels, focusing on repurposing surgical masks for building insulation in a circular economy. Since insulation panels made from recycled materials are suitable for use in disadvantaged contexts, dynamic simulations are performed before and after applying the panels in an apartment of approximately 80 m<sup>2</sup> of floor area, part of a social housing complex in Milan (Italy). The TRNSYS software analysis focuses on the heating season, assessing the impact before and after energy retrofit interventions with an inside application of insulation panels. Additionally, further analyses compare energy savings using commercial insulants like mineral wool and polystyrene. Results show that the reduction in thermal energy demand for heating employing commercial insulants is comparable to the obtained from employing non-commercial insulants. Moreover, the comfort analysis also displays similar results after the employment of commercial and non-commercial insulants.

#### 1. Introduction

The building energy demand share was 30 % of the final energy consumption in Europe in 2021, as stated by the United Nations Environment Program report of 2022 (United Nations Environment Programme, 2022). In the Italian scenario, according to the IEA report about Italian energy policy (IEA, 2024), the energy used in buildings started to decrease in 2017 due to efficiency measures. However, the demand for thermal energy in residential buildings is still high, and the majority of energy consumption is for space heating. A strategy for Energy Retrofitting of the National Building Stock has been issued by the Italian government in March 2021 (MiTE, 2021). It foresees that buildings are expected to contribute 60 % of the annual final energy savings target by 2030. Possible strategies to contain consumption aim to make generation systems more efficient, preferring systems with a low environmental impact, implementing adequate energy management systems, and improving the performance of the building envelope to reduce buildings' dispersion through the external envelope. Alongside the topic of energy efficiency, sustainability has become a key factor in building design, and in general, there is a search for the possible reuse of endof-life household materials (EoLHM). In particular, after the COVID pandemic, surgical masks have resulted in an environmental pollution issue (Badillo-Goicoechea et al., 2021; Wang et al., 2022; Chowdhury et al., 2021). One innovative approach to enhance building envelope efficiency within a circular

economy is repurposing waste materials to create insulation panels for construction. This method supports sustainability by reusing materials and can empower individuals in underserved communities to self-produce and install these panels in their homes. A previous work by Rossi di Schio et al., 2024, analysed the thermal conductivity of insulation panels made from surgical masks following ISO standards (ISO 8301, 1991). The results, Table 1, indicate that surgical mask insulation panels have thermal conductivity similar to commercial insulators, especially for sample densities greater than 60 kg/m<sup>3</sup> (conductivity values of 0.039-0.052 W/(m K) in the density range between 60 and 90 kg/m<sup>3</sup>).

Test ID	Sample characteristics	Specimen density, q	Conductivity, $\lambda$
		(kg/m³)	(W/(m K))
T1*	Masks in an ordered arrangement	90	0.039
T2	Masks in disordered arrangement	90	0.042
Т3	Crumpled masks	76	0.052
T4*	Crumpled masks sanitized	60	0.066
T5	Crumpled masks sanitized	70	0.060
T6*	Crumpled masks sanitized	75	0.059
T7	Crumpled masks sanitized	80	0.054
Т8	Crumpled masks sanitized	90	0.050
Т9	Crumpled masks sanitized treated with flame retardant	60	0.053
T10	Crumpled masks sanitized treated with flame retardant	70	0.050
T11	Crumpled masks sanitized treated with flame retardant	75	0.059
T12	Crumpled masks sanitized treated with flame retardant	80	0.044
T13	Crumpled masks sanitized treated with flame retardant	90	0.052

Table 1 - Results from experimental tests performed on insulating panels made of surgical face masks (Rossi di Schio et al., 2024)

\*Panel characteristics considered in dynamic analysis.



The present work aims to determine the reduction of thermal energy achievable using insulating panels made from reused materials and compare it with commercial insulation panels. Through TRNSYS simulation, the reduction of thermal energy achievable in a residential apartment as a part of a social house in Milan is calculated. Moreover, a comfort analysis is also conducted, determining the value of the comfort indices PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied people) (Fanger, 1970), within the thermal zones of the considered apartment. data are provided by the Meteonorm database (Meteonorm, 2024).

The dynamic analyses aim to determine the thermal demand of the building during the heating season in the presence of various types of commercial and non-commercial insulators applied to the external walls and adjoining unheated spaces. The non-commercial insulators are made from reused materials. Specifically, in previous work, the authors analyzed the possibility of employing reuse materials (specifically surgical face masks) to create insulating panels that can be employed in construction. As re-

Table 2 – Layer characteristics. The elements in yellow concern the post-intervention. Superscripts a, b and c, refer to the experimental results of tests T1, T6 and T4 respectively. s represents the layer thickness,  $\lambda$  is the thermal conductivity,  $c_t$  the thermal capacity,  $\rho$  represents the layer density, and U is the transmittance of the envelope component

Pre- intervention	Element	<i>s</i> (m)	λ <b>(W/ (m K))</b>	<i>ct</i> (kJ/ (kg K))	ρ (kg/m³)	Post- intervention
	Plasterboard	0.015	0.20	1.45	660	
	Insulant	0.08	0.039 ª/ 0.059 <sup>b</sup> /0.066 <sup>c</sup>	0.87	90ª/75 <sup>b</sup> /60 <sup>c</sup>	
External wall	Internal plaster	0.01	0.70	1	1400	$U = 0.376^{a}$
U=1.302 W/(m <sup>2</sup> K)	Hollow bricks	0.08	0.36	0.8	1000	0.495⁵/0.533° W/(m²K)
	Air gap	0.16	-	-	-	
	Hollow bricks	0.08	0.47	0.8	1000	
	External plaster	0.01	0.90	0.8	1800	
	Plasterboard	0.015	0.20	1.45	660	$II = 0.372^{a}/$
Internal wall	Insulant	0.08	0.039 ª/ 0.059 <sup>b</sup> /0.066 <sup>c</sup>	0.87	90ª/75 b/ 60 c	
<i>U</i> = 1.364	Internal plaster	0.01	0.70	1	1400	0.489 <sup>b</sup> /0.525 <sup>c</sup>
W/(m <sup>2</sup> K)	Hallow bricks	0.16	0.36	0.8	1000	W/(m²K)
	Internal plaster	0.01	0.70	1	1400	
	Slabs	0.01	1.00	1	2000	
Floor/ceiling	Light concrete	0.15	0.21	0.8	800	
U = 0.626	Concrete	0.05	1.14	1	2400	<i>U</i> = 0.626
W/(m <sup>2</sup> K)	Hollow bricks	0.20	0.36	0.8	1000	W/(m <sup>2</sup> K)
	Internal plaster	0.01	0.70	1	1400	
Partition wall	Internal plaster	0.01	0.70	1	1400	
U = 1.958	Hollow bricks	0.08	0.36	0.8	1000	<i>U</i> = 1.958
W/(m <sup>2</sup> K)	Internal plaster	0.01	0.70	1	1400	W/(m <sup>2</sup> K)

# 2. Materials and Methods

The building is analyzed through dynamic simulations performed with the commercial software TRNSYS 18 (Klein et al., 2017), and it is located in Milan (lat. 45°28'01" N, long. 9°11'24" E). Weather ported by (Rossi di Schio et al., 2024), the thermal conductivity of cardboard panels filled with surgical masks in different configurations was determined: the thermal properties were analyzed considering different panel densities, in the range of 60-90 kg/m<sup>3</sup>, changing the arrangement of the masks in

the cardboard box (ordered and disordered, crumpled masks), and finally, the thermal conductivity obtained following sanitation performed by hightemperature washing in a dishwasher and after the application of a commercial flame retardant (FEU-ERFEST® Fire protection impregnation for textiles, DIN 4102) was analyzed. The results obtained are reported in Table 1. It is observed that, in general, for the same treatment or type of sample, there is a decrease in conductivity as density increases. Moreover, the thermal conductivity tends to increase for the same density, following sanitation and the application of the flame retardant. This aspect is due to the residual moisture in the material that increases following the treatments (Wang et al., 2023).

# 3. Setting of the Analysis

A dynamic numerical analysis was performed using TRNSYS software to assess the possible energy saving achievable when panels made of surgical face masks for building insulation are used. According to Fig. 1, the analyzed apartment is on the first floor of a building block in Milan (Italy). It is approximately 80 m<sup>2</sup> and consists of six thermal zones. The building characteristics are summarized in Table 2, and they are typical of the Italian building's heritage, which was realized between 1970 and 1990 (Ballerini et al., 2022). The standard heating season goes from the 15<sup>th</sup> of October to the 14<sup>th</sup> of April, with 2404 heating degree days and a winter design temperature of -5 °C, while the hourly and mean monthly outdoor temperature refers to the Meteonorm database (Meteonorm, 2024). The Energy Performance Index for Heating (EPH), the predicted mean vote, and the predicted percentage of dissatisfaction (ISO 7730, 2006) estimated in the different scenarios have been compared.

Six scenarios have been analysed in which different panels have been installed indoors, as reported in Table 3. Scenario S1 is the pre-refurbishment reference case, and scenarios S2-S4 refer to insulating panels made of surgical face masks. In contrast, the last two scenarios consider commercial insulating materials made of mineral wool (scenario S5) and polystyrene (scenario S6). The insulating panel thickness s was set at 0.08 m, while density g and thermal conductivity  $\lambda$  varied according to Table 3. The position of the insulating panels is shown with a red (insulated external walls) or green line (insulated internal walls) in Fig. 1B): the panels have been installed indoors on the vertical walls, and they are coupled with a plasterboard layer 0.01 m thick. All the external and internal walls that separate the apartment from the stairwell and other properties have been insulated.

The heating system consists of a boiler (with an output power of 20 kW) connected to a storage tank 0.1 m<sup>3</sup> and five radiators installed in the different thermal zones (except for the corridor). The radiators, whose characteristics are listed in Table 4, are three-column cast iron terminals whose flow rate is controlled by thermostatic values.

Table 3 – Characteristic of the panels for the intervention. For the panels made of surgical face masks, the specific heat value has been determined by comparing values in the literature and related to fibrous materials (FLUM ROCK, 2024)

				Insulating panels		
Case	Type of panel	U external wall (W/m²K)	U internal wall (W/m²K)	ρ (kg/m³)	<sup>Ct</sup> (kJ/(kg K))	λ (W/(m K))
S1	Reference case	1.302	1.364	-	-	-
S2	Masks panels	0.376	0.372	90	0.87	0.039
S3	Masks panels	0.495	0.489	75	0.87	0.059
S4	Masks panels	0.533	0.525	60	0.87	0.066
S5	Mineral wool	0.339	0.336	90	1.03	0.035
S6	Polystyrene	0.347	0.343	20	1.45	0.036

Thermal zone	Power output (kW)	Radiator surface area (m²)
B1 - Room 1	3.70	1.19
B2 - Room 2	1.90	0.63
LR - Living room	3.15	1.00
K - Kitchen	2.45	0.81
BA - Bathroom	2.45	0.81

Table 4 – Radiator surface area and thermal power output, considering an input/output temperature difference of 60 K

The radiators and the thermostatic valves are modelized employing 320 e 362 (Holst, 1996); in particular, type 362 allows modelling the radiator with a first-order model, and in this way, it also takes into account the transient and dynamic effects that occur when the radiator is turned on and off.

The water temperature setpoint is 70 °C for the boiler outlet, 20 °C for the thermal zones from 6:00 a.m. to 11:00 p.m., and 18 °C at night. The bathroom temperature setpoint is 24 °C during the day and 18 °C at night. The temperature of adjacent apartments is 20 °C, while that of the building block entrance, stairwells, and hallways is determined by the software. The windows mean transmittance (considering both glass and frame) is 2.83 W/(m<sup>2</sup>K). The internal gains refer to four occupants, and electrical equipment is selected by the IEA SFH Task 44 (Dott et al., 2013). For all the thermal zones, the air change rate is 0.5 h<sup>-1</sup>. The building was simulated using type 56 (Klein et al., 2017), and the simulation time step was set to 10 s.

#### 4. Result and Discussion

The estimated EPH values obtained from dynamic simulations are compared in Table 5 along with the annual thermal energy demand reduction (in comparison to case S1 without additional insulation): the presence of insulating panels made of masks (scenarios S2-S4) leads to an energy demand reduction between 39 % and 48 %. The energy consumption is reduced by 3586 kWh in scenario S2, comparable to the values determined for scenarios S5 and S6 with commercial materials due to the insulating panels' comparable thermal conductivity.

Table 5 – Annual results obtained by the simulations: thermal energy demand of the apartment ET, annual apartment energy demand related to the floor area (79.86 m2) EHH, and energy demand reduction of cases S2-S6 with respect to case S1

Scenario	ET (kWh)	EPH (kWh/m²y)	ET reduction (kWh)
S1	7756	97.1	-
S2	4170	52.2	3586 (46.2 %)
S3	4586	57.4	3170 (40.9 %)
S4	4712	59.0	3044 (39.2 %)
S5	4070	51.0	3686 (47.5 %)
S6	4095	51.2	3661 (47.2 %)

The mean radiant temperature and the internal and external surface temperature for thermal zone K (kitchen), referred to as the coldest day of the heating season, are shown in Fig. 2. According to Fig. 2, the presence of the insulating panels yields an increase in the surface temperature: the temperature in the kitchen is very similar for cases S2 and S5, while, for case S1, it remains below 20 °C till 8:00 am.

The predicted mean vote (PMV) and predicted percentage of dissatisfaction (PDD) indexes have been determined and represented in Fig. 3. The PMV is calculated using the empirical model proposed by Fanger (1970): it represents the average vote expressed by the occupants based on their thermo-hygrometric comfort perception.



Feeling very cold is rated -3, while feeling extremely hot is rated +3; 0 indicates a neutral condition. The PPD index indicates the percentage of people who would express dissatisfaction. Hourly data has been calculated by averaging daily data along the heating season for three thermal zones: the bathroom (BA) and the two rooms (B1 and B2). Air velocity is set at 0.1 m/s, clotting factor at 1 Clo (representative of complete wintertime clothing) and metabolic rate at 1.1 Met. In contrast, the air temperature, the mean radiant temperature and the humidity ratio for the calculation of the PMV are determined hourly by the dynamic simulation. Fig. 3 shows that the PDD increase is higher in room B1 than in room B2 because the two zones have different exposition to the external ambient since B1 presents two vertical

walls exposed to the outside air, while room B2 only has one. Therefore, insulating panels of surgical face masks (scenario S2) or rock wool (scenario S5) lead to greater thermal comfort, as expected. Moreover, for all the considered cases, the PDD is higher during the first hours of the day due to the heating system set-point change from 18 °C to 20 °C: the setpoint temperature is reached in one hour in almost all the thermal zones.

Considering PMV values averaged only during the heating season when the system is operational (6:00 a.m. - 11:00 p.m.), values in room B1 were -0.63 for the uninsulated case, while results were -0.53 for scenario S2 and -0.50 for scenario S5. Similar values were obtained for the other room (B2), which were -0.61, -0.54, and -0.53, respectively. In the bathroom, the values were all close to thermal neutrality, with 0.00 for S1, 0.09 for S2, and 0.12 for S5.



# 5. Conclusion

This dynamic analysis presents the energy savings achievable following insulating panels made from reused materials in a residential building located in Milan, Northern Italy; specifically, the analysis concerns the use of insulating panels for building insulation composed of surgical face masks.

The dynamic analysis concerns 6 different scenarios: the same apartment (part of a condominium) designated as a social house was analysed using the TRN-SYS package before the installation of insulating panels and then, after the application of both commercial and non-commercial insulating panels (panels made of surgical face masks). The main findings are:

 The dynamic analyses conducted using panels with face masks reduced the energy required to heat the building, ranging from 39.2 % to 46.2 % compared to the apartment without insulation.

- The dynamic analyses ran considering instead commercial insulating materials applied to the same building led to a reduction in the thermal energy required for heating equal to 47.5 % and 47.2 % in the case of rock wool and polystyrene, respectively.
- The comfort achievable inside the rooms following commercial insulators is similar to that obtained using panels formed from surgical face masks.

The dynamic analyses show that the annual reduction in energy required for heating the considered apartment in the case of commercial insulators is similar to that achievable using insulated panels formed with reused materials if these have a density equal to or greater than 90 kg/m<sup>3</sup>. Future developments will include the analysis of the thermal demand for cooling pre- and postintervention and the analysis of further reusable materials that are employable in construction.
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# Recommendations to Make Reinforcement Learning Practical in Building Control Applications

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#### Abstract

The paper provides an analysis of the application of reinforcement learning (RL) in the domain of building controls, summarizing four years of research. The primary focus is exploring RL's potential to adaptively learn from building data, bypassing the need for individualized extensive building modeling efforts and enabling the transfer and adaption of trained agents to similar building environments. Despite its promising prospects, RL faces challenges such as extended training durations, instability during early exploration phases, and issues in interpreting the actions of trained agents. The research was focused on two core areas. The first area investigates strategies to enhance RL agents' learning efficiency and stability in building control contexts with approaches such as imitation learning, inverse RL, and online learning with guided exploration with surrogate models utilizing rule-based controls, showing significant improvements in the training process. The second area addresses the critical aspects of scalability and interpretability of RL agents. It examines the feasibility of transferring trained agents to various buildings, potentially with new objectives, highlighting RL's adaptability and practical applicability in real-world building control scenarios. In summary, this paper consolidates critical findings from the research and offers actionable insights and recommendations for practical deployment and training RL in building energy management systems without extensive building modeling efforts. It emphasizes the transformative potential of RL in this field and suggests avenues for future exploration and development

#### 1. Introduction

Reinforcement learning (RL) as an advanced control strategy holds significant promise in revolutionizing building controls by offering a dynamic, adaptable approach to optimization without extensive modelling efforts for distinct buildings. (Sutton et al., 2014; Chen et al., 2020). Each action taken by the agent results in a reward, positive or negative, which serves as feedback to guide learning. The agent follows a policy-a strategy for selecting actions based on the current state-that can be either deterministic or stochastic. Critical to RL are the value functions: the state value function (V(s)), which estimates the expected return from a state under a given policy, and the action-value function (Q(s, a)), which estimates the expected return from taking an action in a state and thereafter following a policy. The return itself is a total accumulated future reward, typically discounted by a factor  $(\gamma)$  to prioritize immediate rewards over distant ones and to ensure the return is finite. RL involves a balance between exploration, where the agent tries new actions to learn about their effects, and exploitation, where the agent chooses actions that have previously resulted in high rewards. This dynamic of exploration and exploitation enables the agent to refine its policy through trial-and-error, applying to diverse applications such as robotics, gaming, finance, and healthcare, where systems are required to make sequential decisions to achieve optimal outcomes (Mnih et al., 2013; Lillicrap et al., 2015; Arora & Doshi, 2018; Watkins & Dayan, 1992). Unlike traditional methods like rule-based controls (RBC) and model predictive control (MPC) (Richalet et al., 1978), RL learns optimal actions through repeated interactions and can adapt to changing dynamics over time. Despite its potential, RL faces challenges such as long training times and unstable exploratory behavior in the early stages (Wang & Hong, 2020). However, addressing these challenges could unlock its potential for practical implementation in building control systems, paving the way for more efficient and adaptive management of indoor environments while reducing energy consumption and maintaining occupant comfort.

This paper summarizes insights gathered over a fouryear research period on the application of RL in building energy management. It acknowledges certain limitations, notably the reliance on supervisory control actions and a lack of optimization for multiple low-level control points, while also neglecting multiagent coordination across multiple buildings. The primary focus of the research was to improve the learning efficiency, assessing RL's scalability across diverse building types, and enhancing the interpretability of trained agents without extensive modelling efforts but sometimes assisted with "surrogate" models. A "surrogate" model is an approximate representation of a complex real-world system used to facilitate efficient and safe training of reinforcement learning (RL) agents. In this research practical challenges related to hardware and software implementation are omitted, with emphasis instead placed on theoretical advancements and practical implications. This section below serves as a brief overview of the research approaches investigated.

The approaches investigated in this research over the course of the study consist mainly of four types and are mentioned below:

- Online learning without surrogate models
  - o Pure direct training
  - Imitation learning
- Offline learning without surrogate models
- Hybrid approaches with surrogate models
  - o Offline learning
  - o Inverse RL
  - Online learning with guided exploration
  - Online learning with guided exploration and imitation learning
- Transfer learning
  - o Transductive learning
  - o Inductive learning

The first two approaches, online learning and offline learning methods, examine approaches without the

need for any surrogate modelling techniques, while the hybrid approaches utilize surrogate models to assist with the learning process. There are two types of online learning: i) pure direct training and ii) imitation learning. These are mentioned in detail in Section 2. Section 3 covers offline learning on historical data. There are four hybrid approaches explored in Section 4, which are i) offline learning, ii) inverse RL, iii) online learning with a guided exploration, and iv) online learning with guided exploration and imitation learning.

The research on transfer learning in Section 5 builds on the previous sections addressing the unstable behaviour of the learning agent as well as the issue of scalability of a trained agent such that it can be utilized to optimize for similar tasks on different environments.

#### 2. Novelty and Contributions

This paper's contributions are multi-faceted, reflecting four years of intensive research into practical reinforcement learning (RL) applications in building control systems. Key contributions include strategies to enhance RL agents' learning efficiency and stability through imitation learning, inverse RL, and online learning with guided exploration using surrogate models, significantly improving training processes. Efforts were also made to improve the interpretability of RL agents' actions, essential for practical deployment. Hybrid learning approaches combined offline learning, inverse RL, and online learning with guided exploration, utilizing surrogate models to enhance learning outcomes and mitigate negative impacts of exploratory actions. The paper consolidates findings, offering actionable insights and recommendations for practical RL deployment in building energy management systems, avoiding extensive modelling efforts. Additionally, transfer learning techniques, such as transductive and inductive learning, were investigated to enhance RL agents' scalability, showing potential for reduced training times and improved initial performance. This research significantly advances practical RL applications in building control systems for building energy management with supervisory controls, addressing key challenges and paving the way for future developments.

# Online Learning Without Surrogate Models

# 3.1 Pure Direct Training

Pure direct training is the traditional direct training approach where the RL agent starts without any prior training or knowledge, the so-called tabula rasa, and learns to optimize only by virtue of the interactions with the building environment without any form of assistance from surrogate models or without any pretraining or other learning approaches utilizing rulebased data. The agents start without any prior knowledge with randomly initialized parameters. The agent explores the environment by trial and error and with environmental feedback.

#### Findings and recommendations:

This type of RL agent should not be applied directly to an actual commercial building without pretraining or some kind of assistance from surrogate models. As evident from the results, depending on the complexity of the problem, it can take months or potentially years of training to learn an optimal operational strategy. Such protracted training periods would cause thermal discomfort for the building occupants, and it is unacceptable to bear thermal discomfort for months during the training phase of the RL agent. Moreover, the exploration phase intrinsic to the training phase can inflict damage on the building systems and components during the exploration stage of the training.

## 3.2 Imitation Learning

Imitation learning has been a key learning approach in the domain of autonomous behavioral systems commonly seen in robotics, computer games, industrial applications, and manufacturing, as well as autonomous driving. Imitation learning aims at mimicking a human behavior or another agent that is considered to perform well in a particular task. This is essentially learning to directly map observations to actions. It aids in reducing the task of teaching an agent, by showing the agent the actions to take to complete a specific task. Here an artificial dataset covering the state-space and its corresponding rulebased actions were developed, and the agent was trained to imitate the actions in a supervisory fashion (Dey et al., 2023).

#### Findings and recommendations:

The quality of the starting agent depends on the quality of the rule-based policy developed. With the increasing complexity of a multi-objective problem, it becomes difficult to design a good rule-based policy. The advantage is that it does not require extensive model development, and the agent adapts its starting imitation policy to be more suited to the environmental problem. The challenge of imitation learning is that since the agent blindly follows the imitated policy without any understanding of the environment, this leads to a 'performance dip' where the agent may start to explore in wrong directions before finding a better solution. We have found that even with the 'performance dip' the agent still has a better training progress curve than a pure direct training approach. The 'performance dip' can be addressed by a hybrid approach as mentioned in Section 4.4. The 'performance dip' is a characteristic of the direct imitation learning approach which suggests a superficial level of learning at the beginning, where the agent lacks a deeper comprehension of the consequences and implications of its actions.

# 4. Offline Learning Without Surrogate Models

Buildings are typically managed using rule-based energy management strategies, which consist of conditional rules based on various indoor and outdoor conditions. Offline training relies on learning from regular operational building data that follows these rule-based strategies. Prior to the application of an RL agent, the agent has access to historical building data, which is then pre-processed to create a tuple comprising state (*s*), action (*a*), next state (*s*'), reward (*r*), and a completion flag (*d*). The agent is exclusively trained on this operational data. (Dey et al., 2023)

### Findings and recommendations:

Offline learning on historical rule-based data has led to poor and unacceptable performance. Rule-based building data tends to be sparse, which is often insufficient for effective RL training because it fails to adequately explore the state space. We have found that data augmentation leading to a sufficiently rich dataset exploring the state-space is necessary for learning a good policy at the onset of interacting with a real building.

## 5. Hybrid Approaches

#### 5.1 Offline Learning With Metamodel

Pre-training with a metamodel often proves to be an effective strategy in reinforcement learning when considering deployment in an actual commercial building. This approach not only reduces the training duration but also mitigates the unstable exploratory behavior that can be observed with direct training methods. The RL agent can systematically and comprehensively explore the state space within a simulation environment where there are no repercussions on people and systems as in an actual building. This aids the agent in forming more accurate value estimates regarding the potential outcomes of specific actions in particular states. Furthermore, the metamodel enables extended training periods in the simulation, eliminating the need to wait for months or even years in real time to achieve optimal action learning. While training with a metamodel appears promising, it presents several challenges.

Specifically, the quality of the metamodel depends on the quality of the building data available. Large variability in building data is beneficial as it leads to developing a more accurate metamodel. The RL agent can then explore the state-space using the metamodel without incurring any of the negative consequences of exploration and can also discover regions of high rewards that the agent can exploit in the real building environment. To ensure a fair comparison, we extract the metamodel from the same training rule-based building data which was used for the inverse RL process. (Dey et al., 2023)

#### Findings and recommendations:

The effectiveness of metamodel-based training relies on the accuracy of the metamodel in replicating the real building environment. Any discrepancies or model mismatches between the metamodel and the actual building environment can lead to subpar performance when the RL agent is deployed in the real world. Also, the metamodel extraction process is often challenging and requires engineering expertise. Furthermore, it is difficult to extract an accurate metamodel for complex building environments involving many features. Buildings are unique and thus it becomes difficult to extract an accurate metamodel for each building.

#### 5.2 Inverse Reinforcement Learning

Inverse reinforcement learning (IRL) (Ziebart et al., 2008) is an advanced method within the field of machine learning that seeks to infer the underlying reward function that a demonstrator (often an expert or an optimal policy) implicitly follows, based on their observed behavior in a specific environment. Unlike traditional RL, where the reward function is predefined and the agent learns the best actions to maximize this reward, IRL works in reverse by analyzing the actions of an expert to determine what rewards they appear to be maximizing (Dey et al., 2023). Here, three months of rule-based data from an existing building are utilized to extract a reward function, which was used in determining the value-function of the states. The value-function is then learned by the RL agent, which results in the agent having a similar policy to the rule-based policy thus limiting exploration.

#### Findings and recommendations:

IRL has proved to be effective in shortening training time, providing a stable learning experience, and outperforming standard RL agents trained for the same duration. IRL can partially deduce the intent behind rule-based controls without environment interaction. However, in the research while optimizing for energy consumption, thermal discomfort, and demand costs, it struggled with power demand limit penalties due to inaccuracies in the transitional dynamics, which are challenging to determine from limited rule-based data as a sparse dataset result in an incomplete extraction of the reward function's intent. When a building has operational data for over three months for a specific season, an inverse reinforcement learning (IRL) strategy is recommended, even if metered data or thermal discomfort metrics are absent. IRL tends to maintain existing rule-based policies initially, aiding in reducing early exploration. It serves as an indirect method to mimic and improve upon RBC strategies. If the RBC is poorly designed, however, the RL agent needs to forget the value-function from the extracted reward function and start utilizing the actual reward function. This is done by adopting an importance parameter in the reward function that controls the transition between the extracted reward function to the actual rewards, which requires further research to further stabilize the training progress.

# 5.3 Online Learning W/Guided Exploration

In this approach, the agent starts with no prior training but uses the help of surrogate models to limit exploratory activities in the early learning stages. The surrogate models use regression techniques to learn the system dynamics and the reward function in real time. The models generate artificial trajectories guiding the RL agent away from states that previously led to high penalties by suggesting alternatives until the RL agent develops a more accurate understanding of the value functions. Several types of approaches were conducted where explorations were limited to within bounds around rule-based policy vs. full random explorations, short-term exploration vs. long-term exploration (Dey & Henze, 2024).

#### Findings and recommendations:

We found that training on long trajectories from surrogate models with full random explorations, although successful in reducing the exploration of the agent, had the worst performance on test days. Artificial long trajectories with full random exploratory paths yielded unsatisfactory results as training on paths with imperfect predictions from unseen states in the trajectories led to poor training. Limiting the exploration within a certain bound around a rulebased control strategy by control action paths led to better performance. We regard actions based on established rules as "safe". Initially prioritizing these actions helped improve the accuracy of the system's estimates and the dynamics of rewards related to actions within the rule-based space, as modeled by the surrogates. Consequently, this approach allowed the RL agent to gradually adjust its policy away from these rule-based actions towards areas where it anticipates higher rewards. This incremental adjustment prevents the agent from abruptly moving into unfamiliar state spaces, where it might encounter inaccurate value estimates. Due to the nature of the application, buildings with large thermal time constants might not be effective with this approach as approaches with longer trajectories were not successful.

# 5.4 Online Learning With Guided Exploration and Imitation Learning

This approach is similar to the previous approach except that the agent starts with an imitated rule-based policy but is still assisted with surrogate models for artificial exploration.

#### Findings and recommendations:

This approach addresses the 'performance dip' that is inherent in the imitation learning approach. The surrogate model trajectories prevent the agent from moving further away from the rule-based policy in its early stages.

# 6. Transfer Learning

Transfer learning (TL) involves leveraging knowledge gained from one domain and task to improve the learning performance in a different yet similar domain. TL addresses the challenges of scalability in building domain where it is challenging to develop accurate building models for each commercial building and use that model for pre-training with RL. We investigated two types of TL and present the findings below.

### 6.1 Transductive Learning

In the study on transductive learning, the task and the state-space remain the same but the building domain changes. We trained an agent on a large commercial building, optimizing for costs of energy, thermal discomfort and demand and applied the trained agent to a mid-sized commercial building in the same climate (Lissa et al., 2020; Zhang et al. 2020).

#### Findings and recommendations:

Although this direct transfer of weights approach is beneficial in reducing the training time as well as unstable early-stage training unstable behaviour in the agent, a key challenge lies in transferring the agent to scenarios involving additional tasks or tasks with different input and output architecture of states and action of the RL agent. Moreover, this approach does not lend itself to offering any insight into how the transferred agent will behave in a new environment, which might not help in gaining trust with the adaptation by building control managers.

## 6.2 Inductive Learning

In inductive learning, the source and the target domain are the same while the source and the target tasks are different. A key challenge arises in transferring knowledge to scenarios involving additional tasks or states, despite application in similar building. In this approach, a conditional rule extraction method from a trained agent was employed utilizing decision trees. The target agent learns this conditional policy with supervisory learning on artificial datasets generated from the states and action based on conditional rule-set extracted.

#### Findings and recommendations:

This strategy reduces the reliance on the specific input-output architecture of the trained RL agent and provides an interpretable starting policy due to its conditional ruleset. This interpretability is often absent in direct or partial weight transfer methods used in ML transfer learning methods, where control managers might have difficulty to predict the agent's behavior in new settings. Furthermore, these rules can be integrated with or augmented with human-generated rules, facilitating the transfer of domain knowledge when introducing new tasks to the RL agent. The approach allows for flexibility as building control managers can review and adjust the rules to better suit the target building agent's starting policy. Although this rule extraction method was employed in inductive learning, the method can also be used for transductive transfer learning. A minor setback with the rule extraction method is the agent's tendency to replicate actions without truly understanding the value function of the states and actions. The progress plot shows a slight decrease in performance due to the 'performance dip' before it finds a better policy than the starting policy.

### 7. Future Work

For effective adaptation of AI in building controls, the decision-making processes of AI models must be transparent and comprehensible. However, the inherent complexity of deep neural networks, which underpin many advanced AI algorithms, poses a challenge to their interpretability. Despite this, their depth and structure equip them to efficiently tackle

intricate tasks and derive near-optimal solutions. Gaining insights into how these models function can assist developers in pinpointing inaccuracies or biases in the established policies. A practical method for this is observing an AI agent's actions in a simplified simulator, especially under extreme conditions not covered in training. Creating artificial datasets for these scenarios can help in understanding the model's decisions through inductive learning, leading to performance refinement by adjusting or adding rules. This hands-on verification and validation serve as a tangible bridge between AI's abstract computations and real-world expectations.

Human-in-the-loop (HITL) reinforcement learning (RL) is an emerging interest in artificial intelligence that incorporates human input into the training process to enhance the performance of AI agents in complex environments (Nagy et al., 2023). This approach is especially beneficial in sectors such as robotics, autonomous vehicles, and healthcare, where exploration errors could lead to significant real-world consequences. In building controls, HITL RL integrates established operational strategies and occupant needs, thus mitigating the risks associated with trial-and-error learning. This is achieved by considering their expressed preferences on indoor environmental conditions such as thermal comfort, indoor air quality, visual comfort, or acoustic conditions while optimizing for factors such as energy consumption, demand management, and other user needs (e.g., EV charge scheduling). Examples of feedback received could be occupant preferences collected through edge devices and information about impending electric grid stress events by the system operator. Recent discussions among RL researchers also underscore the importance of HITL in building management, highlighting its potential to improve occupant productivity, reduce energy costs, and aiding in building decarbonization goals.

## 8. General Recommendations

In the absence of operational data, the combination of online learning with guided exploration and imitation learning is recommended if extensive modelling efforts are to be avoided. Buildings having slower thermal response will require a grey-box model or a physics-informed neural network (PINN) as surrogate models to assist with the training.

Normalizing input features or states is beneficial for speeding up the convergence of learning algorithms. By ensuring that all input features are scaled similarly, normalization facilitates faster convergence in gradient-based optimization algorithms. This process results in models that are more generalizable and less prone to overfitting specific scales or magnitudes in the training data. Additionally, many RL algorithms are sensitive to reward scales. Normalizing rewards not only stabilizes the learning process but also makes hyperparameter tuning more uniform across various environments and tasks. This standardization of rewards keeps value function estimates, such as Q-values in Q-learning (Watkins & Dayan, 1992), within a consistent range, which is advantageous during the transfer learning process when weights are transferred directly from one agent to another.

Building control systems present distinct challenges due to their real-world operational context, where data collection can be both time-intensive and expensive. In terms of sample efficiency, algorithms like Soft Actor-Critic (SAC) (Haarnoja et al., 2018) and Proximal Policy Optimization (PPO) (Schulman et al., 2017) outperform Deep Q-Network (DQN) (Mnih et al., 2013), making them more suitable for situations where data gathering is resource-heavy. SAC and PPO are known for their consistent stability during training, whereas DQN struggles with stability issues, particularly in environments with high variability. The specific nature of the problem often dictates the algorithm of choice. For tasks involving discrete action spaces, such as binary decisions or selecting from a limited set of options, DQN excels due to its effectiveness in simpler contexts where computational resources are a concern. However, for tasks that involve complex dynamics, PPO or SAC are preferred for their nuanced approach and potential to achieve near-optimal performance.

It is essential to have a fail-safe or override system in place for the control actions of RL agents to prevent unexpected consequences. Initially, it is crucial to identify and define the proper constraints of the system. For instance, an RL controller setting the temperature to 15°C during occupied hours in winter should automatically trigger an override, as this decision is clearly inappropriate. Such incorrect actions should incur significant penalties to teach the agent about these constraints. A building domain expert should oversee the setup of these overrides, recognizing potential constraints ahead of time. In practical scenarios, a fail-safe mechanism is necessary for cases where there may be gaps in real-time sensor data, preventing unexpected control behaviour. Additionally, it would be advantageous to implement a system that monitors whether the input states deviate significantly from the expected range, allowing the controller to switch to a baseline control until a building control engineer can verify the appropriateness of the untested control actions.

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## Nomenclature

### Symbols

AI	Artificial intelligence
BMS	Building management systems
DNN	Deep neural network
DQN	Deep Q-Network
MPC	Model predictive control

PPO	Proximal Policy Optimization
PINN	Physics-informed neural network
RL	Reinforcement learning
SAC	Soft actor-critic
IRL	Inverse Reinforcement learning
TL	Transfer learning
γ	Discount Factor
S	Current state
а	Action
<i>s</i> '	Next state
d	Done flag

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# Simulation-based optimization for Energy- and Cost-Efficient Refurbishment of an Educational Building

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#### Abstract

This study aims to enhance the energy performance and user comfort of educational buildings, focusing on the BME Building ST as a case study. Using a comprehensive approach that combines dynamic energy simulations and genetic algorithms, we explored optimal renovation alternatives for the building envelope. Various thermal insulation materials and configurations were assessed, leading to improved user comfort and reduced energy demand in all simulated versions. Notably, models with greater thermal insulation exhibited higher comfort levels. Additionally, natural-based materials like wood fibre showed significant potential in reducing embodied carbon emissions, particularly in continental climates such as Hungary. The methodology involved creating a BIM model of the building in Autodesk Revit 2023, followed by advanced energy simulations using the EnergyPlus engine. We generated 160 different building versions with varying insulation materials and thicknesses. These simulations were processed in a Python environment utilizing the Eppy package for managing IDF files and the Pymoo package for implementing the NSGA-II optimization algorithm. The energy performance and user comfort of each version were evaluated to identify the best-performing models. The most energy-efficient model featured 12.5 cm vacuum insulation panels on facades and 25 cm mineral wool on roofs. Financial analysis indicated acquisition costs ranging from 1 to 3.5 million EUR, with estimated global costs over a 20-year period between 6.75 to 9.2 million EUR, compared to the reference building's 7.4 million EUR. The project developed a versatile methodology for multi-objective building energy optimization in a Python environment, applicable to various building types, prioritizing versions with minimal environmental impact and maximal user comfort. The study underscores the potential of energy-efficient renovations to enhance user comfort, reduce energy consumption, and mitigate environmental impacts in educational buildings.

## 1. Introduction

One of the most urgent problems of our time is climate change and the environmental pollution that accelerates it. Over the last century, the Architecture, Engineering, and Construction (AEC) industry, like other indispensable modern industries, has undergone rapid technological development. Engineers have had tools such as Building Information Modelling & Management (BIM) and Life Cycle Assessment (LCA) for several decades. These tools significantly reduce the amount of building materials used in new constructions, thereby reducing the primary energy requirements. Recent improvements in methods and techniques have further optimized the environmental loads produced during the 60-100year design lifespan of buildings, which stages (B1-B7 in LCA) have the greatest environmental impact in a traditional architectural environment (Jeong et al., 2015; Farooq & Sajid, 2021). This optimization extends the lifespan and usability of buildings while reducing their long-term carbon footprint. To understand the field, literature research on energetic optimization was conducted. In 2013, Hamdy et al. used the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) to set up a multi-stage optimization method for Life Cycle Cost (LCC) estimation in a Matlab environment. In 2019, Asdrubali et al. performed a case study on the thermophysical optimization of Italian schools from the 1960s. In 2020, Kiss and Szalay used NSGA-II to optimize the energy performance of dwellings through a modular approach. In 2021, Ghaderian et al. optimized the energy efficiency of educational buildings using similar algorithms in a Matlab. Franco et al. developed a methodology to optimize HVAC operation and user comfort in educational buildings in 2021. D'Agostino et al., in 2021, proposed an automated

workflow to optimize buildings' energy demand and construction cost. In 2022, Nagy et al. examined the Global Warming Potential (GWP) of buildings by analysing heat and moisture transport. Colarossi et al. also performed multi-objective optimization of school buildings focusing on thermo-acoustics in 2022.

Based on this research, using NSGA-II in a Python environment for building energy demand optimization provided a novel approach worth examining. This paper attempts to find the best possible thermal insulation solutions for BME Building ST, adhering to Hungary's building energy regulations (MCT, 2023). The aim is to reduce the building's carbon footprint over a 20-year period (EU, 2012) after the installation of the thermal insulation system, which inherently reduces operational costs during the examined period, while also improving user thermal comfort.

# 2. Methodology

## 2.1 The Studied Building

Building ST was designed and constructed by Budapest University of Technology and Economics (BME) in 1950 (see Fig. 1). The site is part or the BME Campus, having in the area numerous buildings with protection due to their historical value. The ST building itself is not under protection, but the site is under historical, archaeological and world heritage protection (OENY, 2024). The building has a basement level with laboratories, mechanical and building operation premises, and additional shelters underground. Above that, the ground floor and three levels extend in a longitudinal orientation of NW-SE. Connected to this Basement-Ground floor-3 Levels (B-G-3L) structure, another wing has been built, containing the main entrance, the main Auditorium, and the hall.



Fig. 1 - ST building in 2024 at BME campus

In 1985, a 4<sup>th</sup> storey was built upon the existing structure, giving extra space for enlarging the available capacity in the building. These days the building is being used for educational and administrative purposes including classrooms, labs and offices, and the gross area of cc. 6400 m<sup>2</sup>.

The construction of the existing building envelope is shown in Table 1.

Constru	Ucurrent [W/m <sup>2</sup> K]	
3 lys Bit. Sheet w.p. 5 cm sub. Concrete 2-25 cm slope slag 10 cm polysterene 11 cm RFC slate Steel strucure	Roof	0.29
38 cm brick, or	Facada	1.43
26 cm RFC beam 8 cm paving brick	(up to 3 <sup>rd</sup> floor)	0.75
25 cm brick 8 cm mineral wool 4 cm air gap 2*4 mm shale paving	Façade (4th floor)	0.40

Table 1 – Construction structure of the existing envelope

On Fig. 2 a schematic representation of the Ground floor is shown. Similar colours represent similar functions of rooms, providing the basis of the thermal zones for the initial building energy simulations detailed later (see Section 2.3).



Fig. 2 - Floor plan and zones of the ST building's ground floor

A known problem of the building is the general summer overheating, which drastically decreases the usability of the facility in the summer period. Thermal images have been made checking the building envelope (Fig. 3) and were used to provide useful information about the structure of the building for improving the building model.



Fig. 3 - Thermal picture of the façade of the ST building

# 2.2 Applied Thermal Insulation Materials & Building Elements

Requirements for the energy performance of buildings are usually set by national authorities, applying rules and regulations established by international conventions and agreements. The following energy performance requirements needed to be met as minima for the designed building elements and constructions for building envelope elements within the project, with values in Table 2 or lower. As a model simplification, technological insulation applied to make plastering possible in case of vacuum panel or aerogel insulations and the fire propagation barriers were not considered. Based on literature research, a palette of possibly applicable thermal insulation materials was collected (Jelle, 2011; Lakatos, 2022), supplemented by applicable window and curtain wall systems, with available Environmental Product Declarations (EPD) fitting EN ISO 14025:2010 and EN ISO 15804:2012+A2:2019 standards that collected the products' environmental loads during their estimated lifespan of 50 years. The applied thermal insulation materials and thicknesses served as variables for optimization and as a basis of comparison in cases of dynamic energy simulations. For windows and curtain walls, Schüco apertures with 3-layer glazing were selected, fitting the requirements in Table 2.

Table 2 – Thermal transmittance design requirements and applied thermal insulation material thicknesses

Construction	U <sub>design</sub> [W/m <sup>2</sup> K]	Applied thickness range (increment) [cm]
Façade	0.24	Mineral wool 14-20 (2), Woodfibre 16-22 (2), Aerogel 1-5 (1), VIP 2.5-12.5 (2.5),
Roofs	0.17	Mineral wool 15-25 (5), XPS 12-18 (3)
Windows	1.10	-
Curtainwalls	1.40	-

## 2.3 Building Energy Simulations

The basis of the building energy model (BEM) was a BIM model built in Autodesk Revit 2023 (see Fig. 4). The model was based on the documentation of the building and on-site diagnostics and surveying.



Fig. 4 - REVIT model of the ST building

Within Revit, Advanced Energy Settings were manipulated to provide a realistic basis for simulation.

Export Complexity was set to Complex with Mullions and Shading Surfaces to ensure these elements were included in the IDF file (Input Data File for EnergyPlus simulations), which is automatically created based on the BIM model when running the first System Analysis in Revit. This method uses the EnergyPlus engine and creates the file in Windows' Temporary folder, making it possible to use and reuse the model in later simulations within EnergyPlus. Building Type was set as "School or University," and Building Operation Schedule was set as 24/7 Facility. For Conceptual Types of constructions of the external envelope, High Mass Construction -No Insulation type was selected. While setting HVAC Systems, we faced the challenge that Revit does not have district heating as an option for HVAC systems, so after some consideration, a Central VAV system was chosen as the basis, which was later manually modified in the IDF files. As limitations, we must mention that modified HVAC systems and electrical and lighting systems or building automation solutions were considered out of scope. With the IDF file, which is the EnergyPlus input text file containing all the relevant data of the examined building, the next step was to prepare all the IDF files with the required thermal insulation materials and thicknesses applied to the necessary surfaces. For this, the Eppy (Santosh, 2023) package was used within a Python 3.10 Environment. This way, 160 different versions of the building in separate IDF files were created based on variables in Table 2. Due to the used package, moisture transfer performance and hygrothermal effects were not considered. Also, the effects of thermal bridges were considered using simplified methods.

Meteonorm 8 was used to create the EnergyPlus Weather file (EPW) for the location of the building, to ensure simulations were as realistic as possible, regarding daylighting and outside weather data.

Lastly, EnergyPlus' v23.1 IDD file was necessary, which is a dictionary file providing accessibility of data in IDF files for different versions of EnergyPlus. To run all the 160 building energy simulations, a multiprocessing code was used – and modified as necessary – from the Eppy documentation, to enable parallel processing on multiple cores of computers, significantly reducing runtime. Using the Pandas data manager toolkit in Python, the results of simulations were handled together. After examining these results and noticing major trends, a second round of energy simulations was run for the construction versions which fulfilled the requirements (see Table 1), supplemented by the new set of windows and curtain walls. This way, 72 versions from the original 160 remained for further examination.

## 2.4 Thermal Comfort

Thermal comfort analysis were based on the simple ASHRAE 55-2004 standard, when running building energy simulations in EnergyPlus (U.S. Dept. of Energy, 2023), the program provides a summary of the "Time Not Comfortable Based on Simple ASHRAE 55-2004" expressed in hours, which sums up the time during the simulation period when thermal conditions in each zone of the building are not comfortable for people wearing summer or winter clothes (EnergyPlus Input/Output References, 2023). To have a comparable result of thermal comfort in every examined building version, we subtracted this value from the 8760 hours of a year (the same as the simulation period), obtaining a value of "Comfortable hours" meaning the amount of time within a year when people do not experience any thermal discomfort in any thermal zones of the building based on simulation results. We must mention that various factors affecting thermal comfort in buildings, such as changes in the usage schedule, were left out of scope. Nor were active or passive shading solutions applied to examine their effect on user comfort.

### 2.5 Environmental Loads

To measure environmental loads of products or systems, many calculating methods and theories had been set up in the past decades, of which one of the most widely used and internationally accepted is the life-cycle assessment (LCA) which since its early-stage use in the 1960s, has already been internationally standardized in ISO 14040:2006 and accepted, and it is constantly developed with new approaches (Szalay et al., 2022). To determine the environmental loads of applied materials and elements, EPDs of applicable thermal insulation materials and viable summaries of environmental loads based on EN ISO 14025:2010 and online EPD catalogues were researched (Institut Bauen & Umwelt, 2023). Also, because of manufacturers' need for constant improvement and environmental consciousness, many of them now provide EPDs based on EN ISO 15804:2012+A2:2019 prepared for their specific products. In this paper the applied indicator for the examined thermal insulation materials and building elements was the Global Warming Potential (GWP), which summarizes all activities through the examined subject's estimated lifespan, summing them up into the unit of measurement as kgCO<sub>2</sub>eq.

# 2.6 Financial Analysis

Financial analysis was conducted based on the fees and advised prices in the Guide for Construction Cost Estimation 2023 (Hunginvest, 2023), which is a generally accepted collection of core prices and fees in the Hungarian AEC industry, to estimate acquisition costs of the examined thermal insulation systems. Financial analysis was done only on the 72 building versions which, by their characteristics, fulfilled the requirements. Within the framework of this paper, when discussing operating costs, only the sum of costs for electricity and district heating were considered and other utilities, such as drinking water, sewage, or mandatory maintenance costs, were not involved in the calculations, as these are not strictly related to the building's energy demand and thermal comfort, which is the main scope of this work. Since the focus is on the operation of the building over a 20-year period after the application of the new thermal insulation systems and apertures. To apply the Global Cost method (EU, 2012), a yearly price increase factor of 5% and a yearly discount factor of 3% were applied in all examined cases. Initial utility costs of 0.40 EUR/kWh for electricity and 0.50 EUR/kWh for district heating were applied, which are considered usual for public institutions in Hungary as of May 2024.

# 2.7 Optimization

To search for the Pareto-optimal solutions for the thermal insulation system of the building, which means finding the solutions in the model space that are non-dominated by others, causing a frontier of equally good solutions from the perspective of the examined parameters, called the Pareto front, the Pymoo NSGA-II (Blank, 2023) Python package was used. NSGA-II provides a set of possible best solutions for decision-makers, allowing them to focus only on the solutions with the best trade-offs within the set and making the weak solutions fall out of scope. NSGA-II (Deb et al., 2002) is an extension of genetic algorithms, incorporating non-dominated sorting and crowding distance. During optimization, the population size was 72, involving all the examined construction versions. Other optimization parameters were used as Pymoo's default, such as the number of generations being 100, while a crossover and mutation rate of 0 was used due to no interest in creating theoretical constructions, ensuring that realistic model versions were used, and the actual Manhattan crowding distance (Brownlee, 2020) was applied when setting up the Pareto front.

# 3. Results

# 3.1 Energy Demand

All the examined model versions performed within the range of 490-503 MWh yearly energy demand, while the reference building's energy demand in its current state is 622 MWh per year. This means a rough 20% decrease in energy demand in all the examined construction versions compared to the reference model. In Fig. 5, a plot of the yearly site energy demands and the number of yearly comfort hours in the building versions is shown. There is a relatively straight inverse relationship between these two parameters in the examined construction versions: the lower the energy demand, the higher the number of comfort hours. This can be explained by the fact that thicker insulation reduces the effect of external climate on the building within the examined ranges of materials and thicknesses. The construction version performing best in this comparison is the one with 12.5 cm VIP on the facades and 25 cm Rockwool insulation on the roofs, while the following versions are all the thickest insulated ones.



Fig. 5 - Yearly site energy demand - Comfortable hours

As a major trade-off, a decrease in yearly site energy demand is notable with the increase of embodied GWP, meaning generally, the more material we build into the system, the less the energy demand will be (see Fig. 6). The decrease in yearly energy demand is noticeable with the increase of embodied GWP, meaning the more material we install in the form of thermal insulation, the less the energy demand will be. Based on the results, it can be stated that XPS roof insulation versions (pink outline) have significantly lower embodied GWP values compared to Rockwool roof insulation versions (blue outline). This is due to the difference in specific embodied GWP values of XPS and Rockwool, 160 and 270 kgCO<sub>2</sub>eq./m<sup>3</sup>, respectively, and the difference in their design thermal conductivity values of 0.035 W/(m K) and 0.040 W/(m K), respectively, which allows for thinner roof insulations from XPS with similar thermal characteristics. The Pareto front consists of wood fibre and VIP facade insulation versions, which have the lowest specific embodied GWP values of the examined façade thermal insulation materials with values of 53 to 115 kgCO2eq./m<sup>3</sup>, respectively. This makes wood fibre versions the most environmentally friendly façade thermal insulation solution, even though they need to be applied with the highest thicknesses of the examined materials.

It is worth mentioning that the aerogel insulations have the highest embodied GWP of the examined materials, which pairs with the highest yearly site energy demand, indicating that this material performs the worst in this comparison.



Fig. 6 - Yearly site energy demand - Embodied GWP

#### 3.2 User Comfort

A comparison plot of the embodied GWP and the number of comfortable hours in the building with the Pareto front is shown in Fig. 7. A general trend of increasing comfortable hours parallel with the increase of embodied kgCO<sub>2</sub>eq. of each version is noticed. All the elements of the Pareto front are within the range of 6222 to 6242 hours a year, which is a definitive step forward from the reference model's 5800 hours by approximately 430 hours a year, but too low to be called significant. To increase user comfort, other types of variables should be introduced, such as shaders, changes in the usage schedule of the building, or using more detailed analysing methods, such as PMV or PPD (Fanger, 1970), are advised.



Fig. 7 - Embodied GWP - Comfortable hours

#### 3.3 Environmental Loads

Fig. 8 shows the connection between specific site GWP, summed up for 20 years by a constant yearly energy demand, and embodied GWP. Since site

GWP and energy demand are closely related, the shape of the plot is naturally like Fig. 6. On a 20-year scale, all the examined versions have a specific site GWP between 770 to 790 tCO<sub>2</sub>/m<sup>2</sup>. The reference building has a predicted 956 tCO<sub>2</sub>/m<sup>2</sup> for the next 20 years, meaning the examined model versions show a specific GWP decrease of approximately 20%.



Fig. 8 - Specific Site GWP for 20 years - Embodied GWP

#### 3.4 Financial Analysis

The financial analysis was two-fold. First, the estimation of acquisition cost of building versions was done, resulting in a range of 1 to 3.5 million EUR for acquisition costs for the 72 financially examined model versions. Secondly, the estimated global cost of model versions was performed, resulting in a range of 6.75 – 9.2 million EUR of global costs over the 20-year period after installation compared to the reference building's estimated 7.4 million EUR global cost for the same period, considering no acquisition cost. The financially best-performing model version turned out to be the one with 20 cm of mineral wool insulation uniformly on façades and roofs with an estimated global cost of 6.75 million EUR. Financial estimations could have considerable uncertainties, but with the side effects of comfort improvements and the reduced environmental footprint, these results prove the usefulness of the examination.

### 4. Conclusion

The application of several thermal insulation solutions on an educational building from an energetic optimization approach was examined. Numerous model versions provide feasible solutions to decrease the energy demand of the building, such as the application of mineral wool and wood fibre façade insulation systems. All the examined versions would reduce the environmental footprint of the building on a 20-year scale compared to the reference building, but user comfort could not increase significantly within this approach, since many interventions that would help with this was beyond the scope of the current research. Determining the best version of the examined constructions is challenging on an objective scale, but observable major trends and parameters can provide significant help in making decisions regarding energy-related refurbishment of buildings, which can lead to better quality and comfort of facilities in the long term. Shading solutions or schedule changes, among others, are variables that can be included in the scope in the long term, providing a significantly larger population size to optimize through with possibly lower global cost and reduced environmental footprint. The methodology is applicable to other buildings, while the goal of developing for districts or campus-scale buildings.

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# Achieving a Deeper Understanding of User-Related Influences on Artificial Lighting Energy Demand Using High-Performance Computing

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#### Abstract

Occupancy behaviour, including presence at the workplace, has a significant influence on a building's energy requirements. However, modelling occupancy behaviour is complex, multidisciplinary, and stochastic rather than deterministic. As little information about the intended use is available during the building planning phase, general assumptions about occupancy behaviour are made during building simulation and system planning, based on empirical and standardised models. However, these are formulated as generally as possible to achieve the broadest possible applicability. For example, despite improved simulation techniques, assumptions about occupant behaviour in the workplace often lead to deviations from the real situation, i.e. energy performance gaps. A better understanding of the factors that influence occupant behaviour, their weighting, and the improved models derived from them are proving to be crucial for eliminating performance gaps. Using advanced statistical methods and High-Performance Computing, representative samples of potential scenarios were created in this study to fully quantify the impact on energy performance. This was based on minuteby-minute occupancy and energy data from a one-year series of measurements in an open-plan office of Bartenbach, Austria. This research, based on High-Performance Computing, presents a breakdown of organisational and individual factors influencing energy-related occupancy behaviour. The results provide a promising basis for future research and pave the way for more targeted and energyefficient building planning.

#### 1. Introduction

#### 1.1 The Influence of User Behaviour

The deviations between predicted and actual energy requirements are known as energy performance gaps (EPG). The real energy demand is usually greater than the assumptions on energy demand from planning and simulation. Furthermore, performance gaps can exist not only in terms of energy demand but also, for example, in relation to the performance indicators of comfort and health. In the context of the building design phase, uncertainties in building modelling (such as insufficient geometric and material properties, and environmental data) as well as institutional restrictions and technical limitations of existing modelling tools can be identified in the literature as causes of EPGs (Lee & Selkowitz, 2006; Van Dronkelaar et al., 2016). In the context of the construction phase, the main causes include suboptimal installations and system calibrations (and thus inefficient system operation) as well as qualitative deviations in construction specifications (Menezes, 2012). However, the greatest cause of performance gaps can be identified as uncertainty regarding user behaviour while planning and the associated system designs (Calì et al., 2016), especially deviations resulting from the occupancy models used (Niu et al., 2016; de Wilde, 2014). These are currently mostly based on generally applicable models to bridge information gaps in the building design phase about subsequent room utilisation (cf. models in sia, 2006). It has been shown that these models fail when occupancy behaviour is very dynamic, e.g. strongly varying presence at the workplace due to frequent follow-up meetings (Hammes et al., 2021), which can account for around a quarter of managers' working time (Panko, 1992). In addition, organisational and social factors can influence occupancy dynamics, for example through flexitime arrangements. This information usually only becomes apparent after commissioning. With such uncertainties, it is not surprising that, depending on the actual occupancy dynamics, there are large ranges in terms of system-related energy requirements (cf. Hammes et al., 2021). In addition to occupancy patterns, uncertainty also includes user preferences. Preferences, e.g. regarding visual comfort, can differ greatly between individuals (Despenic et al., 2017).

The negative consequence of energy performance gaps is usually a higher energy requirement and therefore higher operating costs, as well as the risk of incorrect system dimensioning. The latter can result in inefficient operation, which in turn can be reflected in energy requirements and can also be to the detriment of user comfort. For these reasons, the improvement of planning and simulation methods is currently one of the most important challenges facing the construction industry (Menezes et al., 2012). Above all, it is important to create a better user mapping through improved occupancy models to reduce deviations between planning and operation. The need for this has already been recognised by the scientific community and several papers have been written on the subject. In addition, the energy-related influence of user behaviour and its mapping has been included in international research efforts (IEA EBC Annex 66 & IEA EBC Annex 79).

### 1.2 Related Work

Zou and Alam (2020) use a post-utilisation evaluation to identify causes of the EPG using content analysis and statistical analysis methods using the example of a multi-storey office building and to develop a stakeholder-oriented methodological framework to close the EPG. Manual override of automatic systems and inaccurate predictions of energy demand outside general business hours were identified as user-related causes (Zou & Alam, 2020). Here, too, user behaviour is determined by more influencing factors than by framework conditions set by the organisational structure. Using support vector regression based on operational data from an office building, significant improvements in the prediction of individual user profiles were achieved for the case study compared to existing models (Weninger & Hammes, 2023).

Menezes et al. (2012) provide a general overview of the causes that can lead to performance gaps. The authors also show how the findings from post-occupancy evaluation (POE - the system evaluation after commissioning) can be used to create more accurate energy performance models. Their results show that by combining measurement data with predictive energy modelling, the accuracy of energy forecasts can be improved (Menezes et al., 2012).

The role of POE in the breakdown of performance gaps and their closure via improved planning and simulation methods becomes clear via the thematic literature. The comparison of measured data and simulation results proves to be essential to ensure the validity of models (Fabi, 2013). To break down the energy-relevant user behaviour, this study is therefore also based on post-occupancy data.

#### 1.3 Objective

The negative consequences of EPGs currently pose a significant challenge, particularly those EPGs that arise due to the indeterminacy of user behaviour. A precise measurement of their extent and a breakdown of relevant influencing factors can counteract this. This study therefore aims to use post-occupancy data and High-Performance Computing (HPC) to break down the user-related energy demand regarding the influencing factors and, based on this, to derive recommendations for improved planning and simulation techniques.

As artificial lighting is one of the largest consumers of electrical energy in commercial buildings, accounting for around one third (Chow et al., 2013), the study focusses on this trade. Furthermore, office buildings are the most common type of building in most countries in terms of floor space and energy requirements (Labeodan, 2015). The study is therefore further focused on office buildings.

## 2. Methodology

#### 2.1 Study Object and Data Base

The post-occupancy data on which this study is based result from the 160 m<sup>2</sup> open-plan office of Bartenbach GmbH, which was converted into a LivingLab in 2019 (Fig. 1). Since commissioning, over 100 sensors have been used to record the indoor and outdoor climate and energy consumption of the lighting system components as well as user-related variables such as occupancy patterns and interaction behaviour with the lighting systems in high resolution. In addition to the latter, all system states of the integral artificial and daylight lighting system are also logged. The recording of user-related variables is carried out in compliance with data protection aspects. The Bartenbach LivingLab has already been able to derive several improvement measures for energy efficiency and comfort from post-occupancy evaluations.

A special feature of the open-plan office relevant to the study is a high daylight input (daylight autonomy (DA) of 81.56%, based on the normative workplace lighting of 500 lx and reference time of 08:00-18:00, excluding summertime, see (Hammes et al., 2021)), which means that the use of artificial light is primarily limited to the morning and evening hours. Furthermore, daylight and artificial light can be controlled zonally per desk group (cf. Fig. 1), which offers advantages for energy efficiency and especially comfort, as individual lighting preferences can be better mapped (Hammes et al., 2020). There are a total of nine lighting zones (=workplace zones), four along the skylight and five along the south façade (Fig. 1). The study includes 18 people, two people per zone. The activity profile of the employees involved in the study object corresponds to that of project managers, which is associated with a corresponding occupancy dynamic (cf. time study for managers by Panko & Kinney, 1992). The core working hours in the study period from Mon-Fri are 09:00-12:00 and Mon-Thu 14:00-17:00. The employees have the option of flexitime and working from home. Accordingly, there is a high degree of dynamism among residents regarding occupancy times at the workplace. To reduce energy-unfavourable artificial lighting operating times during absences, there is a passive infrared presence control system for each workplace. In addition, there is daylight control of the artificial light to the standardised 500 lx per zone.



Fig. 1 – Interior of the LivingLab at Bartenbach GmbH in Aldrans, Austria - south façade with half-closed sun protection on the right, skylight on the left (image source: Bartenbach GmbH)

The artificial light energy requirement of a zone results from the logical OR linking of the presence profiles of all persons in this zone. To realise presence detection in the best possible way, the detection range of the passive infrared sensors used is limited to the workplace.

For the study setting described above, the data basis for the study is formed by attendance data per individual workstation (pseudonymisation was used to ensure data protection), illuminance values and the dimming level of the artificial light for each zone. The latter two pieces of information were used to break down the illuminance value per zone according to the proportion of daylight and artificial light. The data covers a period from February 2022 to January 2023. The resolution is per minute or change of state.

## 2.2 Variant Creation via High-Performance Computing

The lighting zones are utilised more or less efficiently depending on the respective user combination and the associated occupancy dynamics at the workplace. This means that with increasing overlap of working times in the energy-relevant morning and evening hours, the zone is utilised more efficiently in terms of energy if the joint absences are high during these times. Furthermore, the position of the workplace is also relevant, as there are different daylight potentials per zone.

There are two people per table group, i.e. for each of the 9 controllable lighting zones. Varying the combination of presence profiles and the assigned workplace zone results in a total of 1.25\*1013 combinations (all possible combinations for 9 different pairs distributed over nine different workstation zones). Considering that individual users can have very individual behavioural patterns, it can be assumed that, depending on the combination of different user characteristics, significant differences may occur in the influences on the key performance indicators. In addition, previous studies have already shown that the relevance of the position increases with improved user pairing (Hammes et al., 2022). Therefore, expanding the understanding of the underlying profile properties proves to be necessary to make them usable for planning and simulation as well as to reduce performance gaps.

To gain an understanding of formative user characteristics, a representative sample size of potential occupancy scenarios was created using HPC. 10.24 million samples were generated using Monte Carlo simulation. A sample represents a completely randomised variation of user pairings and their position in the room. Repetitions of identical user distributions in the room were avoided. In addition, the HPC was used to determine the specific artificial lighting energy requirement for each sample, based on the measured illuminance of the daylight input per zone, the artificial lighting energy required to achieve the 500 lx and the combined presence profiles. The calculations were carried out on the VSC-5 of the Vienna Scientific Cluster (Austrian National Supercomputing Centre). Several batches were used, distributed across multiple nodes with each batch parallelized to be evaluated on 128 CPU cores. The calculation of the samples took approximately 60,000 hours of core time.

## 2.3 Characteristics of the Generated Data

The real artificial lighting energy requirement is 237 kWh (based on the lighting zones in the study object over the observation period Feb 2022 - Jan 2023). For a direct comparison of the measured value-based data with simulation-based data, the

occupancy models according to (sia, 2006) were matched with the measured illuminance levels or the derived demand values for artificial lighting energy per zone (172 kWh). The results show significant deviations from the real energy demand (38%).

The representation of the 10.24 million different samples generated by HPC as a histogram, with the energy demand as the abscissa, shows an approximately normal distribution (see Fig. 2). All user pairings (regardless of their position in space) occur almost equally frequently. The identified mean value of the artificial lighting energy demand with standard deviation is 239 kWh ± 12. The most unfavourable combination of the generated samples in terms of energy results in an artificial lighting energy demand of 285 kWh. The minimum identified is 183 kWh, i.e. there is a range between the minimum and maximum value of 102 kWh. The range between the minimum and maximum values of the samples and the deviation from the simulation highlights the need for a better understanding of the defining characteristics of user-related performance gaps and a quantification of possible ranges of energy demand. Fig. 2 also shows 247 kWh for the upper quantile (Q3), 230 kWh for the lower quantile (Q1) and correspondingly 17 kWh for the interguartile range (IQR). The median is 239 kWh. The upper whisker is 273 kWh, and the lower whisker is 205 kWh.



Fig. 2 – Artificial light energy requirement for the 10.24 million samples generated via HPC as a frequency distribution

#### 2.4 Data Evaluation and Limitations

In a first step, the data generated using HPC was analysed to determine which presence profiles and combinations are responsible for particularly low or particularly high energy consumption. Advanced statistical methods, such as variance analysis (ANOVA), are primarily used for this purpose. In addition, their diurnal and seasonal influence is evaluated as well as the influence of the room position. The post-processing analyses were carried out in Python (version Python 3.10, primary libraries used: pandas 2.0.0, scipy 1.11.1, scikit-learn 1.3.0). Supplementary statistical analyses were carried out with JASP (version 0.18.3.0).

As meetings often take place at the workplace, there is a risk of incorrect detections due to people moving between zones. In addition to this sensor-related limitation of the study, there was no gender-specific evaluation. Furthermore, two data logging system failures totalling 11 days should be mentioned.

#### 3. Results and Discussion

An examination of the frequencies of individual user combinations in the border areas of the histogram, i.e. the minimum and maximum energy ranges, shows that certain user combinations occur more frequently than other user combinations. For both low energy values and the very high energy range, 10,240 samples each were considered, which corresponds to 0.1% of the entire data set of 10.24 million. This is associated with nine user combinations per sample. Fig. 3 shows the frequency combinations of individual user combinations as an example for the minimum range (the same was done for the maximum range). Based on this distribution, the most important user combinations were analysed to list the special features that have a positive or negative impact on energy requirements and therefore possibly influence the extent of performance gaps.



Fig. 3 – Frequency distribution of all 153 possible user combinations for the low energy demand area according to Fig. 2

The attendance data at the workplace was recorded in high resolution. This means that measurement data is available at time intervals of less than 1 min over the study period. The arithmetic mean over the time of day of the five profile combinations that occur most frequently in the minimum ranges compared with the five profile combinations that occur most frequently in the maximum ranges shows clear differences, particularly in the morning and evening hours (cf. Fig. 4a and 4b). These are the times that have the greatest influence on energy demand due to the study setting (see Hammes et al., 2022). While the most frequent user combinations for high energy demand are characterised by high presence in the morning hours (in Fig. 4b, yellow-green area), the most frequent user combinations from the low energy range show almost no presence here. It can also generally be seen that the attendance probability is higher for the identified user combinations from the maximum range (more yellow). This results in a higher probability of artificial lighting during the day, especially when the sky is overcast.



Fig. 4 – Averaged presence over the time of day for the five most frequent user combinations that occur in the area of a) minimal energy demand and b) maximal energy demand. Users pseudonymized. Higher probability of presence if the color is yellow, lower probability of presence if the color is blue

These differences are also supported by the statistical analyses. A two-way ANOVA was conducted to determine if there was an interaction between the factors profile type and hour of the day on energy demand. Prescence times were normally distributed within all groups, with skewness and kurtosis statistics between -2 and +2. There was no homogeneity of variances, as assessed by the Levene's test for equality of variances (p < 0.05); however, because the assumption of normal distribution was satisfied with an equal number of datapoints in each group, the two-way ANOVA is considered robust to this violation (Maxwell et al., 2017).

The results show significant main effects in both factors (both p < 0.001), with generally higher attendance times in higher energy requirement profiles  $(M_{high} = 5,036 \text{ min}, M_{low} = 2,485 \text{ min})$ . More interestingly, there was also a statistically significant interaction between profile type and hour of the day, F(14, 120) = 1.98, p < 0.05,  $\omega^2 = 0.03$ . Bonferroni-corrected post-hoc tests show that the differences are primarily due to the edge of the day in the morning. Significant differences (both p < 0.05) between both profile types can be demonstrated in the morning between 08:00 and 09:00 and between 09:00 and 10:00. There were no significant differences for the remaining time periods. It turns out that the option of flexitime regulation is perceived very differently by each person, which is reflected in the energy profiles.

An examination of the frequencies of relevant combinations for the entire data set, i.e. for all 10.24 million samples, shows that the relevant profile combinations for a lower energy requirement also tend towards the lower energy level, while relevant profile combinations for a higher energy requirement are shifted to the maximum (Fig. 5a and 5b). The mean value of the distribution of the data for Fig. 5a is 237 kWh, for Fig. 5b 239 kWh, for comparison across all samples the mean value is 239 kWh. Less favorable combinations occur slightly more frequently. A Chi-Square Goodness of Fit Test for an adjusted sample size of 5,000 samples was performed to determine whether the frequencies of lower and higher energy requirement profiles were equally distributed over the different energy levels. The frequencies did significantly differ between the two profile types,  $X^2(8, N = 5,000) = 135.87$ , p = < 0.001, supporting the assumption that the profile types can be assigned to the respective lower or higher areas of the distribution. As the user combinations generated via HPC occur equally frequently per zone, this emphasizes that with zoned lighting concepts it is essential how the zones are occupied.



Fig. 5 – Percentage distribution of those samples containing the 10 most relevant profile combinations for a) low energy demand and b) high energy demand; Each applied to all samples

A final check of the energy deviations between relevant combinations of minimum and maximum ranges over the time of day and month shows a continuous difference in the morning hours over the year (Fig. 6). Deviations in the evening hours occur primarily in the first half of the year.



Fig. 6 – Deviation between the average daily and monthly resolved energy profiles from the identified minimum and maximum range, applied to the 10 most relevant profiles in each case

## 5. Conclusion

The results of this study help to decipher the causes of the EPG, especially in the lighting area, and to identify dependent variables. For this study, a high occupancy time in the morning and evening hours was identified as a particularly influential factor on the EPGs. Statistically significant interactions were found between profile type and the morning hours of 08:00-10:00. While the energy significance of zoned lighting concepts and their advantages for user comfort have already been demonstrated several times (i.e. in Hammes et al., 2020), the combination of profiles is essential for the energy requirements of dynamic occupancy. The study results also show a very wide variation in the probability of presence at the workplace, which in the study object is due to flexitime arrangements and the high number of follow-up meetings. Such dynamic processes are difficult to depict in simulations, which can lead to generally valid models usually resulting in energy-inefficient operation, which in turn becomes visible in EPGs.

The results of the study show that existing planning models can only incompletely depict dynamics in the morning and evening hours, which calls into question their suitability for application. However, the development of an applicable model requires a significantly larger data set and further research in the areas of user individuality and work processes. For more accurate building planning and simulation and thus a lower risk of performance gaps, it would therefore be advisable to classify the results for different organisational and building typologies. In this sense, the approach presented in this paper can be seen as a first step towards improved user modelling in simulation processes. Further research activities can also be carried out to quantify the influence of occupancy behaviour and other factors, such as weather and user position in the room, on total energy consumption and thus make it easier to plan by deriving improved models for the simulation.

The presented work also emphasises the importance of POEs to gain insights for improving planning and simulation after commissioning and thus reducing EPGs. POEs also allow measures to be derived after commissioning to improve energy requirements. Accordingly, optimisation algorithms could derive improved user distributions in the room and thus reduce EPGs.

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# Strategic Synergy: Enhancing Building Performance Through Advanced Simulation and Shading Integration

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#### Abstract

Leveraging advanced simulation processes and optimization algorithms, this research aims to enhance energy performance and daylight harvesting for a case-study building, the Bullitt Center, Seattle, Washington, U.S.. Specifically, it studies the role of shading devices to conserve energy. Central to this research is the utilization of simulation processes and optimization algorithms as powerful tools to analyse and fine-tune building performance. Through systematic examination, the research offers nuanced insights into the dynamic interplay between architectural elements and environmental conditions, highlighting the potential of advanced simulation methodologies to address contemporary challenges in building design and performance.

#### 1. Introduction

The pursuit of sustainable building practices is imperative in contemporary architecture, necessitating innovative strategies to enhance energy efficiency and thermal performance. One of the primary drivers behind the adoption of sustainable building practices is the urgent need to mitigate climate change. According to the International Energy Agency (IEA) (2024), buildings are significant contributors to greenhouse gas emissions, accounting for approximately 30 % of global carbon dioxide emissions. Therefore, reducing the environmental impact of buildings through sustainable design and construction practices is crucial for mitigating climate change and achieving global sustainability goals.

In addition to environmental concerns, sustainable building practices also address social and economic challenges. Sustainable buildings offer numerous benefits to occupants, including improved indoor air quality, enhanced thermal comfort, and better overall well-being. For example, green buildings have been shown to reduce absenteeism and increase productivity among occupants, leading to economic gains for building owners and employers (Chen et al., 2023). Furthermore, sustainable buildings often have lower operating costs due to reduced energy and water consumption (Tushar et al., 2019), making them financially attractive investments in the long term (Waage et al., 2005).

The integration of advanced simulation techniques is fundamental for achieving sustainable building practices and optimizing building performance. These techniques serve as powerful tools for architects and engineers to analyze and refine various aspects of building design, including energy efficiency, thermal comfort, and daylighting. By incorporating advanced simulation techniques into the design process, designers can make informed decisions that enhance building performance while minimizing environmental impact.

One crucial aspect of integrating advanced simulation techniques is the evaluation of building energy consumption and thermal performance. Additionally, advanced simulation techniques play a key role in assessing the impact of shading devices on building performance. Shading analysis software such as Radiance and Daysim enable designers to predict natural daylight levels within buildings and evaluate the effectiveness of shading strategies in reducing solar heat gain and glare (Reinhart, 2018). By simulating different shading scenarios, architects can optimize the design of shading devices such as louvers, overhangs, and blinds to maximize daylight penetration while minimizing energy consumption for lighting and cooling. In the realm of sustainable building design, optimizing building performance with shading devices emerges as a cornerstone strategy. Shading devices, encompassing louvers, overhangs, blinds, and awnings, offer robust solutions to counteract solar heat gain, minimize glare, and augment natural daylighting within built environments (Sghiouri et al., 2018). The integration of shading devices into architectural design and the meticulous management of solar radiation represent pivotal steps towards enhancing energy efficiency, thermal comfort, and indoor environmental quality.

Furthermore, simulation-based design optimization enables architects to assess the energy performance of buildings with different shading configurations. Energy simulation software like OpenStudio, DesignBuilder, and Honeybee (Grasshopper plugin) allow for the modeling of energy consumption under varying shading scenarios, enabling the identification of optimal strategies to minimize energy usage while maintaining thermal comfort and daylighting levels (Barber & Krarti, 2022). By strategically positioning shading devices to modulate direct sunlight and diffuse natural daylight, architects can create more comfortable and productive indoor environments for occupants.

In the pursuit of sustainable building design and the optimization of building performance, addressing the complexities of heat gain mitigation holds paramount importance (Park et al., 2024). Architects and engineers endeavor to minimize heat gain, reduce energy consumption, and cultivate healthier, more comfortable indoor environments. This endeavor involves the strategic integration of advanced simulation techniques alongside the incorporation of shading devices, insulation enhancements, and calibrated openings into building design. By navigating these complexities, professionals can effectively manage solar radiation, enhance thermal comfort, and achieve energy efficiency goals.

Given these premises, the exploration within this work delves into the seamless integration of advanced simulation techniques and shading devices to optimize building performance.

#### 2. Methodology and Materials

In the context of enhancing building performance and sustainability, this study aims to address challenges associated with heat gain mitigation and the integration of shading devices. A relevant case study for examining these objectives is the Bullitt Center, Seattle, Washington, U.S., recognized as a pioneering example of sustainable building design (Fig. 1). With its emphasis on passive design strategies and efficient shading devices, the Bullitt Center offers an ideal context for exploring the effectiveness of advanced simulation techniques in optimizing energy efficiency and indoor comfort.



Fig. 1 – A view of the existing Bullitt Center, showcasing its sustainable architectural design and innovative features

To model the relationship between the study objectives and the Bullitt Center, a specific part of the building, such as the facade, can be selected for analysis. This area incorporates shading devices designed to mitigate solar heat gain, and advanced simulation tools can be utilized to evaluate their performance in reducing heat gain while maintaining sufficient levels of natural daylighting (Fig. 2). Energy modeling played a crucial role in the feasibility phase of the project to establish envelope thermal parameters supporting the net-zero energy design goal. The targeted Energy Use Intensity (EUI) was set below 20 kBtu/ft2-yr (63 kWh/m2-yr) and reduced to 16 kBtu/ft2-yr (50 kWh/m2-yr) as design progressed. In its first year, the Bullitt Center achieved an actual EUI of 29.65 kWh/m<sup>2</sup>-year, which is 41 % better than the predicted EUI of 50.80 kWh/m<sup>2</sup>-year (Hanford, 2015; Peña, 2014).



Fig. 2 – Views of the existing Bullitt Center, focusing on the integrated shading louvers and the roof with its shadow

## 2.1 Simulation and Analysis

This section focuses on the simulation and analysis of the Bullitt Center's energy performance, leveraging advanced computational tools and techniques. The simulations were conducted using Honeybee and Ladybug plugins, which interface with EnergyPlus and OpenStudio engines. These tools allow for detailed energy modeling and environmental analysis, providing comprehensive insights into the building's performance.

The building was initially modeled in Revit, including the shading louvers, which were parametrically designed. This model was then exported to Rhino for further refinement (Fig. 3).



Fig. 3 – View of the existing Bullitt Center modeled in Revit with parametric louvers

However, due to the limitation in Grasshopper where not all windows had shading devices, the HB Louver Shades component was not initially selected. Consequently, the shading louvers were remodeled parametrically in Grasshopper as an array to ensure accurate representation in the simulation (Fig. 4). Only the number and distance of the louvers were modeled parametrically; their rotation was not considered since the existing building does not support this option. The louvers function only as vertical elements adjusted manually by users to different thresholds.

The building has been divided into five zones for the simulation. Each floor constitutes a zone, with Zone 1 comprising the ground floor and its mezzanine. The detailed simulation focused particularly on Zone 3, incorporating the use of louvers to assess their impact on energy performance.



Fig. 4 – View of the existing Bullitt Center modeled in Rhino/Grasshopper with parametric louvers

Furthermore, the methodology involves a detailed analysis of shading devices using simulation tools like Radiance and Daysim. These tools enable designers to simulate daylight levels and solar radiation distribution within interior spaces under different shading scenarios. By evaluating the performance of shading devices and their impact on daylight penetration and thermal comfort, optimal shading strategies can be identified.

The Bullitt Center employs an innovative HVAC system aligned with the principles of the Living Building Challenge. This system emphasizes energy efficiency and sustainability, relying on renewable energy sources. The building utilizes natural ventilation strategies, supplemented by mechanical systems when necessary to ensure adequate indoor air quality and thermal comfort.

The dedicated outside air system (DOAS) with a heat pump was also incorporated into the Grass-hopper simulation to accurately reflect the HVAC system used in the building. Heating and cooling setpoints were 23 and 27 °C, respectively.

The simulation incorporated the following thermal properties for the Bullitt Center as shown in Table 1.

Component	Property	Value
Windows	SHGC	0.31
	U-Value	0.17 W/(m <sup>2</sup> K)
Exterior Walls	U-Value	0.189 W/(m <sup>2</sup> K)
Exterior Roof	U-Value	0.149 W/(m <sup>2</sup> K)
Interior Walls	U-Value	0.284 W/(m <sup>2</sup> K)

Table 1 – 1	Γhermal	properties	for the	Bullitt	Center
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## 2.2 Simulation Process and Data Interpretation

The detailed simulation focused particularly on Zone 3 (Fig. 5), incorporating the use of louvers to assess their impact on energy performance (Area: 758.58 m<sup>2</sup> including circulation spaces).

Simulations were initially run without louvres to evaluate the energy performance (energy use intensity, EUI) and annual daylight performance using the Honeybee and Ladybug plugins. These simulations aimed to establish a baseline understanding of the building's energy consumption and natural lighting conditions before introducing shading devices. Although the primary focus was on Zone 3, simulations were run for all zones to capture the holistic energy performance of the Bullitt Center, because energy performance in one zone can affect adjacent zones due to heat transfer through internal walls, floors, and ceilings. Also, a heating, ventilation and air-conditioning (HVAC) system operates across the entire building. Evaluating all zones ensures the system is optimized for the building as a whole, rather than just a single area.

The simulation revealed an EUI of 35.04 kWh/m<sup>2</sup>year, closely aligning with the actual recorded EUI of 29.65 kWh/m<sup>2</sup>-year (Table 2). This close alignment indicates the accuracy and robustness of the simulation approach.

Table 2 – Simulation	results	without	louvers
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Parameter	Without Louvres
EUI (kWh/m²-year)	35.04 (All zones)
Solar Gain (kWh)	27,356.62 (Zone 3)
Cooling Load (kWh)	2201.27(Zone 3)



Fig. 5 – The plan of the selected floor displays its dimensions and layout

According to the results, without louvres, Zone 3 experienced a high solar gain of 27,356.62 kWh. This significant amount of solar heat gain contributed to increased cooling demands and potential overheating. The cooling load in Zone 3 without louvres was 2,201.27 kWh. This high cooling demand was directly related to the high solar gain and internal heat sources.

Minimizing overheating in a building simulation is crucial for maintaining occupant comfort and reducing energy consumption. Moreover, optimizing the configuration of shading devices is essential for minimizing overheating while maintaining sufficient daylight in a building. Daylighting performance is essential for both energy efficiency and occupant comfort. The useful daylight illuminance (UDI) and daylight autonomy (DA) metrics were selected for evaluating daylight performance. Table 3 presents the average daylight performance metrics without the use of louvres. Figures 6 and 7 illustrate the simulation results, showcasing how daylight is distributed and utilized within Zone 3.

Table 3 - Thermal properties for the Bullitt Center

Metric	Without Louvers
UDI	72.04 % (Average)
DA	42.05 % (Average)



Fig. 6 - UDI distribution without louvres in Zone 3



Fig. 7 – DA distribution without louvres in Zone 3

# 2.3 Solar Radiation Mitigation and Shading Integration

The energy simulation process provided critical insights into the performance of the Bullitt Center after the implementation of shading louvres. The results were particularly focused on Zone 3, though simulations were run for all zones to ensure a comprehensive analysis of the building's overall energy performance.

After implementing the louvres across all zones, the simulation showed an EUI of 34.45 kWh/m<sup>2</sup>-year. This value is a slight improvement over the initial EUI (without louvres), indicating that the shading devices effectively reduced the building's overall energy consumption.

Detailed results for Zone 3, the zone with the most thorough analysis, demonstrate significant reductions in solar gain and cooling load (Table 4).

Table 4 – Simulation results with louvers

Parameter	With Louvres
EUI (kWh/m²-year)	34.452 (All zones)
Solar Gain (kWh)	6908.94 (Zone 3)
Cooling Load (kWh)	671.80 (Zone 3)

Implementing louvres reduced the solar gain in Zone 3 to 6,908.94 kWh. This reduction highlights the louvres' effectiveness in blocking excess solar radiation, thus minimizing heat gain through the building's glazing. The cooling load in Zone 3 decreased to 671.80 kWh after the implementation of louvres. This reduction is crucial for maintaining comfortable indoor temperatures without over-reliance on the HVAC system. The implementation of louvres resulted in a 74.76 % reduction in solar gain and a 69.47 % reduction in the cooling load for Zone 3.

The louvres were designed to cover all the glazing surfaces in Zone 3, providing consistent shading across all windows. The number and distance of louvres were modeled parametrically, ensuring optimal shading performance.

To assess the impact on daylighting on daylighting with louvres, UDI and DA metrics were evaluated. The implementation of louvres led to a reduction in UDI and DA, indicating that while solar heat gain was minimized, the availability of natural daylight also decreased as shown in Table 5. Figures 8 and 9 illustrate the daylight distribution in Zone 3 without louvres.

Table 5 - Thermal properties for the Bullitt Center

Metric	Without Louvres	With Louvres	Reduction (%)
UDI (100-2000 lux)	72.04 %	46.60 %	35.31%
DA	42.05 %	5.54 %	86.83%
(300 lux)			

The UDI decreased by 35.31 %, and the DA metric saw an even more dramatic reduction, decreasing by 86.83 %, indicating a significant drop in the percentage of occupied hours during which natural daylight alone meets the minimum illuminance level. The results highlight the trade-off between reducing overheating and maintaining adequate daylight levels. While louvres effectively reduce solar heat gain, their impact on daylighting must be carefully managed to ensure that spaces remain adequately lit by natural light.

The assessment reveals that shading louvres significantly influence both energy performance and daylight availability. By reducing solar gain and cooling loads, louvres improve energy efficiency but also reduce the amount of useful daylight. Therefore, optimizing the configuration of shading devices is crucial to balance thermal comfort and natural light, ensuring both energy efficiency and occupant comfort in sustainable building design.



Fig. 8 – UDI distribution with louvres in Zone 3



Fig. 9 - DA distribution with louvres in Zone 3

## 2.4 Multidisciplinary Approach and Optimization Algorithms

Optimization algorithms are essential in navigating the complex trade-offs inherent in building performance. Two notable components used in this context are the Wallacei X Component and the Galapagos Component in Grasshopper. Galapagos component is an evolutionary solver in Grasshopper, widely used for single-objective optimization problems. While effective, it may not handle multi-objective optimization as efficiently as other specialized tools.

Wallacei X Component was selected for this study due to its robust capability to handle multi-objective optimization problems. In the Wallacei X Component, the objectives were set to:

- Maximize Daylight Autonomy (DA): ensures sufficient natural light during occupied hours.
- Maximize Useful Daylight Illuminance (UDI): ensures that the illuminance levels are within a range that is useful for typical tasks without causing glare.
- Minimize Energy Use Intensity (EUI): reduces the overall energy consumption of the building, enhancing energy efficiency.

The genes in this optimization process were:

- Distance between Louvres: adjusting the spacing impacts both shading effectiveness and daylight penetration.
- Number of Louvres: varying the quantity influences the balance between reducing solar gain and maintaining natural light levels.

After running the simulations, the optimal configuration was found to be a distance of 4 cm between each louvre, with a total of 17 louvres from the top to the bottom of the windows (Fig. 10). This configuration was determined to best achieve the objectives of improving daylight performance and reducing energy consumption.

After the optimization process using the Wallacei X Component, the results showed significant improvements in daylight performance metrics while maintaining an acceptable balance in energy use intensity. The UDI improved to 70.88 %, close to the 72.04 % without louvres and significantly higher than the 46.60 % with full louvres. This indicates a successful balance in maintaining useful daylight levels. The DA also improved to 34.40 % from 5.54 % with full louvres, demonstrating better natural light during occupied hours compared to the full louvre scenario, though still lower than the 42.05 % without louvres.





Fig. 10 – Visualization of the optimized louvers integrated into the existing Bullitt Center model in Rhino/Grasshopper, alongside the input data displayed in the Wallacei X Component

Table 6 – Comparison of Simulation Results: Impact of Louvres Integration and Optimization

Parameter	Without Louvres	With Full Louvres	Optimized Louvres
UDI (100-2000 lux)	72.04 %	46.60 %	70.88 % (Average)
DA (300 lux)	42.05 %	5.54 %	34.40 % (Average)
Cooling (kWh)	2,201.27	671.80	2255.75
Solar gain (kWh)	27356.62	6,908.94	22087.41
EUI (kWh/m²-year)	35.038	34.452	34.927

The cooling load with optimized louvres was slightly higher at 2,255.75 kWh compared to the scenario without louvres but significantly lower than with full louvres. The solar gain also reduced significantly to 22,087.41 kWh from 27,356.62 kWh without louvres, although it was higher than the solar gain with full louvres. This reflects the trade-off between maximizing natural light and controlling solar heat gain. The EUI for the optimized louvre configuration is 34.927 kWh/m<sup>2</sup>-year, which is slightly higher than with full louvres (34.452 kWh/m<sup>2</sup>-year) but still lower than without louvres (35.038 kWh/m<sup>2</sup>year). The slight increase compared to the full louvre configuration can be attributed to the need for balancing daylight and thermal performance, where more daylight penetration leads to slightly higher cooling demands.

#### 3. Future Study and Limitations

The current study assumed a fixed louvre configuration without considering the dynamic adjustment or rotation of louvres. This simplification may not fully capture the potential benefits of adaptive shading strategies, leading to suboptimal performance in terms of energy efficiency and daylighting. By dynamically adjusting the orientation of louvres throughout the day, the building's performance in terms of solar gain reduction and daylighting optimization could be further enhanced.
A detailed analysis could be conducted to understand of how different façade orientations affect the performance of shading louvres. Given the varying positions of the sun throughout the day, different façades may experience distinct levels of solar radiation and daylight penetration, necessitating customized shading solutions.

# 4. Conclusion

The optimized louvre configuration demonstrates a well-balanced approach to enhancing daylight performance and controlling thermal gains. Although there was no significant reduction in total EUI, the optimization effectively improved UDI and DA, indicating better daylight performance while still maintaining energy efficiency. While the current study provides valuable insights into the optimization of shading louvres for building performance enhancement, there are opportunities for future research to address these limitations and further refine the design and implementation of shading strategies. By exploring the integration of rotation louvres, conducting façade-specific performance analyses, and addressing computational challenges, future studies can advance the state-of-the-art in building performance optimization and contribute to more sustainable and comfortable built environments.

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# Is Solar Hydrogen a Viable Solution for Energetically Self-Sustainable Off-Grid Buildings?

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#### Abstract

A micro-cogeneration solution based on an alkaline fuel cell, supplied by solar hydrogen to satisfy electric and thermal energy demands in an off-grid building, is investigated. Hydrogen is produced by using PV surpluses through an alkaline electrolyzer and stored in a pressurized gas tank. Regarding a reference building with a gross footprint of 100 m<sup>2</sup> affected by severe winter climate conditions and heated by a radiant floor supplied by an airwater heat pump, TRNSYS simulations showed that 14.4 kW<sub>P</sub> of PV power and 5 m<sup>3</sup> of hydrogen tank volume ensure the building energy self-sustainability. Indoor comfort conditions are achieved by observing air temperatures always in the range of 19-21 °C during winter. The thermal power recovered from the fuel cell reduced DHW demand noticeably. Results show that hydrogen acts as an inter-seasonal storage with summer overproductions needed for the fuel-cell winter operation. An economic analysis confirms that the system is profitable when compared with electric storage made of batteries periodically replaced.

# 1. Introduction

The building energy requirements in the EU are responsible for more than 36% of greenhouse emissions (UN Environmental Program, 2024). Energy requalification of the existing stock is effortlessly achievable in grid-connected buildings by installing heat pumps driven by PV generators with suitable emitters, in which proper management of the electric surpluses is attainable even without energy storage systems (Perrella et al., 2024). Evident difficulties remain in off-grid buildings that, conversely, require the installation of storage systems to meet both electric and thermal requirements (Hakimi & Hasankhani, 2020) with energy's self-sustainability attained by reserves of fossil primary sources, preferred for the easy refuelling and the favourable costs. To limit the worsening of the environmental footprint, micro-cogeneration systems integrated with renewable sources to provide heat and electricity simultaneously could be used (Kallio & Siroux, 2022). However, the intermittence of solar irradiance makes the match between energy production and consumption difficult. A feasible solution is given by PV/T generators interacting with water tanks and batteries to manage thermal and electrical surpluses (Gugul, 2023). Nevertheless, accurate management of thermal energy is required to avoid a worsening of the PV cells' performance due to thermal drift effects (Bevilacqua et al., 2020). An alternative solution suitable in off-grid buildings is represented by alkaline fuel cells (AFC), which convert the chemical energy of hydrogen into electric and thermal energy, after that an electrolysis process driven by PV generators makes available the pressurized gas in proper tanks. AFCs are safe with a lifespan of over 20 years if supplied by pure hydrogen. In this paper, the performances of a cogenerative AFC, installed in a reference off-grid building, are explored. AFC is supplied by solar hydrogen produced by managing PV surpluses that drive an alkaline electrolyzer, producing pressurized hydrogen and oxygen. Electric energy is absorbed for base loads (lighting and appliances) and to supply an electric air-water heat pump that heats the building through a radiant floor. AFC thermal power is recovered in a water tank, equipped with an integrative electric resistance, for the supply of DHW at least 45 °C. The components interaction (PV panels, electrolyzer, AFC, hydrogen tank, water tank, airwater heat pump, building), was simulated in TRN-SYS (VV.AA., 2018) under a severe winter climate. Indeed, AFC, electrolyser and hydrogen storage have been largely studied by TRNSYS in the past, as reported in Wei et al. (2022) which evaluated solar panels and wind turbines to drive electrolysis in Canada. In Dezhdar et al. (2023) a hybrid storage system including batteries and hydrogen tanks was studied through TRNSYS simulations. Zeng et al. (2023) used TRNSYS to design an energy system based on AFC and hydrogen storage in China. Saleem et al. (2020) considered different configurations of solar-hydrogen generation systems in diverse climates. Many investigations were validated by experimental data, therefore TRNSYS is a reliable tool for simulating solar hydrogen as a "sui-generis" storage system to manage energy surpluses in grid-connected buildings. Conversely, in this paper, TRNSYS is used for sizing the components that ensure thermal and electric self-sustainability in an isolated building. An economic analysis compared this solution with an alternative system made of conventional batteries to verify its profitability.

# 2. Methodology

#### 2.1 Off-Grid Building Features

The (real) isolated single-storey building (plant gross area 100 m<sup>2</sup>, net inter-floor height of 2.80 m) with an unheated attic was modelled geometrically by SketchUp® and thermodynamically by TRN-BUILD. The proposed plant could be hosted in a disused barn of 60 m<sup>2</sup> adjacent to the building. A sketch of two building prospects is shown in Fig. 1.



Fig. 1 - NW and SE prospects of the reference off-grid building

The building was simulated as a single thermal zone heated by a radiant floor. The roof pitches (53 m<sup>2</sup> each) are oriented East and West tilted at 15° to host PV arrays. The Window-to-Wall ratio is 9%, 12%, 10% and 25% respectively for South, East, West and North. Vertical opaque walls have a U-value of 0.248 W/(m<sup>2</sup>K), the ground floor has an equivalent U-value of 0.284 W/(m<sup>2</sup>K) and the ceiling deck (unheated attic as upper boundary condition) has 0.402 W/(m<sup>2</sup>K). The window U-value (wooden frame hosting a 4/15/4 system with low-ε panes) is 1.40 W/(m<sup>2</sup>K) with a normal solar factor of 0.589. Fig. 2 shows indoor air temperature and heating load profiles for an indoor set-point of 20 °C. The maximum heating load is 5.4 kW, the more frequent value is 3.8 kW and the heating requirement is 167 kWh/m<sup>2</sup>. No cooling power is required in summer to set 26 °C.



Fig. 2 – Hourly profiles of indoor air temperature and heating loads for an indoor set-point of 20  $^\circ$ C in the considered climatic zone

The intended use is a farmhouse with yearly average daily demands for DHW and electricity depicted in Fig. 3, based on a typical occupation pattern (Pflugradt, 2024). The electric profile refers exclusively to the base load, mainly concentrated in the central and evening hours, whereas DHW demand is distributed among early morning, midday and evening. The 80 m<sup>2</sup> of active radiant floor was simulated as an active layer, made of serpentine polymeric pipes (k=0.35 W/(m·K)) drowned in 5 cm of lightweight concrete, over a floor deck of 20 cm to use as thermal storage, externally insulated by 10 cm of EPS (k=0.035 W/(mK)). The pipe's pitch is 5 cm with an internal diameter of 10 mm, supplied by a constant water flow rate of 0.33 kg/s and variable inlet temperature. The heat pump is activated when a zone thermostat measures indoor air temperature under 19 °C (dead band 2 °C).



Fig. 3 – Yearly average daily profiles concerning electric base consumptions and  $\mbox{DHW}$ 

# 2.2 Climatic Data

The building site has an altitude of 1440 m above sea level with 2897 HDD (Heating Degree Day), classified as Csb following the Koppen rating. Climatic data are provided by a TMY file: Fig. 4a) shows the trend of the outdoor air temperature whereas Fig. 4b) the horizontal solar irradiance.



Fig. 4 – Hourly outdoor air temperature (a) and solar irradiation on the horizontal plane (b) for the considered site

### 2.3 Main Plant Components

### 2.3.1 Air-Water Heat Pump

The heat pump (HP) performances are determined as a function of the outdoor air and the supplied water temperatures. The device is equipped with an inverter avoiding the COP penalization in part-load mode. Following the heating loads depicted in Fig. 2, the heat pump rated heating capacity (outdoor air temperature at 7 °C and supplied hot water at 45 °C) is 6 kW with a corresponding COP of 3.46. The real COP, determined by associating a proper file describing the performance curves provided by the manufacturer (see Fig. 5), allows for the calculation of the real share of absorbed electricity.



Fig. 5 – Heat pump COP as a function of the outdoor air temperature ( $T_{\text{OA}})$  for two values of the supplied hot water

#### 2.3.2 PV generator

Electric energy is provided directly by PV panels made of mono-crystalline cells installed coplanar with the roof pitches. The caption surface was set as a parameter for the system design. The panel peak power is 450 W with a rated efficiency of 20.6%. Temperature coefficients for current and voltage are respectively +0.044 %/°C and -0.272 %/°C needed to consider the thermal drift effect and the efficiency decrement. The projection of the solar radiation on the caption surface was carried out by the Reindl model. Electric surpluses drive an electrolyzer for hydrogen production and the maximum installable power is 21.6 kW<sub>p</sub>.

#### 2.3.3 Electrolyzer

The electrolyzer produces water electrolysis and gas compression to facilitate storage. It is constituted by a single stack with 21 cells in series and an electrode surface area of 0.25 m<sup>2</sup>, operating at a constant pressure of 7 bar. The electrolyzer is designed to operate in a variable power mode through a specific conditioning power unit: when it is ON, the setpoint power is set to the maximum between the excess of power and an idling power that, for the considered device, was set to 500 W. Conversely, the electrolyzer is set OFF so that the PV surplus lower than 500 W is dissipated in the integrative electric resistance of the water tank's (800 litres). The electrolyzer control depends also on the state of charge (SoC) of the pressurized hydrogen storage: if it exceeds 0.95, the electrolyzer is OFF and the total surplus is used again for DHW production, to restart when the SoC goes down to 0.7 to confer control stability.

### 2.3.4 Hydrogen pressurized tank

This tank is charged by the electrolyzer whereas it is discharged to supply the fuel cell. The transient mass balance must be verified in every timestep, considering that the gas tank is subjected to a constant hydrogen consumption, depending on the Fuel Cell size, but variable hydrogen supply due to the magnitude of the PV surplus. A halved tank manages the oxygen storage. The tank volume is another parameter varied for the system design.

# 2.3.5 Alkaline Fuel Cell (AFC)

The fuel cell is made of 2 stacks in parallel equipped with 32 modules in series each, to obtain 220 V as output voltage (operating voltage of 7.374 V per module) with an electrode area of 100 cm<sup>2</sup>. An empirical relationship describes the current-voltage characteristic at normal operating temperature. The generated heat is calculated simplistically without detailed dynamic thermal models but following the approach proposed by (Brown et al., 2001) setting a stack operating temperature of 70 °C when crossed by a current of 8.1 A. An internal heat exchanger recovers thermal power for the DHW tank. The AFC is activated also in diurnal hours when the sum of base loads, HP absorbed power and the water tank's resistance is greater than PV output.

# 2.4 Mini-Grid Management

The flow chart in Fig. 6 shows how a mini-grid installed in the off-grid building verifies the electric fluxes for design purposes (BL=Base Load, HP=absorbed by heat pump, EL=Electrolyzer, PVP= PV power, PVS=PV surpluses, ER= surplus for water tank's electric resistance, DHW= electric resistance activated with temperature below 45 °C). The correct component sizes are verified if, in every simulation timestep, the produced power is greater than the required electric load:

$$AFC+PVP \ge BL + HP + DHW$$
 Eq. 1



Fig. 6 – Electric fluxes management in the reference off-grid building carried out by an internal micro-grid

The non-absorbed power, detected when Eq. 1 provides positive results, is converted into thermal energy by the heat pump, stored in the building through the radiant floor (until the indoor air temperature is 21 °C) and in the water tank for DHW whose temperature can exceed 45 °C.

# 3. Results

Simulations started from 1st January until 31st December with a timestep of 1 minute. The following results are obtained starting with hydrogen storage full at 40 % (hypothesizing the accumulation of hydrogen overproduction in the previous summer). A parametric study has shown that the minimal plant configuration that ensures the verification of Eq. 1 in every timestep requires 14.4 kWp of PV peak power (16 modules in series arranged in two arrays) and 5 m<sup>3</sup> of hydrogen storage volume (V). Fig. 7 depicts, for the coldest week (last week in January), the trends of the PV and AFC electric powers, and indoor air and operative temperatures. In contrast to the variable PV output, it is worth noting the constant (1,865 W) and misaligned power production from AFC. Simultaneous production was detected with scarce solar irradiance highlighted by the curves' overlap. In diurnal hours, AFC is not operating on sunny days due to the significant PV power production (over 9,000 W). Thermal energy for heating is managed adequately by detecting indoor air temperature that never falls under 19 °C, whereas overheating situations are avoided.



Fig. 7 – Temperature and power profiles for a plant configuration equipped with PV=14.4  $kW_p$  and V=5m³ in January

Tab. 1 shows that the recovered thermal power from AFC (%Eth,saved), of about 300 W, determines energy saving percentage varying between 70%-80% of the DHW demand (19 kWh/m<sup>2</sup>). The PV surplus (PVS) managed by the electrolyzer and the water tank on an annual basis is over 18,000 kWh. Large shares are available in summer due to the limited heat pump operation. Fig. 8 shows that the main electric consumption source is represented by the heat pump in winter and the intermediate months, with consumptions that decrease with the outdoor air temperature growth. The water tank's electric resistance (1.2 kW) absorbs limited electricity, by benefiting from the thermal power recovered from the AFC. Tab. 1 shows that AFC (%AFC) intervenes mainly during the coldest months to compensate for the lower PV output. Annually 76.6% of power is provided by the PV generator (%PV). The hydrogen balance (H<sub>2</sub> Bal.) is negative in winter (absorption greater than production), however, larger productions in the other months prevent the pressurized tank from being empty throughout the year. The annual trend of SoC (Fig. 9) shows March as the critical month.



Fig. 8 – Monthly electric energy absorbed by the three consumption sources in the off-grid building

	PVS (kWh)	%PV	%AFC	H <sub>2</sub> Bal. (m³/month)	$\%E_{th,saved}$
J	522	58.8%	41.2%	-198.50	84.8%
F	719	71.8%	28.2%	-118.65	83.1%
Μ	1,252	78.6%	21.4%	9.70	80.3%
Α	1,802	82.9%	17.1%	169.26	78.7%
Μ	2,209	81.1%	18.9%	304.36	76.7%
J	2,451	81.9%	18.1%	169.15	70.9%
J	2,607	80.1%	19.9%	29.21	73.8%
Α	2,368	77.4%	22.6%	43.75	76.6%
s	1,688	72.7%	27.3%	-124.84	78.2%
0	1,284	74.0%	26.0%	46.77	79.2%
Ν	728	66.5%	33.5%	-115.92	82.2%
D	483	59.3%	40.7%	-206.75	83.8%
Ŷ	18,11 4	76.6%	23.4%	7.54	79.3%

Table 1 – Main monthly results with PV=14.4 kW<sub>p</sub> and V=5 m<sup>3</sup>

Moreover, the summer overproduction led to SoC>95% three times determining the electrolyzer switch-off, however hydrogen production restarted when SoC went down to 70%. In these cases, DHW reaches 80°C. Noticeably, the hydrogen volume at the end of the simulation is almost equal to the content at the start, therefore this configuration allows for a neutral yearly cycle that avoids storage issues over a long period.



Fig. 9 – Yearly dynamic trend of the SoC regarding the hydrogen pressurized tank assuming PV=14.4  $kW_{\rm p}$  and V=5m³

If the plant configuration foresees a lower caption PV surface or a lower hydrogen tank volume, during winter there is no availability of hydrogen to supply the AFC. In these circumstances, Eq. 1 is not verified, but this could be overcome by avoiding the activation of the heat pump. This determines a worsening in terms of thermal comfort. Despite %E<sub>th,saved</sub> being subjected to slight variation due to similar AFC operation time, indoor air temperatures often drop under 19 °C because the radiant floor is not supplied. Alternatively, the size of AFC can be reduced to absorb less hydrogen flow rates, but %E<sub>th,saved</sub> reduces proportionally due to the lower

recovered thermal energy, and again indoor air temperatures are negatively affected. This situation is depicted in Fig. 10 (3rd week of February) assuming PV=12.6 kW<sub>p</sub> (14 panels in series arranged on two arrays), V=5 m<sup>3</sup> and a smaller AFC made of 2 stacks in parallel with 24 cells in series that produces 1400 W (-25%). In contrast, if the PV size increases, also the hydrogen tank volume and the AFC size must be increased accordingly, due to the wider hydrogen availability. In particular, a greater PV peak power determines larger PV surpluses, therefore hydrogen production increases requiring larger gas tanks. Paradoxically, the recovered thermal energy recovered from the AFC decreases, because a large PV production produces a limitation of the AFC operative hours, and this aspect prevails on the thermal power growth achievable with the AFC size, as shown in Fig. 11, with evident deviances, especially in winter. Leaving the hydrogen storage at 5 m<sup>3</sup>, the available volume at the end of the year increases with the PV size, producing eventual issues in longterm tank management.



Fig. 10 – AFC production and indoor air temperature assuming PV=12.6 kW  $_{p},$  V=5 m³ and a smaller AFC (undersized by 25%)



Fig. 11 – Recovered thermal energy with PV size, assuming V=5  $m^{a}$  and AFC power of 1865 W

The effects related to the PV size on the accumulated hydrogen are depicted in Fig. 12. It can be appreciated that deviances are significant in winter, whereas the volumes tend to stabilize in summer for the intervention of the electrolyzer control (SoC >0.95). It is confirmed that with the PV peak power growth, the hydrogen quantity to manage at the end of the year increases. Differences are significant in March: the hydrogen content in the tank increased by 36 Nm<sup>3</sup>, which becomes over 57 Nm<sup>3</sup> passing to 21.6 kW<sub>p</sub>. By setting the installed PV peak power and by varying the hydrogen storage volume (considering 6 and 7 m<sup>3</sup>) no evident deviances were detected and, consequently, not reported. The monthly percentage of the energy made available from the AFC as a function of the caption surface, setting V=5 m<sup>3</sup>, is shown in Fig. 13. As expected, the AFC contribution decreases with the PV peak power growth and in summer due to the large availability of solar irradiance. Therefore, to emphasize the micro-cogeneration features of the proposed system, the essential PV surface is recommended.



Fig. 12 – Trends of the stored hydrogen in the pressurized tank with V= 5 m<sup>3</sup> varying the PV caption surface



Fig. 13 – Percentage of the energy provided by the AFC with V= 5  $m^{3}$  and varying the PV caption surface

# 3.1 Economic Evaluations

The studied system was compared with a plant configuration in which electric surpluses are managed by batteries. A capacity of 30 kWh, resulting from the average daily electric demand required in the critical month (January), was considered. The comparison was made in terms of Net Present Value (NPV) and Discounted Payback (DP). The considered costs are 1,500 €/kWp for PV panels and 600 €/kWh for batteries; regarding the hydrogen section: 10,125 € for AFC and auxiliaries, 15,000 € for electrolyzer and auxiliaries, 35,000 € for compressed hydrogen and oxygen storage in gas cylinders (Elassawi et al., 2023; Hassan et al., 2023). The AFC requires maintenance costs of 500 €/year, whereas the PV generator (periodic cleaning) of 360 €/year. The saved costs concern the avoided purchased electric energy, considering an item of 0,25 €/kWh, and the avoided gas consumption for DHW production (at 1.2 €/Sm<sup>3</sup>) for the solution with batteries (being a not a cogeneration plant). Energy inflation and discount rates respectively of 8% and 4.5% were considered in a lifespan of 25 years. Precautionary, the AFC and electrolyzer replacement at the 15th year was assumed. The initial cost of € 81,725 is recovered in 14 years with an NPV of € 45,000, which becomes € 86,182 hypothesizing no replacements. The alternative solution costs € 36,000 with results listed in Tab. 2 considering different periods for the battery stock replacement. A longer PB than the proposed solution can be appreciated when batteries are replaced every 5 years. Similar NPVs are obtained if battery stock is replaced periodically every 6-7 years. The proposed system has an NPV better than the scenario with battery stock replaced every 10 years assuming an AFC duration of 15 years.

Table 2 – NPV and DP obtained for the alternative solution assuming different periods of the battery stock replacement

Battery replacement	NO replacement	After 5 years	After 10 years	After 15 years
NPV $(\epsilon)$	110,443	-41,112	50,632	80,938
DP (year)	8	>25	8	8

### 4. Discussion

TRNSYS simulations have allowed for identifying the main parameters affecting the design of a microcogeneration system conceived to ensure the energy self-sustainability of an isolated off-grid building based on a fuel cell supplied by hydrogen produced by electrolysis. Summarizing:

- AFC size must be calibrated considering the maximum absorption of the heat pump during winter nights when PV power is not available (the worst air-water heat pump operative conditions). Indeed, if AFC is undersized, discomfort risks occur because the heat pump cannot work due to the unavailability of the required electric power.

- PV peak power must be evaluated carefully because it determines the real share of electric surplus available for hydrogen production. If it is too low, the risk is to attain a building not energetically selfsustainable, but if it is too high the hydrogen overproduction makes its management difficult for a long period due to the achievement of saturated storage systems, both chemical and thermal.

- An increase in the PV size (to compensate for efficiency decrement due to panel ageing), must be combined with simultaneous gas-pressurized tank growth (modular system). But this reduces the AFC operation limiting the recovery of the thermal energy for producing DHW, and penalizing the performance of the micro-cogeneration system.

- Hydrogen acts as an inter-seasonal storage exploiting the summer overproduction.

### 5. Conclusion

For the reference building TRNSYS simulations have shown that:

- the optimized plant configuration requires 14.4 kW<sub>P</sub> of PV, a hydrogen gas tank of 5 m<sup>3</sup> and an AFC providing 1865 W at 220 V, satisfying simultaneously electric and thermal loads.
- An annual hydrogen balance of about 7 Nm<sup>3</sup> in the pressurized tank avoids the achievement of saturated storage systems in the long term.
- recovered heat allows a saving of almost 80% in the DHW demand;
- the considered micro-cogeneration system is profitable showing similar discounted payback to that achievable with electric storage made of

batteries replaced every 5 years, even assuming the AFC and electrolyzer change at the 15<sup>th</sup> year. A similar NPV is obtained assuming battery replacement every 6-7- years.

The reference building requires elevated electric loads in winter when PV production is low, confirming the system's goodness in difficult conditions. Results can be extended in localities with more favourable winter conditions by calibrating the sizes of PV and storage volume. In the future, analysis involving also summer cooling will be conducted.

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# Assessment of the Simultaneity Factor Between PV Production and Electric Demand in a Real Scholar Canteen Belonging to a REC Through TRNSYS Simulations

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### Abstract

Solutions conceived to mitigate the mismatching between electricity production and demand in buildings are decisive in maximizing the benefits of Renewable Energy Communities. In this context, Building Energy Simulation (BES) tools can be used for accurately assessing energy flows considering variable conditions, especially if equipped with electric generation systems for heating and cooling. In this paper, a PV generator for a scholastic canteen belonging to a municipal REC, in which the main electric load is represented by a VRF heat pump, is evaluated by TRNSYS simulation to optimize the self-consumption share. A monitoring campaign targeted at the collection of real electrical profiles and climatic data was carried out to validate the building-plant model. A simultaneity factor (SF) between electric demand and production was introduced to evaluate actual self-consumption and electric surplus to share within the REC. Results showed the decisive role of Demand Side Management, whereas monocrystalline cells perform better than other technologies avoiding installing the maximum installable PV peak power. For the considered case study, despite the building being occupied occasionally, an SF of about 75% can be achieved.

### 1. Introduction

The reduction of CO<sub>2</sub> emissions and the contrast to climate change increasingly involve the existing building stock (UN Environmental Program, 2024). In this sector, to support the transition from fossil fuels to renewable sources, an appealing concept is represented by the Renewable Energy Community

(REC), regulaed by the European law "Renewable Energy Directive Recast 2018/2001". The main goal of the REC implementation is the provision of environmental, economic and social community benefits by sharing produced powers in local areas. Indeed, RECs allow anyone to cooperate in the management of energy fluxes, while preserving subjective rights and duties, considering the proximity between production and consumption sites. Considering the multitude of difficult objectives, RECs are increasingly under investigation in the relevant literature. For instance, (Heuninckx et al., 2022) identified the motivations for joining a REC evaluating different stakeholders, as well as the elements to consider in the design phase involving social, economic, technical and environmental aspects. The opportunity to extend the "zero-energy building" concept at the neighborhood scale was investigated in (Marique et al., 2014) taking into account the impact of urban form on energy needs, on-site production and the energy transportation system. The choice of how a REC must be planned mainly depends on the size and building typology and the local climate, which is also decisive in assessing the renewable production. In this context, among the different available technologies to generate electric power, photovoltaics are even more contemplated in light of the favourable installation costs (Franzoi et al., 2021), as confirmed by case studies of RECs carried out in Belgium, Spain, the Netherlands, and Greece (Lode et al., 2022). On the other hand, technical challenges such as energy cost reduction and grid stability are significant parameters to take into account for the

correct system design. Grid stability can be enhanced by involving buildings with a high share of self-consumed power production, especially when characterized by particular occupation patterns. "Moreover, the share of self-consumed energy also impacts the profitability of RECs, as financial incentives are determined based on this rate. In light of this, the study is targeted to properly size a PV generator foreseen in a school canteen located in the mountain town of Soveria Mannelli (South Italy, 39°05'°N, 16°22'E) to maximize the self-consumed electric power considering different parameters such as the generator size, the cell's technology and the Demand Side Management (DSM) for matching electric production and consumption (Arcuri et al., 2018). These profiles were determined through a parametric study carried out in the TRNSYS environment to quantify the self-consumed rate using a simultaneity factor between demand and production (VV.AA., 2018). The building-plant model was validated by monitoring electric consumption and using real climatic data for a period of one month, calculating the Root Mean Square Error (RMSE) between simulated and acquired values. The use of real climatic data allowed for determining the building's thermal energy requirements and the electric consumption being the main electric load represented by a VRF heat pump for heating applications. PV size was managed by varying the array number and considering the available roof surface for installation. Regarding the PV technology, three commercial products with diverse power temperature coefficients were simulated to consider the thermal drift effect on the power output (Bevilacqua et al., 2020). The electric consumption profiles were varied by shifting the operation hours of the main electric loads. The case study building was chosen for the particular occupation pattern, being persons concentrated mainly for a few hours of the day and only for three days per week, making the meeting between production and consumption difficult. Considering that the location is characterized by a severe winter climate with particular socio-economic features, since the site is classified as a disadvantaged and isolated area, the REC implementation represents a pragmatic solution to promote social and economic development, assuming renewable technologies are properly designed to

favour correct management of the energy fluxes inside the community, confirming BES suitable tools to achieve this goal.

# 2. Methodology

### 2.1 Building-Plant Description

The interaction between the building fabric, the heating plant components and the PV generators was simulated by TRNSYS 18 using climatic data of the considered site. The single-story building, whose intended use is as a school canteen, was simulated as a single thermal zone geometrically implemented by the TRNSYS3d plug-in (Fig. 1a). It is characterized by a regular rectangular shape made of hollowed external walls equipped with 5 cm of air-gap (see Table 1), not insulated because it was built before the promulgation of national laws concerning the energy consumption limitation. The opaque envelope is completed by a ground floor (Table 2) and an unheated attic separated from the heated environment by an inter-floor concrete deck. The roof (Table 3) is made of a double pitch of concrete and tiles, with approximately 15 degrees of slope, and is oriented North-East (for 200 m<sup>2</sup>) and South-West (150 m<sup>2</sup>), with the latter considered for the PV installation. The gross floor area is about 330 m<sup>2</sup> with an inter-floor height of 3.4 m. Windows are aluminium framed mounting clear double panes and equipped with PVC screens. The envelope is not shaded by fixed external obstructions. The thermal energy requirements are quite significant because the building is crumbling (see Fig. 1b). Since heating is provided by a VRF air-air heat pump also electric consumption is also negatively affected.

The heat pump has a rated heating capacity of 37.5 kW with a maximum electric absorption of 12.5 kW. The generator produces an air-flow rate of 12,000 m<sup>3</sup>/h distributed by 5 emitters uniformly distanced inside the canteen. This device was simulated by the Type 954 implemented in the TESS library. As the Scroll compressor is equipped with an inverter, simulations considered the COP variation only with source temperatures (outdoor and supply air). These data are provided by attaching an external file with the proper format to obtain in the output the real share of electric absorption under actual

operating conditions. This item represents the greatest load in terms of electric consumption, as described in the following. Since the indoor environment is not equipped with a thermostat for air temperature control, the heat pump is manually activated from 09:00 to 13:00 on Monday, Wednesday and Thursday.



Fig. 1 - Modelled and real NE prospect of the analyzed building

Table 1 – Thickness (s), Thermal resistance (R), density ( $\rho)$  and specific heat of the vertical wall layers (U-value=0.956 W/(m²K))

	s [mm]	R [m2 K/W]	Q [kg/m3]	c [kJ/kg K]
Plaster	15	0.017	1800	0.84
Hollow brick	250	0.513	1400	1
Air gap	50	0.179	1.2	1
Brick	120	0.150	1800	1
Plaster	15	0.017	1800	0.84

Table 2 – Thickness (s), Thermal resistance (R), density  $(\rho)$  and specific heat of the ground floor layers (U-value=1.727 W/(m²K))

	s [mm]	R [m² K/W]	Q [kg/m³]	c [kJ/kg K]
Ceramic Tiles	10	0.01	2300	0.84
Concrete screed	60	0.103	900	1
Concrete	200	0.121	2200	1
Gravel	150	0.125	1700	0.8
Ceramic Tiles	10	0.01	2300	0.84

Table 3 – Thickness (s), Thermal resistance (R), density ( $\rho)$  and specific heat of the roof layers (U-value=1.105 W/(m²K))

	s [mm]	R [m² K/W]	Q [kg/m³]	c [kJ/kg K]
Plaster	10	0.17	1800	0.84
Slab lightening blocks	180	0.3	1800	1
Concrete screed	60	0.103	900	1
Wooden laths	100	0.18	1800	1
Roof tiles	10	0.012	1800	0.84

# 2.2 Simultaneity Factor

The design of the renewable system represented by a PV generator on the grid-connected building is based on the maximization of the simultaneity factor between electric production and consumption. This parameter can be evaluated through Fig. 2, which depicts a typical situation comparing profiles concerning an electric consumption pattern (black line) and PV production (red line) on a clear day. It can be appreciated that, during the PV operation, an electric rate is directly used to satisfy the building's electrical loads (B), and another significant part (C), instead, is a surplus to share within the REC. In a monitoring campaign long "N" with data acquired every "i" timestep, the simultaneity factor can be determined by the following relation (Luthander et al., 2015):

$$SF = \frac{\sum_{i=1}^{N} B}{\sum_{i=1}^{N} (A+B)}$$
(1)



Fig. 2 - Random profiles for the simultaneity factor calculation

The TRNSYS simulations allowed us to carry out a parametric study in which the size, the type of employed PV technology and DMS were changed to identify the configuration that maximizes the result of Eq. 1, reducing the issues related to electric surpluses management. In the parametric study, three different PV technologies were considered: traditional panels equipped with mono and polycrystalline silicon cells, and another case involving tandem cells with amorphous and micro-crystalline silicon, with the main electrical features listed in Table 4, varying the installed peak powers. The favourable installation of the PV generator involves the roof pitch oriented South-West, for which an available surface of 120 m<sup>2</sup> was considered to take into account technical constraints. So, 54 mono-crystalline modules (2.19 m<sup>2</sup> each) for a maximum peak power of 24.3 kW, 60 polycrystalline modules (1.98 m<sup>2</sup> each) for a maximum peak power of 20.4 kW and 84 modules with amorphous cells (1.42 m<sup>2</sup> each) for a maximum peak power of 11.34 kW, can be potentially installed. Simulations were conducted for a year with a timestep of 1 hour by setting the present activation of the electric loads.

Table 4 – Main electric features of the considered PV panels in the parametric study

	Ppk	Isc	%Ppk	<b>*</b> REF
	[W]	[A]	[%/°C]	[-]
Monocrystalline	450	11.42	-0.35	0.206
Polycrystalline	340	9.35	-0.37	0.172
⊗-Si/⊗c-Si	135	3.41	-0.24	0.095

In order to state the TRNSYS results' reliability, a validation procedure based on the calculation of statistical indices such as NMBE and CV-RMSE following the ASHRAE Guideline 14-2014, was carried out. These indices were calculated by Eq. 2 and Eq. 3 comparing measured (y) and simulated ( $\hat{y}$ ) data concerning the electricity consumption for a period of one month.

$$CV(RMSE) = \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n - p}}$$
(2)

$$NMBE = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)}{(n-p) \cdot \bar{y}}$$
(3)

### 2.3 Climatic Data

The school canteen is located in Soveria Mannelli (CZ), a mountain site in South Italy characterized by 2374 HDD (Heating Degree Day). In Fig. 3, the data related to the real outdoor air humidity and temperature in the period 20/03/2024 - 20/04/2024, collected by a weather station located in the proximity of the building and employed for the building-plant model validation, are displayed. The considered days still belong to the heating period, and the huge climatic variability can be appreciated, in light of outdoor air temperatures that range between a minimum of 2.6 °C and a maximum of 27.2 °C, with an average value of 12.3 °C. In addition, the average value concerning the relative humidity is about 67%, therefore weather conditions describe a building-plant system adequately solicited from a

thermal viewpoint and, consequently, this period appears suitable for the model validation. In Fig. 4, the experimental data related to horizontal solar radiation are depicted. These refer to the weather station located at the University of Calabria (with similar latitude) distinguishing between beam and diffuse components. In the TRNSYS environment, the projection on the different tilted surfaces (including the pitched roofs) was carried out by using the Reindl model. The fictitious sky temperatures, required for the calculation of the infrared exchanges of the external envelope surfaces, are not experimentally available. Therefore, in simulations, the Aubinet correlation is implemented in a specific TRNSYS Type that uses experimental values of outdoor air temperature, cloudiness factor and vapour pressure of external air. The latter was calculated starting from the monitored relative humidity and the saturation pressure corresponding to the outdoor air temperature. The glazed surfaces were selected from the software library by choosing a window with a thermal transmittance (U-value) of 2.8 W/(m<sup>2</sup>K) and a normal solar factor of  $g_1=0.70$ , values both close to the data of the real components. Window screens were considered never activated during the building occupation to favour daylight. Thermal losses affecting the ground floor were considered by setting the external surface with a boundary condition represented by the soil temperature. This parameter was varied to tune the buildingplant model, nevertheless, the initial value was imposed equal to the site's yearly average air temperature (11.2 °C). Another parameter varied to calibrate the model is represented by the natural ventilation, which was set to 0.5 ach per hour as the initial value.

### 2.4 Experimental Set-Up

Different probes have been employed to monitor the parameters used for validation. A triple-phase Wi-Fi energy meter was employed to measure and collect in-cloud data concerning the building's electric consumption. The accuracy is 1% with a maximum measurement of 120 A per channel. The probe was installed near the school energy meter.

Temperature and humidity were detected by a thermo-hygrometer equipped with a Pt100 with an

accuracy of  $\pm 0.1$  °C and operative range - 30 °C+100 °C for the temperature, and  $\pm 0.1\%$  with an operative range of 0-100 % RH for the relative humidity.



Fig. 3 – Experimental data of outdoor air temperature and humidity for the validation of the building-plant system model



Fig. 4 – Experimental data of beam and diffuse solar irradiance on the horizontal plane used for the model validation

The global solar irradiance on the module plane is measured with a Secondary Standard Eppley Laboratory using pyranometers arranged with a spectral range of 295–2800 nm, sensitivity of 8  $\mu$ V/Wm<sup>-2</sup>, a 95% response time of 5 s, a non-stability and nonlinearity of 0.5%, and uncertainty at an hourly average of 2%. The beam solar irradiance is measured with a CH1 pyrheliometer with a sensitivity of 10.45  $\mu$ V/(Wm<sup>-2</sup>), a 95% response time lower than 5 s, and a non-linearity of 0.5%.

# 3. Results

# 3.1 Model Validation

Fig. 5 shows the trends of the monitored electric consumption in the period 20/03/2024 - 20/04/2024.

It can be appreciated that:

- An abrupt increase of electric consumption can be detected with the electric heat pump operation at the first switch-on in the operative days, due to the large absorbed starting power.
- The absorbed power difficulty stabilizes;
- In the period starting from Friday 05/04 and for the whole successive weekend, the heat pump was left continuously functioning because the municipality used the building for a local celebration, appreciating the power modulation due to the part-load operating mode.
- Every day, a base load of about 2300 W of absorbed electric power was detected throughout the monitored period, due to a programmed activation of a hydraulic pump for 5 hours per day (from 6:00 a.m. to 12:00 p.m.) used to supply an autoclave system connected to all the neighbouring buildings. This electric consumption is registered exclusively on the school canteen energy meter. The base electric load, represented only by artificial lighting made of LED, was neglected during simulations because very low.
- The validation was carried out in the period 05/04/2024-09/04/2024, employing climatic data (TMY) of the nearest city (Lamezia Terme), to achieve more robust results because the heat pump operated in continuous mode. After a series of several attempts, natural ventilation to 1.4 ach per hour, the temperature of the soil of 8.5 °C and a rated electric absorption of the heat pump of 10.4 kW, allowed for detecting an appreciable overlapping between the trends of simulated and experimental electric consumption (Fig. 6). The reasons for the identified setting can be explained by the high envelope air permeability, the presence of groundwater under the building and the heat pump ageing that could provide performances different from those declared by the manufacturer.

Indeed, the heat pump was simulated with a rated COP of 3.62, lower than the declared 4.61. In the past, the heat pump was affected also by technical issues such as a loss of low-

boiling fluid inside the internal units.

- The calibrated TRNSYS model simulated by a timestep of 1 hour offers an NMBE and CV-RMSE of -2.81% and 27%, respectively, in agreement with the thresholds of 10% for NMBE and 30% for CV-RMSE indicated by the ASHRAE for the calibration of a whole building simulation assuming an hourly data for one month. This result confirms that the building-plant system was properly tuned to attain reliable results even when different plant configurations are investigated in terms of electric production and consumption.





Fig. 6 – Comparison between measured and simulated electric consumptions in the period 05/04/24-09/04/24

### 3.2 Parametric Study

Results of the parametric study are summarized in Table 5: it is worth noting that SF increases with the installed peak power and, as expected, the monocrystalline technology is the best choice, assuring an SF of about 70% when 24.3 kW<sub>p</sub> (18 panels in series on 3 arrays) are installed. The polycrystalline cells are negatively affected by the lower allowable collection surface (in turn, due to the smaller electric conversion efficiency) and by the highest power temperature coefficient. The amorphous technology represents the worst choice and it appears not to be indicated to self-consume the power output. Indeed, an SF of only 14.8% was determined with the maximum installable peak power of 11.34 kW. It can be appreciated that 20 polycrystalline panels on two arrays (13.6 kW<sub>p</sub>) produce remarkable SF (57.6%) despite the installed peak power not being so different from the maximum collection surface installable with amorphous technology.

Table 5 – Simultaneity factor as a function of  $\ {\rm PV}$  peak power and  $\ {\rm PV}$  technology

	Ppk	SF
	[kW]	[%]
	24.30	69.9%
Monocrystalline	16.20	62.4%
	8.10	47.9%
	20.40	65.5%
Polycrystalline	13.60	57.6%
	6.80	42.5%
	11.34	14.8%
α-Si/μc-Si	7.56	8.8%
	3.78	3.0%

Fig. 7 highlights how the SF is distributed during the year for the best configuration of 24.3 kW made of monocrystalline cells. It can be appreciated that the activation of the heating plant in October paradoxically produces an abrupt drop of SF, more pronounced in November and December, when a better match between production and consumption is expected. This means that the punctual PV production does not meet the electric demands, also due to the less availability of solar irradiance. Conversely, a better situation is detected in summer as the building is not occupied by students with a corresponding decrease in electric demand and a greater probability of meeting the PV power output. The annual results presented in Table 5 benefit from the high SF value detected during the summer when the building is unoccupied. However, significant issues related to the management of electrical surplus arise in winter.



Fig. 7 – Monthly SF values with 24.3 kW of monocrystalline panels assuming the current management of electric profiles

In order to analyze the role of DSM, another simulation campaign was carried out with other functioning schedules for the heat pump and the hydraulic pump. This time, SF was determined assuming the heat pump operation from 11:00 to 15:00 (relevant to the building occupation pattern) and the hydraulic pump from 9:00 to 15:00 to synchronize solar radiation availability with electric loads. Fig. 8 shows that the new DSM produces evident improvements in winter with percentage gains ranging from 3% in March and 15% in November. In summer results remain unchanged due to the heat pump's stop. At an annual level, the forward timeshift of the electric loads produces an SF increase of more than 5 percentage points, passing from 69.9% to 75.2%. In Fig. 9 the SF monthly results are shown considering the case in which the varied DSM is combined with an accurate control of the indoor air temperature by equipping the simulated thermal zone of a thermostat operating in the band 19-21 °C. The results worsened because the control produces a limitation of the heat pump operative hours with a corresponding reduction of electric consumption. Looking at Eq. 1, this seems to produce beneficial effects due to the limitation of the rate A, although this determines also a penalization of B because the power produced cannot be self-consumed, and this aspect prevails on the first. If the thermostat assures an enhancement of the indoor comfort conditions, a simultaneous increase in PV power surplus requires to be managed within the REC. An SF enhancement is anyway detected when compared with the results depicted in Fig. 7 determining a yearly SF of 72.5%.



Fig. 8 – Monthly and yearly SF values with 24.3 kW of monocrystalline panels with different DSM of electric loads



Fig. 9 – Monthly SF values with 24.3 kW of monocrystalline panels assuming a different DSM for the main electric loads

Finally, Fig. 10 depicts the SF trend with the peak power assuming mono-crystallin silicon cells with the improved DSM. It can be appreciated as a linear increment until an installed peak power of about 20 kW, successively SF increases slightly. As a consequence, the installation of greater PV powers is not recommended in front of a slight SF increase.



Fig. 10 – SF trend with the installed PV peak power assuming an improved  $\mathsf{DSM}$ 

# 4. Conclusion

A simultaneity factor between electric PV production and consumption was introduced by referring to a particular case study represented by a municipal building employed for a few hours and only 3 days per week. The simultaneity factor was calculated by varying the PV size, the PV technology and the modality of management of internal electric loads, represented prevalently by a VRF heat pump for heating and a hydraulic pump for water storage, through TRNSYS simulations. The reliability of results was achieved by a validation procedure that allowed for an NMBE and CV-RMSE of -2.8% and 27% respectively, compliant with the recommended values by ASHRAE, calculated through the comparison of simulated and experimental data collected for one month long. Results highlight how the amorphous technology is not suitable for buildings belonging to RECs due to the limited contribution given in terms of self-consumed power. Conversely, high performances can be achieved with mono-crystalline cells producing SF of about 75% when evaluated on an annual basis. This percentage is influenced positively by the limitation of the summer electric consumption due to heat pump inoperability. Despite the maximum installable peak power on roof surfaces with suitable irradiance conditions being 24.3 kW, it is not recommended to install over 20 kW because the SF augment is negligible. A significant role is given by the Demand Side

Management (DSM): results showed that by shifting the device functioning toward the central hours of the day, SF increases appreciably due to better synchronism with the solar irradiance availability. The limitation of the heat pump functioning attained by a zone thermostat does not give additional improvements since the prevalent role of PV power reduction in phase with the required electric load. This study confirms that BES software can be employed profitably to assess the optimized configuration of a building-plant system involved in a local REC. This preliminary study focuses on maximizing the benefits related to identifying the optimal productiondemand configuration for electricity. In subsequent studies, the results obtained will be utilized to extend the analysis to an energy community composed of multiple public and private users. This will assess whether the observations made for a single building serve as a valid methodology for the optimization of an energy community.

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# Exploitation of Energy Performance Certificate Database in Urban Energy Modelling

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#### Abstract

Cities are crucial for the energy transition, as recognized by the European Union in policies such as the Fit for 55 package and the Climate-Neutral and Smart Cities mission. The former calls for the revision of several directives, among which the Energy Performance of Buildings Directive (EPBD) plays a major role, targeting the phasing out of fossil fuels and the achievement of minimum performance objectives for all existing buildings. It reinforced the role of the Energy Performance Certificate (EPC) as a shared evaluation schema. However, considering the 30-50% coverage of EPCs in the European building stock, new methodologies and models are required to assess the building stock extensively. Considering the valuable data contained in EPCs, these can be used to train Urban Building Energy Models which leverage the potential of Earth Observation. This study proposes a new method to segment the building stock according to thermographic pictures, resorting to EPC information for the energy class distribution analysis. Thermographic values are used to assess thermal losses and replicate the energy class distribution accordingly. Different EPC data are assessed in order to understand the best configuration both in terms of share between training and validation data and of the need for potential pre-filtering. The method appears to be reliable - with 66% of buildings classified correctly on average - yet simple, thus being attractive for policymakers to define retrofitting campaigns able to meet European requirements. With simplicity and flexibility being the main strengths of the method, it is also possible to consider additional inputs and make the model more complex to improve the accuracy.

# 1. Introduction

The energy transition challenge is to be addressed at first in cities, which have the potential to effectively cut two-thirds of their energy-related emissions (IEA, 2016). Moreover, initiatives such as the EU Climate-Neutral and Smart Cities mission (European Commission, 2023) – providing funding to local administrations for the implementation of measures for climate neutrality – fostered the debate on the most effective ways to reduce impacts and mitigate the effects of climate change.

The energy performance of the building stock, together with the possibility to cover the total demand as much as possible from Renewable Energy Sources, has been considered in international policies, issued by the European bodies, thus favouring an increase in the yearly deep renovation rate of the building sector from the current 0.2% up to the target of 3%.

The Energy Performance of Buildings Directive (EPBD) recast (Council of the European Union, 2023b) – framed into the Fit for 55 package (Council of the European Union, 2023a), which aims to align the EU with its decarbonisation goals – set a minimum performance objective in the upgrade of all buildings falling into the energy performance class G and defined a path for the complete decarbonisation of the building stock. Both processes are based on the Energy Performance Certificate (EPC) – required before renting or selling and after deep renovation processes – in which an auditor compares the real performance to the ones of a reference building and provides a comprehensive evaluation. The relevance of energy performance is pointed out

also by the recast of the Energy Efficiency Directive (European Parliament and Council, 2023), which introduced the "energy efficiency first" principle, requiring all policies – both energy-centred and not – to consider their implications on this topic.

In this framework it is necessary to elaborate tools able to support energy policy by assessing the building stock on a wide scale, starting from the identification of the worst-performing buildings. Indeed, EPCs cover only a small portion of the building stock e.g., in Italy 10% (Pagliaro et al., 2021), making it necessary to model the remaining share through energy models and algorithms (Johari et al., 2020). Still, EPCs can be used to gather the inputs to define archetypes in Urban Building Energy Models, which consider both geometrical and energy-related parameters to estimate energy consumptions, thus going beyond the problem of unbundled data gathering - costly in terms of time and money (Deng et al., 2023). Data homogenisation - referring the information to entire buildings - can be performed through Geographic Information Systems (GISs), powerful tools in energy modelling thanks to the possibility to consider different layers and spatial resolutions (Yu et al., 2021).

This paper – starting from the potential to use EPCs in training datasets for Urban Energy Models recognised in existing studies (Conticelli et al., 2024; Johari et al., 2023) – aims to leverage infrared thermography to estimate energy consumptions of the *Barriera di Milano* neighbourhood in Turin, Italy. A review by Martin et al. (2022) has highlighted the potential of thermography in quantifying thermal losses, one of the principal indicators for energy classification. Therefore, from the assessment of the surface temperature difference between buildings – considering a constant internal temperature as set by law – it is possible to classify buildings according to their thermal signature.

# 2. Simulation

This research aims to improve a previously established method for buildings' energy classification based on the combination of EPCs and infrared thermography (Anselmo et al., 2023). The process – whose workflow is pictured in Fig 1 – can be divided into two main components: 1) data gathering and pre-processing of both inputs – the EPC dataset and the thermographic picture; 2) attribution of a class itself. This second step, in which the class distribution observed in the EPCs is replicated based on thermal losses, is better detailed in Section 2.3.1. A sample of the EPCs is not used for the training, being kept for validation.



Fig. 1 – Workflow of the proposed methodology

While a first element to consider for the refinement of the drafted methodology is the segmentation of the building stock, this paper focuses on the optimal selection of training data from the EPCs database, highlighted in green in Fig. 1. It is believed that by guaranteeing the trustworthiness of the training dataset, final results can be highly improved.

### 2.1 Data Preparation

EPCs are gathered from the open portal of the Piedmont Region (Osservatorio ITC della Regione Piemonte, 2024) divided by section and filtered based on cadastral sheets in order to keep only those on the Area of Interest (AoI). Based on the available information, selection and aggregation criteria are defined, considering whether the same parameter is repeated in different sections – and therefore in different tables. All data – processed through DB Browser for SQLite – are merged first according to a univocal ID to return a single entry for each EPC and then by considering the address to have one value for each volumetric unit, the minimum unit of geospatial data derived from the Municipal Technical Map.

Also thermal values derived from Infrared Thermography are referred to volumetric units. The QGIS zonal statistics tool was run to obtain the median temperature value – chosen instead of the average to mitigate the relevance of extreme values – from a thermal orthophoto produced with pictures acquired through a FLIR A8581 MWIR HD camera.

# 2.2 Correlation Analysis

In order to understand the most critical indicators to be considered when estimating the energy performance from EPCs, it is necessary to first look for correlations between the energy class and specific characteristics of the buildings.

According to Conticelli et al. (2024), the period of construction is the principal information among building parameters, because it mirrors the evolution of the technical and normative standards in the building industry. Therefore, this analysis started from the year of construction. It was also decided to consider the year of the last renovation in order to check whether refurbishments correspond to significant increases in energy performance by making the building compliant with legislation.

Finally, the potential correlation with the Surfaceto-Volume (SV) ratio is explored, so as to understand whether there is a building typology whose consumptions are generally lower.

# 2.3 Energy Classification

#### 2.3.1 Class attribution

This thermography-based methodology applies the class distribution observed in the EPCs dataset to the volumetric units based on roof temperature values. By assuming a constant internal temperature – defined by law to be 20 °C for residential buildings – the temperature of the envelope returns the thermal losses. Therefore, by ordering volumetric units according to the temperature value, it can be assumed that the order goes from the least to the most performing building.

The class distribution can be observed for the whole EPC database or filtering the entries according to specific fields. Therefore, different samples are extracted. First, the use of the building will be considered: as the premises are based on residential buildings, it can be assumed that the selection of residential buildings only would refine the results. The other two elements to base the selection on are the motivation for the EPC issue and the scale of the analysis. EPCs are released both before selling or renting a building or building unit and after a deep renovation; it can be assumed that the EPCs released after refurbishing are more reliable, based on technical sheets of newly-installed technology – as the thermal transmittance of fixtures – while the obsolescence of existing systems in units to be rented or sold may cause data gaps. As for the scale of analysis, it is relevant to note that this method uses the volumetric unit as the minimum unit of analysis. What needs to be explored is the difference between considering a single EPC issued for the whole building or multiple EPCs for single building units.

In all cases, how the classification changes when increasing the share of buildings used for training, keeping the remaining for validation will be assessed. In particular, combinations of 20% for training and 80% for validation, 50/50% and 80/20% will be considered. As a result, a total of 15 simulations will be carried out:

- Three without EPC filtering.
- Three based on EPCs covering whole buildings only.
- Three extracting only the EPCs issued for residential units or buildings.
- Three for EPCs issued after deep renovations.
- Three for EPCs issued before renting or selling the unit.

### 2.3.2 Validation

As previously mentioned, pre-defined shares of EPCs will be used when training the estimation model, keeping the remaining for validation, carried out by comparing correct and incorrect class attributions. True positives and false positives will be considered to compute the Receiver Operating Curve (ROC), which plots on the X axis the share of misallocations and on the Y axis the share of correct classifications. In this research, all volumetric units classified within a ±1 deviation from the exact class are considered as True Positives. Variations based on alternative filters and sampling on the full EPC dataset are assessed.

# 3. Discussion and Result Analysis

### 3.1 Data Preparation

The four tables concerning the four EPC sections required to gather the necessary information were processed through SQL code in DB Browser for SQLite and aggregated according to the address in order to return one value for each civic number, to be attached to volumetric units. As a result, 346 out of 688 volumetric units in the AoI (50%) were characterized with EPC data.

On the other hand, the median roof temperature – crucial to define the performance of the building envelope – was computed for each volumetric unit, with values ranging from -1.09 °C to 15.94 °C.

# 3.2 Correlation Analysis

The first analysis considered the potential correlations between specific information considered into EPCs, starting with the year of construction. However, a clarification is needed: out of 346 buildings for which the correlation is assessed, 266 (77.1%) are in the two least performing classes; it is not surprising to observe a widespread presence of these two classes in all the observed categories.

Although there is not a direct relationship between the year of construction and the energy performance class, in Fig. 2 it can be observed that the most recent buildings are included in the most performing classes, thus remarking the relevance of recent energy policies, especially from 1990s. A similar trend could be observed also on the opposite side of the graph: with the exception of class D, it can be noticed that by increasing the energy class, the oldest building of every class has been realised progressively later. On the other hand, it is not possible to observe any correlation between the year of the last renovation - reported in 79 cases (23%) - and the energy performance. Therefore, by looking at the wide presence of buildings refurbished after 2010 in classes F and G, it can be assumed that most renovations are not related to energy performance.



Fig. 2 – Correlation between year of construction and year of renovation and the energy performance class

A similar reasoning can derive from the observation of the relationship between the energy classification and the SV ratio, with a homogeneous distribution of the values. It is only possible to mention a slight tendency towards a worsening of the class when increasing the SV ratio – standing for less compact building typologies.

### 3.3 Energy Classification

### 3.3.1 Class distribution observation

Together with the roof temperature, the class distribution which can be observed in the EPC dataset is the crucial input. In this study, this component is varied by filtering the EPCs according to five criteria and further subdividing with different shares between the training and validation sets. From this, it results that different class distributions are observable in the AoI, plotted in Fig. 3.



Fig. 3 - Class distribution according to different filtering

The prevalence of the two least performing classes – mentioned above – can be widely observed, with most classifications including more than 50% of the values in these two. This is valid especially when no filter is applied and for residential buildings, since more than 90% of buildings belong to classes E to G. On the other hand, it can be observed that by considering only renovated buildings there is a wider incidence of the higher classes – especially A – despite the lack of correlation observed in Section 3.2. A final element to be highlighted is the scarce presence of class B buildings: in the full database, only seven volumetric units – approximately half of the ones falling in classes A and C – are included in this class.

### 3.3.2 Class attribution

The class attribution is based on the roof temperature; thus all classifications are comparable in terms of the area where least performing buildings are located. This is the Western part, around Respighi Square, generally characterised by a prevalence of class G buildings. On the contrary, it can be observed that there are homogeneous urban portions, in particular in the Eastern part – around Cravero Street – where there is a stronger incidence of classes D and E. Due to the low share of buildings included in the higher classes, it is not possible to observe a clear concentration of volumetric units in classes from A to C – unless by observing the classification according to EPCs following a renovation, where there is a cluster of 11 buildings in the two most performing classes.



Fig. 4 - Energy classification based on EPCs after renovation

Moving to a comparison between the different filtering categories, it is strongly related to the observations on the distribution of the different classes. The highest performances can be observed by segmenting the building stock according to renovation EPCs – shown in Fig. 4 –, while the opposite results from the residential EPCs – plotted in Fig. 5. Nevertheless, the latter is comparable with the full dataset, with no filtering applied: most buildings are residential, so this segment significantly influences the trends of the entire district. Also EPCs deriving from renting or selling and the dataset considering whole buildings show similar values, despite the former having a slight tendency to higher classes.



Fig. 5 – Energy classification based on EPCs of residential buildings

When considering the EPCs covering the whole building, it can be observed that in two cases – out of the three training/validation combinations – a small homogenous area located between Cravero and Ancina Streets and Taranto Avenue has buildings falling in the same class, D; in the remaining case, three buildings are classified as A. This is particularly relevant for the draft of energy policies: it can be foreseen that the whole portion is to be renovated simultaneously, taking advantage of the homogeneity of the district – which simplifies the preliminary phases.

### 3.3.3 Validation

The different classifications were validated against subsets of the EPC database – as described previously – in order to check the class differences, both positive and negative.

There is a general tendency towards overestimating the energy class, especially when testing the results of the estimation based on residential EPCs. However, there are no areas in which a high number of buildings are misclassified. As for the characteristics of the misclassified buildings, there is not a direct correlation between errors and the period of construction, while most differences are observed for buildings with an SV ratio lower than 0.4 - 70% in the 20/80 combination of residential EPCs classification.

For plotting the ROC – Fig. 6, which compares true and false positives, all classifications within a  $\pm 1$ 

class difference were considered as correct (true positives). Results are satisfactory, with most classifications proving to be above the chance level - indicating the results given by a random classification (with True Positives probability equal to 50%) -, thus making the validation results trustworthy. The only classification which proved to be wrong in every configuration is the one carried out according to the EPCs issued after renting or selling, confirming the assumptions stated in the introduction about a lower reliability deriving from problems in gathering the necessary data. Further problems can be observed when considering the 20%/80% configuration of the EPCs issued for residential buildings and the 80%/20% configuration of the renovation dataset; the renovation dataset in the 20/80% configuration corresponds to the chance level. Problems in classifying according to EPCs issued after renovation show a lack of correlation observed in Section 3.2.



Fig. 6 - Receiver Operating Curves

Synthetic observations can be observed by looking at the 40 and 60 percentile and the median value of all the curves. For true positives, these correspond – respectively – to 53%, 59% and 57%, making the general results satisfactory. The best results are observable for classifications based on the EPCs issued for whole buildings – which do not require any data aggregation –, further confirming the initial assumptions. However, this result is downsized considering the lower number of volumetric units used for validation, 12 on average in the three combinations.

# 4. Conclusion

This study refined a methodology presented in a previous publication (Anselmo et al., 2023) which combines aerial thermography and data mining from Energy Performance Certificates for energy performance classification. EPCs were used to both train and validate the model, with different filters and combinations, allowing the identification of worst performing buildings.

The results proved the efficiency of the method and the incremental nature of the resulting energy performance evaluation accuracy, with an accuracy which reached 80% in some cases. Once having gathered the necessary inputs - mainly EPCs and temperature values - the methodology can be fully automated, not requiring any human resource to perform the classification: this could be appealing for Public Administrations in their work to make the building stock compliant with European Directives, in particular the EPBD (Council of the European Union, 2023b). The automation could consider also the implementation of an Artificial Intelligence algorithm, automatically correlating input data to an energy class: this would be particularly relevant when extending the AoI and therefore increasing the amount of training data.

From the scientific point of view, this work paves the way for the realisation of highly accurate UBEMs, simulating building performance on a district or urban scale by integrating remotely sensed pictures and EPC data for detailed archetyping. A detailed refinement of such methodology on building scale could eventually lead to the possibility of issuing EPCs without the need for extensive on-site surveys, estimating the U-value and the necessary geometric parameters accurately.

Nevertheless, some weaknesses emerged. First, the limited extension of the AoI, constraining the

heterogeneity of the training samples – unfavoured by the homogeneity of the district too. Second, it would be relevant to perform the classification on limited segments of the building stock, in order to have a specific characterisation based on the building age and type. Finally, further information could be added such as the case of the window-to-wall ratio, a crucial indicator when assessing thermal losses; this could be derived from both the segmentation of a 3D model and the share between sunlit and useful surfaces in the EPCs.

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# Nomenclature

### Symbols

AoI	Area of Interest			
EPBD	Energy Performance of Buildings			
	Directive			
EPC	Energy Performance Certificate			
EU	European Union			
GIS	Geographic Information System			
ROC	Receiver Operating Curve			
SV	Surface-to-Volume			
UBEM	Urban Building Energy Model			

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# TRNSYS Dynamic Simulation Model of a Typical Air-Handling Unit: Experimental Calibration and Validation Based on Field Operation Data in the South of Italy

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### Abstract

The building sector is responsible for about 36% of global final energy use and Heating, Ventilation and Air-Conditioning (HVAC) systems are responsible for about 50÷60% of the building sector's energy demand. In this paper, a detailed dynamic simulation model of a typical HVAC system including a single duct dual-fan constant air volume Air-Handling Unit (AHU) has been developed via the TRaNsient SYStems software platform (TRNSYS 18). The simulation outputs were compared with field operation data measured during 14 experiments performed with reference to a fully instrumented HVAC set-up serving the SENS i-Lab of the Department of Architecture and Industrial Design of the University of Campania Luigi Vanvitelli (Aversa, south of Italy). The comparison was carried out to validate and assess the simulation model accuracy. The results highlighted a high capability of the developed model in simulating the experimental behaviour, with maximum percentage differences between the predicted and experimental values up to -6.0%, 18.3%, -9.1%, -10.6%, -15.3% in terms of heating coil energy, cooling coil energy, humidifier electric demand, heat pump electric consumption and refrigerating system electricity request, respectively.

# 1. Introduction

#### 1.1 Background

The building sector is a major contributor to climate change, accountable for over 36% of the world's total energy consumption and roughly 37% of its

greenhouse gas emissions (Global Status Report, 2022). Heating, Ventilation and Air-Conditioning (HVAC) systems are the most used equipment for maintaining indoor comfort in buildings. The most common HVAC systems include Air-Handling Units (AHUs) that are made up of a number of sensors and parts (such as fans, coils, valves, dampers, filters, actuators, etc.). HVAC systems represent a significant source of energy consumption together with a significant environmental impact; in particular, they are responsible for about 50÷60% of the building sector's energy demand and 10÷20% of the overall energy consumption (Cao et al., 2016; Mirnaghi et al., 2020). Therefore, optimizing the design and performance of such systems can be an important solution to reduce the relative consumption and environmental impact. These challenges can be addressed from an experimental or numerical point of view; taking into account the significant time and resources that are required for field study and lab research (Granderson et al., 2020; Mitali et al., 2021), utilization of accurate simulation models for HVAC systems emerges as a promising alternative option, offering several potential advantages, such as: a) conducting sensitivity and what-if analyses in order to better understand the performance upon varying the boundary conditions, b) suggesting innovative solutions and optimization actions to enhance energy performance, greenhouse gas emissions reduction and costs savings, c) improving the control of indoor comfort, as well as d) developing innovative control logics or maintenance programs based on

data-driven automated fault detection and diagnosis methods (Rosato et al., 2022a,b). The BEST Directory of the International Building Performance Simulation Association (IBPSA)-USA website (IBPSA, 2024) lists more than 170 platforms for modelling and simulating building-integrated energy systems; among these software, TRNSYS is recognized in the scientific community as one of the best dynamic simulation tools as it takes into account the intermittent character of loads driven by occupants and the part-load features of generating systems, as well as the interaction between building loads, systems' outputs and climatic data (Sun et al., 2017; Qiu et al., 2020).

However, validation of simulation models is essential to accurately assess the predictive performance with respect to field operation (Granderson et al., 2020). Some scientific studies have faced this issue by developing simulation models of existing HVAC systems (Sun et al., 2017; Montazeri and Kargar, 2020; Kim et al., 2019; Qiu et al., 2020). Sun et al. (2017) developed a simulation model for a single duct dual-fan variable air volume (VAV) AHU installed in a research centre located in Iowa (USA) utilizing the TRSNYS software (TRNSYS, 2024). Montazeri and Kargar (2020) employed the simulation tool HVACSIM+ (HVACSIM+, 2024) to model the same HVAC system operating in USA. On a similar note, Kim et al. (2019) utilized EnergyPlus software (EnergyPlus, 2024) to create a simulation model for an HVAC system including a VAV AHU installed in a small commercial building in Knoxville (USA). Furthermore, TRNSYS has been utilized to simulate a VAV AHU unit installed in a building located in Shanghai (China) by Qiu et al. (2020).

# 1.2 Novelty, Goals and Structure

In this study, a detailed dynamic simulation model of a single duct constant air volume AHU installed at the SENS-i lab of the Department of Architecture and Industrial Design of the University of Campania Luigi Vanvitelli (south of Italy) has been developed, calibrated, and validated against field experiments performed under various boundary conditions during both summer and winter conditions. Section 2 describes the experimental set-up and tests; Section 3 details the TRNSYS simulation model, while Section 4 illustrates the results of the experimental validation of the proposed model. The main goals of this study can be summarized as follows: a) make available to stakeholders an experimentally validated digital twin of a typical HVAC system; b) evaluate the capability of TRNSYS platform in modelling a single duct constant air volume AHU; c) assess the model accuracy with respect to Italian climatic conditions covering both summer and winter seasons; d) support a widespread adoption of HVAC systems based on single duct constant air volume AHU for indoor comfort control.

With respect to the scientific studies already available in the literature (Montazeri & Kargar, 2020; Sun et al., 2017; Kim et al., 2019; Qiu et al., 2020), this study is innovative taking into account that a) the aforementioned papers primarily focus on HVAC system operation in the USA or China, overlooking the specific climatic conditions in Italy (it is important to note that climate conditions play a crucial role in the performance of HVAC systems), b) it focuses on a constant air volume AHU, while the other scientific works investigated variable air volume AHUs, and c) only two researchers (Sun et al., 2017; Qiu et al., 2020) utilized the standalone simulation tool TRNSYS in their studies, but only Sun et al. (2017) conducted the experimental validation of the simulation model (to address this gap, the present study integrates both TRNSYS simulation and experimental testing within identical boundary and climate conditions).

# 2. Experimental Setup and Tests

The SENS i-Lab (SENS i-Lab, 2024), located in the Department of Architecture and Industrial Design of the University of Campania Luigi Vanvitelli (Aversa, southern Italy, latitude: 40°58'21" North, longitude: 14°12'26" East), is equipped with a typical HVAC system consisting of a single duct dualfan constant air volume AHU, able to regulate indoor air temperature, indoor air relative humidity, indoor air velocity and indoor air quality inside a test room. Fig. 1 reports the schematic of the AHU including all the interconnected components: supply air fan (SAF) and return air fan (RAF), humidifier (HUM), cooling coil (CC) coupled with an air-to-water electric refrigerating system (RS) via a cold tank (CT), post-heating coil (PostHC) connected to an air-to-water electric heat pump via a hot tank (HT). A mixture of water and ethylene glycol (6% by volume) is used as a heat carrier fluid. The AHU is fully equipped with accurate sensors to monitor and record all the key operating parameters (shown in Fig. 1). Additional details regarding the AHU components, sensors and control logic strategy can be found in (Rosato et al., 2022a,b).

The experimental electric power EP<sub>RAF,EXP</sub>, EP<sub>SAF,EXP</sub>, EP<sub>HUM,EXP</sub>, EP<sub>RS,EXP</sub> and EP<sub>HP,EXP</sub> consumed by the RAF, the SAF, the HUM, the RS, and the HP, respectively, are calculated as follows:

$$EP_{RAF,EXP} = (V_{RAF} \cdot A_{RAF})_{EXP} \cdot \cos \varphi_{RAF} \qquad Eq. 1$$

$$(V^{L1} \cdot A^{L1}) = \cos \varphi_{RAF}$$

$$EP_{SAF,EXP} = \frac{(V_{SAF} + V_{SAF})_{EXP}}{\sqrt{3}} + (V_{L^2} + A_{L^2}) + \cos(\theta_{L^2} + A_{L^3}) + \cos(\theta_{L^2} + A_{L^3}) + \cos(\theta_{L^2} + A_{L^3}) + \cos(\theta_{L^2} + A_{L^2}) + \cos(\theta_{L^2} + \cos(\theta_{L^2} + A_{L^2}) + \cos(\theta$$

$$\frac{\left(\mathbf{v}_{\text{SAF}}\cdot\mathbf{A}_{\text{SAF}}\right)_{\text{EXP}}\cdot\cos\phi_{\text{SAF}}}{\sqrt{3}} + \frac{\left(\mathbf{v}_{\text{SAF}}\cdot\mathbf{A}_{\text{SAF}}\right)_{\text{EXP}}\cdot\cos\phi_{\text{SAF}}}{\sqrt{3}}$$

$$= \frac{\left(\mathbf{V}_{\text{HUM}}^{\text{LI}}\cdot\mathbf{A}_{\text{HUM}}^{\text{LI}}\right)_{\text{EXP}}\cdot\cos\phi_{\text{HUM}}}{\sqrt{3}}$$

$$\frac{\left(V_{\text{HUM}}^{\text{L2}} + A_{\text{HUM}}^{\text{L2}}\right)_{\text{EXP}} \cdot \cos \varphi_{\text{HUM}}}{\sqrt{3}} + \frac{\left(V_{\text{HUM}}^{\text{L3}} + A_{\text{HUM}}^{\text{L3}}\right)_{\text{EXP}} \cdot \cos \varphi_{\text{HUM}}}{\sqrt{3}} \qquad Eq. 3$$

$$\begin{split} & EP_{RS,EXP} = \left(V_{RS}^{L1} \cdot A_{RS}^{L1}\right)_{EXP} \cdot \cos \varphi_{RS} + \\ & \left(V_{RS}^{L2} \cdot A_{RS}^{L2}\right)_{EXP} \cdot \cos \varphi_{RS} + \left(V_{RS}^{L3} \cdot A_{RS}^{L3}\right)_{EXP} \cdot \cos \varphi_{RS} \\ & EP_{HP,EXP} = \left(V_{HP}^{L1} \cdot A_{HP}^{L1}\right)_{EXP} \cdot \cos \varphi_{HP} + \\ \end{split}$$

$$\left(V_{HP}^{L2} \cdot A_{HP}^{L2}\right)_{EXP} \cdot \cos \phi_{HP} + \left(V_{HP}^{L3} \cdot A_{HP}^{L3}\right)_{EXP} \cdot \cos \phi_{HP}$$
 Eq. 5

where  $\cos\varphi$  is the power factor (assumed equal to 0.95 as suggested by the manufacturers, whatever the components), A and V represent the electric phase current and phase voltage, respectively, at phase L1 or L2 or L3 measured for each AHU component.

The experimental cooling power CP<sub>RS,EXP</sub> supplied by the RS, cooling power CP<sub>CC,EXP</sub> exchanged between air and heat carrier fluid via the CC, thermal power TP<sub>HP,EXP</sub> supplied by the HP, and thermal energy TP<sub>PostHC,EXP</sub> exchanged between air and heat carrier fluid via the PostHC are calculated by using the following formulas:

$$CP_{RS,EXP} = \rho_{F} \cdot c_{F} \cdot \dot{V}_{F,in,RS,EXP} \cdot \left(T_{F,in,RS,EXP} - T_{F,out,RS,EXP}\right)$$
 Eq. 6

$$CP_{CC,EXP} = \rho_{F} \cdot c_{F} \cdot \dot{V}_{F,in,CC,EXP} \cdot \left(T_{F,ont,CC,EXP} - T_{F,in,CC,EXP}\right)$$
 Eq. 7

$$TP_{_{HP,EXP}} = \rho_{_{F}} \cdot c_{_{F}} \cdot \dot{V}_{_{F,in,HP,EXP}} \cdot \left(T_{_{_{F,out,HP,EXP}}} - T_{_{_{F,in,HP,EXP}}}\right) \hspace{1.5cm} Eq. \hspace{0.1cm} 8$$

$$TP_{\text{PostHC,EXP}} = \rho_{\text{F}} \cdot c_{\text{F}} \cdot \dot{V}_{\text{F,in,PostHC,EXP}} \cdot \left(T_{\text{F,in,PostHC,EXP}} - T_{\text{F,out,PostHC,EXP}}\right) \qquad Eq.~9$$

where  $\dot{V}_{\text{F,in,RS,EXP}}$  ,  $\dot{V}_{\text{F,in,CC,EXP}}$  ,  $\dot{V}_{\text{F,in,HP,EXP}}$  , and  $\dot{V}_{\text{F,in,PostHC,EXP}}$  are the measured heat carrier fluid volumetric flowrate entering the RS, the CC, the HP and the PostHC, respectively, TF, in, RS, EXP, TF, in, CC, EXP, TF, in, HP, EXP, and TF,in,PostHC,EXP are the measured temperatures of heat carrier fluid entering the RS, the CC, the HP and the respectively, PostHC, TF,out,RS,EXP, TF,out,CC,EXP, TF,out,HP,EXP, and TF,out,PostHC,EXP are the measured temperatures of heat carrier fluid exiting the RS, the CC, the HP and the PostHC, respectively, pF and cF are, respectively, the density and the specific heat of heat carrier fluid. The calibration and validation of the developed simulation model were performed by contrasting the predicted values with the data measured during 14 daily experiments, carried out from 9:00 am to 6:00 pm upon varying the boundary climatic conditions during both cooling and heating seasons; in particular, 8 tests were performed during winter (W1, W2, W3, W4, W5, W6, W7, W8), while 6 tests were carried out during summer (S1, S2, S3, S4, S5, S6). In particular, during summer the outdoor air temperature ranged from a minimum of 21.46 °C (test S6) up to a maximum of 41.22 °C (test S3), whereas during winter it varied from a minimum of 6.24 °C (test W5) up to a maximum of 23.85 °C (test W4). Data were measured and recorded every second. Additional details regarding the experimental tests can be found in (Rosato et al., 2024).



Fig. 1 - Schematic of the AHU of the SENS i-Lab

### 3. Simulation Model

In TRNSYS 18 a mathematical model (named "Type") represents each component. Each TRNSYS Type requires some inputs to be specified in order to calculate the corresponding outputs. Fig. 2 presents a flow diagram indicating the main TRNSYS Types used in the model, together with the main corresponding inputs and outputs. In this study, the AHU was simulated with a time-step of 1 second. In the TRNSYS Type 930 (modelling the RAF and the SAF), an energy balance that considers pressure impacts determines the air's output state; the volumetric air flowrate is simulated according to the RAF/SAF velocity set by the end-user electric via specific equations derived from separate experiments. The simulated power consumption EPRAF,SIM/EPSAF,SIM of the RAF/SAF is calculated via the following equations (derived from separate experimental tests) as a function of the RAF/SAF velocity percentage OL<sub>RAF</sub>/OL<sub>SAF</sub> (ranging between 0 and 100%) set by the end-user:

$$\begin{split} & EP_{RAF,SIM} = -0.000000142 \cdot OL_{RAF}{}^5 + \\ & 0.00002882 \cdot OL_{RAF}{}^4 - 0.0013779 \cdot OL_{RAF}{}^3 + \\ & 0.040138 \cdot OL_{RAF}{}^2 - 0.15187 \cdot OL_{RAF} + 17.101 \\ & EP_{SAF,SIM} = 0.0000136 \cdot OL_{SAF}{}^4 - 0.0009289 \cdot OL_{SAF}{}^3 + \\ & 0.14404 \cdot OL_{SAF}{}^2 - 1.324 \cdot OL_{SAF} + 87.297 \end{split}$$

The mixing of outdoor air and return air is modelled via the TRNSYS Type 648. In the TRNSYS Types 508c and 753e are modelling the CC and the PostHC, respectively; the air is passing over a coil inside which a colder/hotter heat carrier fluid is flowing; these Types use the "bypass fraction approach" to predict the outlet conditions of both heat carrier fluid and air; according to the AHU manufacturer, the bypass fraction is 15% for the CC and 10% for the PostHC. The following equations are used to calculate the simulated cooling power CP<sub>CC,SIM</sub> and thermal power TP<sub>PostHC,SIM</sub> supplied by the CC and the PostHC, respectively:

$$\begin{split} CP_{cC,SIM} &= \rho_{F} \cdot c_{F} \cdot \dot{V}_{F,in,CC,EXP} \cdot \begin{pmatrix} T_{F,out,CC,SIM} - T_{F,in,CC,EXP} \end{pmatrix} & Eq.12 \\ TP_{PostHC,SIM} &= \rho_{F} \cdot c_{F} \cdot \dot{V}_{F,in,PostHC,EXP} \cdot T_{F,in,PostHC,EXP} - \\ \rho_{F} \cdot c_{F} \cdot \dot{V}_{F,in,PostHC,EXP} \cdot T_{F,out,PostHC,SIM} & Eq.13 \end{split}$$

where  $T_{F,out,CC,SIM}$  and  $T_{F,out,PostHC,SIM}$  are the simulated temperature of the heat carrier fluid exiting the CC and the PostHC, respectively.

The TRNSYS Type 941 models a single-stage air-towater HP/RS. It generates output values for absorbed power, RS cooling capacity, or HP heating capacity. This model requires a performance input map (based on a user-supplied data file) that includes the values of heating capacity and electric power consumption as a function of both outside air temperature and heat carrier fluid temperature entering the HP/RS. The performance maps of the HP and the RS used in this study are reported in Figs. 3 and 4, respectively; they indicate the COefficent of Performance (COP) of the HP (Fig. 3) and the Energy Efficiency Ratio (EER) of the RS (Fig. 4).



Fig. 2 - Flow chart with inputs and outputs of TRNSYS Types

The values in Figs. 3 and 4 have been obtained by modifying the manufacturer performance maps (derived via the Magellano software developed by the manufacturer itself (AERMEC, 2024)) according to experimental tests conducted in the SENS i-Lab and described in the Section 2. The manufacturer assessed the performance of both the HP and the RS based on experimental tests performed according to (European Standard EN 14825). In particular, with respect to the manufacturer values, both the electric power consumption and the heating power outputs of the HP were decreased by 25%, while the electric power consumption values of the RS were increased by 25% and the cooling power outputs of the RS were reduced by 40% in order to be compliant with the measured values. As a result, the COP values of the HP remained the same as the manufacturer's specifications, while the EER values of the RS decreased by 48% compared to the manufacturer's performance map. The following equations are used in this paper to calculate the simulated values of cooling power CPRS,SIM and thermal power TPHP,SIM supplied by the RS and the HP, respectively:

$$\begin{split} CP_{\text{RS,SIM}} = \rho_{\text{F}} \cdot c_{\text{F}} \cdot \dot{V}_{\text{F,in,RS,EXP}} \cdot \left(T_{\text{F,in,RS,EXP}} \cdot T_{\text{F,out,RS,SIM}}\right) & \text{Eq.14} \\ TP_{\text{HP,SIM}} = \rho_{\text{F}} \cdot c_{\text{F}} \cdot \dot{V}_{\text{F,in,HP,EXP}} \cdot \left(T_{\text{F,out,HP,SIM}} \cdot T_{\text{F,in,HP,EXP}}\right) & \text{Eq.15} \end{split}$$

where T<sub>F,out,RS,SIM</sub> and T<sub>F,out,HP,SIM</sub> are the simulated temperatures of the heat carrier fluid exiting the RS

and the HP, respectively. In the TRNSYS Type 641 (modelling the humidifier), the outlet state of the air is defined based on an energy balance where the heat losses are neglected. The following equation is derived from measured data to calculate the simulated humidifier electric power consumption EP<sub>HUM,SIM</sub> as a function of the measured opening percentage OP<sub>V,HUM,EXP</sub> (ranging between 0 and 100%) of the valve supplying the humidifier:

 $EP_{HUM,SIM} = OP_{V,HUM,EXP} \cdot 34.022$ 

Eq.16



Fig. 3 – COP of the HP upon varying  $T_{\text{OA}}$  and  $T_{\text{F,out,HP}}$ 



Fig. 4 – EER of the RS upon varying  $T_{\text{OA}}$  and  $T_{\text{F,out,RS}}$ 

# 4. Experimental Validation of the Simulation model

The proposed TRNSYS model has been validated by comparing the simulation results with 453,600 experimental data points. The Eq. 17 is used to calculate the percentage difference between the simulated and experimental daily values of electric (EE), cooling (CE), and thermal energy (TE) for each component of the AHU, including SAF, RAF, HUM, RS, HP, CC, and PostHC:

where XY,SIM is the simulation value of EE/CE/TE associated to the specific AHU component Y, while X<sub>Y,EXP</sub> is the experimental value of EE/CE/TE associated to the same AHU component Y obtained during the same test. Figs. 5 and 6 report the values of  $\Delta EE_{SAF}$ ,  $\Delta EE_{RAF}$ ,  $\Delta EE_{HUM}$ ,  $\Delta EE_{RS}$ ,  $\Delta EE_{HP}$ ,  $\Delta CE_{RS}$ ,  $\Delta CE_{CC}, \ \Delta TE_{HP}$  and  $\Delta TE_{PostHC}$  as a function of the summer and winter tests, respectively. In this context, positive values indicate that the simulated energy values are greater than the measured values. Tables 1 and 2 indicate the minimum and maximum values of the parameters  $\Delta EE_{SAF}$ ,  $\Delta EE_{RAF}$ ,  $\Delta EE_{HUM}$ ,  $\Delta EE_{RS}$ ,  $\Delta EE_{HP}$ ,  $\Delta CE_{RS}$ ,  $\Delta CE_{CC}$ ,  $\Delta TE_{HP}$  and  $\Delta TE_{PostHC}$ during summer and winter, respectively, also indicating the test corresponding to the minimum/maximum value. The results illustrate that the proposed model effectively captures the real-world performance of both the SAF and the RAF. This is evident from the values of  $\Delta EE_{SAF}$  and  $\Delta EE_{RAF}$ , consistently ranging from -3.4% to 3.8% for each respective field. The variations in percentages observed between the experimental and simulated values can be attributed to the utilization of equations derived from interpolated experimental electric demands to calculate the electric energy consumption of the simulated SAF and RAF; while these equations exhibit high R<sup>2</sup> values exceeding 0.99, they do not entirely capture the transient behaviour of the SAF and RAF, particularly during the initial stages of testing. The comparison of measured and predicted values highlights the overall accuracy of the simulation for both the RS and HP systems, although there is room for improvement, as indicated by the largest deviations observed: -15.3% for  $\Delta EE_{RS}$ , -9.9% for  $\Delta CE_{RS}$ , -10.6% for  $\Delta EE_{HP}$ , and -10.5% for  $\Delta TE_{HP}$ . These percentage differences can be explained by taking into account that the TRNSYS Type 941 does not consider the transient effects of both the inlet fluid temperature and the outdoor air temperature, but it assumes a steady-state operation of both the RS and the HP (while a transient behaviour is usually recognized during field tests). With respect to the humidifier, it can be noticed that the parameter  $\Delta EE_{HUM}$  is characterized by a minimum value of -9.1% (test W3) during winter, while its maximum value is 4.2% during summer. The differences between the experimental and simulated data can be attributed to the fact the HUM electric energy consumption has been

evaluated based on an equation interpolating the measured values and, therefore, it is not always able to accurately capture the transient operation of the HUM, especially at the beginning of its activation requiring a few minutes to reach steady-state conditions.

Table 1 – Minimum and maximum values of  $\Delta EE_{SAF}$ ,  $\Delta EE_{RAF}$ ,  $\Delta EE_{HUM}$ ,  $\Delta EE_{RS}$ ,  $\Delta EE_{HP}$ ,  $\Delta CE_{CC}$ ,  $\Delta TE_{HP}$  and  $\Delta TE_{PostHC}$  with reference to the summer tests

	Minimum	Maximum
$\Delta EE_{SAF}$	1.4% (test S5)	3.8% (test S2)
$\Delta E E_{RAF}$	-1.8% (test S1)	0.2% (test S4)
$\Delta EE$ HUM	-5.4% (test S4)	4.2% (test S1)
$\Delta EE$ rs	1.9% (test S4)	8.4% (test S6)
$\Delta E E_{HP}$	-10.6% (test S6)	3.4% (test S5)
$\Delta CErs$	-9.9% (test S3)	3.8% (test S1)
ΔCEcc	-3.9% (test S4)	1.1% (test S6)
$\Delta T E_{HP}$	-8.3% (test S6)	1.6% (test S3)
$\Delta TE_{PostHC}$	0.0% (test S6)	4.85% (test S3)

Table 2 – Minimum and maximum values of  $\Delta EE_{SAF}$ ,  $\Delta EE_{RAF}$ ,  $\Delta EE_{HUM}$ ,  $\Delta EE_{RS}$ ,  $\Delta EE_{HP}$ ,  $\Delta CE_{RS}$ ,  $\Delta CE_{CC}$ ,  $\Delta TE_{HP}$  and  $\Delta TE_{PostHC}$  with reference to the winter tests

	Minimum	Maximum
$\Delta EE$ saf	-2.4% (test W7)	2.1% (test W1)
$\Delta EE$ raf	-3.4% (test W5)	-2.4% (test W1)
$\Delta EE$ ним	-9.1% (test W3)	-2.4 % (test W2)
$\Delta EErs$	-15.3% (test W1)	4.9% (test W4)
$\Delta EE_{HP}$	-9.8% (test W7)	9.7% (test W4)
$\Delta CE$ rs	-8.6% (test W7)	1.6% (test W2)
ΔСЕсс	-5.7% (test W6)	18.3% (test W1)
$\Delta T E_{HP}$	-10.5% (test W7)	3.9% (test W2)
$\Delta TE_{PostHC}$	-6.0% (test W3)	-1.9% (test W1)

In particular, during the W3 test the humidifier was activated only 4 times, each time for a limited period of about 7 minutes, with significant unsteady operation. In relation to the CC and the PostHC, the variance between simulated and measured performance (with the highest deviations being 18.3% and -6.0%, respectively) can be ascribed to two primary factors: a) air temperature is measured in a single specific point (while a non-uniform air temperature distribution is generally recognized at the inlet and outlet), and b) a constant bypass factor is assumed (even if it changes with the operating conditions).

# 5. Conclusion

In this paper, a detailed dynamic simulation model of a typical HVAC system including a single duct dual-fan constant air volume air-handling unit has been developed and experimentally validated via the software TRNSYS 18. The comparison between simulation and measured data underlined a high degree of accuracy of the model in reflecting the measured field performance, with maximum

percentage differences between predicted and experimental values up to -6.0%, 18.3%, -9.1%, -10.6%, -15.3% in terms of heating coil energy, cooling coil energy, humidifier electric demand, heat pump electric consumption and refrigerating system electricity request, respectively. Therefore, the analysis highlighted a) the capability of TRNSYS platform in simulating complex system dynamics and its utility in advancing HVAC research and design, as well as b) the accuracy and efficacy of the developed simulation model in capturing real-world performance of the HVAC system. However, there are still shortcomings due to its inability to fully represent and simulate the transient operation of AHU components (and this is one of the main reasons causing the discrepancies between predicted and measured data). Future work will focus on enhancing the accuracy of the proposed AHU digital twin, with particular reference to the heat pump and the refrigerating system, by means of artificial neural networkbased models (trained based on the field performance values) allowing to accurately represent the system beyond its steady-state functioning.



Fig. 5 - Percentage difference between simulated and experimental performance of AHU components as a function of summer tests


Fig. 6 - Percentage difference between simulated and experimental performance of AHU components as a function of winter tests

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## Nomenclature

# Symbols

А	Current intensity (A)
AHU	Air-handling unit
CC	Cooling coil
CE	Cooling energy (kWh)
СОР	Coefficient of performance
СР	Cooling power (kW)
D	Percentage difference (%)
EE	Electric energy (kWh)
EER	Energy efficiency ratio
EP	Electric power (W)
HP	Heat pump
HUM	Humidifier

HVAC	Heating, ventilation and air-condi-
	tioning
OL	Velocity percentage (%)
OP	Opening percentage (%)
PostHC	Post-heating coil
RAF	Return air fan
RS	Refrigerating system
S1-S6	Tests performed during summer
SAF	Supply air fan
Т	Temperature (°C)
TE	Thermal energy (kWh)
ТР	Thermal power (kW)
V	Voltage (V)
V	Volumetric flow rate (m <sup>3</sup> /s)
VAV	Variable air volume
W1-W8	Tests performed during winter

# Subscripts

CC	Cooling coil
EXP	Experimental
F	Heat carrier fluid
HP	Heat pump
HUM	Humidifier
PostHC	Post-heating coil
RAF	Return air fan
RS	Refrigerating system
SAF	Supply air fan
SIM	Simulated data

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# Examining the Influence of Climatological Parameters on Building Cluster Geometry and Design Features in a Rural Indian Context: The Case of Sugganahalli Village (India)

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#### Abstract

Nature has been fundamental in influencing the design of traditional habitations across the globe. Climatological factors such as wind directions, sun path, precipitation, etc., play a vital role in the design of buildings for occupants and community comfort keeping the local lifestyles into account. This research aims to explore the impact of climatological parameters (solar geometry and wind patterns) on the design of vernacular settlements. This study particularly looks into orientation of streets and building units, materials, and building features. The study is based on real-time on-site fieldwork complemented with computational models.

# 1. Introduction and Motivation

Sugganahalli village is located approximately 100 kilometers from Bengaluru (India) and consists of varying building typologies, involving vernacular (predominantly timber and stone with earth-based plaster), conventional (Fired clay bricks and cement mortar plaster), and mixed/transitioning building types. Architectural features present in the vernacular typologies respond to the existing climate and social requirements, predominantly characterized by sloped roofs, courtyards, overhangs, absence of compound walls, and pedestal stone in front of houses for gatherings see Fig. 3. Vernacular knowledge is time-tested and refined over generations to be the most optimal for the environment, climatic context and lifestyle (Henna et al., 2021; Priyadarshani et al., 2023). This knowledge is now slowly being lost to modernization. With the rising demand for conventional dwellings to cater to the aspirational needs of the community, a decline in vernacular construction is evident (Moothedath et al., 2015). With the shifts in material use, space allocation for functionality is also changing. The influence of this archetype shift does not necessarily conform to the traditional knowledge previously used and has led to practical difficulties and shifts in community living patterns (Shastry et al., 2014).

The work aims to identify the impact of vernacular dwelling features that help to regulate indoor air temperatures. The objectives of the work are:

- To examine Sugganahalli village (India) settlement cluster (geometry, mutual shadowing, and ventilation patterns) in response to prevalent climatic conditions.
- 2. To examine the impact of vernacular and conventional building features (Roof profile, material assembly, window and door sizes, attic spaces, ceiling height) on indoor air temperatures.



Fig. 1 - Map representing the different typologies in Sugganahalli Village

# 2. Methodology

# 2.1 Documentation of the Cluster & Dwelling

On-site mapping of buildings was done in order to document the building typologies, the lifestyle of the people, and the features of the buildings, see Table 1. The on-site air temperature was recorded for the two types of dwellings, (Conventional and Vernacular) using Supco LTH sensors (accuracy  $\pm 0.5$  °C). The installed sensors measured both indoor and outdoor temperatures.

A site map was developed (see Fig. 1) showing varying building typologies in the settlement.



Fig. 2 - Subtypes within vernacular and conventional dwellings

The dwellings in the settlement were classified into three types:

- Conventional (burnt bricks or AAC blocks for walls with cement plastering and RCC roof).
- 2. Vernacular (Earth-based materials, i.e., stone masonry or mud walls, mud or lime plaster, and timber frame with tiles or thatch).
- 3. Mixed (Initially built with vernacular materials and retrofitting done with conventional materials).



Fig. 3 – Images of the village's vernacular (left) and conventional (right) dwellings

Table 1 shows the features, building practices, and materials utilized in both of these building typologies. Fig. 2 illustrates the typical plans of the building typologies found on site.

Two representative dwellings were identified, as shown in Fig. 3. To do a comparative study, the dwellings were selected for different typologies (conventional and vernacular), ensuring similar dimensions, planning, orientation, and building features.

Table 1 – Difference in conventional and vernacular dwelling features

Feature	Conventional	Vernacular		
Material	Brick / Cement	Stone / Mud		
Walls	230 mm	450 mm		
Openings	D–900 x 2100 mm	D- 900 x 2000 mm		
	W– 900 x 750 mm	W– 750 x 600 mm		
Roofs	Flat roof	Sloped / Courtyard		
Roof Ma-	RCC slab / As-	Timber frame with		
terial	bestos sheets	thatch/tiles		
Long-axis	East-West	East-West		
orientation				
U-value	1.58 (W/m <sup>2</sup> -K)	1.00 (W/m <sup>2</sup> -K)		
(wall)				
Age of the	12 – 15 years	70-100 years		
dwelling				
Material	Manufactured	Locally sourced (1km		
source		radius- hillock)		



Fig. 4 – 3-D Conventional house with context modeled on Autodesk Revit®



Fig. 5 – 3-D Vernacular house with context modeled on Autodesk Revit®

# 2.2 Simulation

The Sugganahalli village cluster, consisting of around 150 buildings, has been modeled in Design Builder and Revit. Settlement-level block models have been used to study the overall cluster-level planning strategies. Wind patterns (see Fig. 8) and solar gain (see Fig. 9, Fig. 10) were the major parameters studied at the site level. A cluster-level analysis was done to investigate solar exposure (see Fig. 13) using Autodesk CFD.

At the building level, the impact of the cluster, ventilation rates, vernacular features, and materials were examined using the Design Builder tool.

Validation of the building model in Design Builder was done with on-site recorded data. The RMSE (%) and MBE (%) are within acceptable limits as dictated by ASHRAE guidelines. ("Standards and Guidelines," n.d.), i.e. RMSE – 30% and MBE – 10%



Fig. 6 – Validation of conventional dwelling for indoor air temperature



Fig. 7 – Validation of vernacular dwelling for indoor air temperature

The simulation model shows a good fit to the existing building on-site based on RMSE and MBE values calculated using Equations 1 and 2.

$$RMSE\% = \frac{100}{\bar{x}_i} \sqrt{\frac{\sum_{1}^{n} (x_i - x_s)^2}{n}}$$
(1)

$$MBE\% = \frac{\sum_{1}^{n} (x_i - x_s)}{\sum_{1}^{n} (x_i)} \times 100$$
(2)

x <sub>i</sub> - Measured data	n – Number of readings
x <sub>s</sub> - Simulated data	$ar{x}_i$ - Mean of measured data

# 3. Results and Discussions

## 3.1 Site Level Analysis

The analysis was done at site level for wind patterns (direction) and flow (see Fig. 8) and solar irradiance (see Fig. 13). The dwellings on site are majorly oriented such that the longer side faces the East-West direction. The clustering of the blocks is such that the longer wall is mutually shaded by the surrounding blocks. Even though each building has the longer side facing the East-West direction, the overall form of the settlement has the shorter side facing the East-West direction (see Fig. 1).

Wind analysis for the settlement was done by taking the major wind direction and speed for the location ("Global Wind Atlas," n.d.). The clustering of the houses resulted in wind movement, as shown in Fig. 8. The longer side of the dwellings (East-west orientation) are oriented perpendicular to the wind direction. The impacts of orientation (see Fig. 9 and Fig. 10) and mutual shadowing (see Fig. 11 and Fig. 12), were individually examined to understand whether the cluster geometry and the building features had a role to play in keeping the indoor temperature comfortable.



Fig. 8 – Wind analysis for major wind direction in the settlement (developed using Autodesk CFD)



Fig. 9 – Impact of orientation on mean indoor air temperature (conventional dwelling



Fig. 10 – Impact of orientation on mean indoor air temperature (vernacular dwelling)

# 3.2 Building Level Analysis

# 3.2.1 Cluster orientation

The orientation of the cluster was examined for the 8 ordinal directions at increments of 45°. The whole cluster was rotated for this simulation and not individual dwellings.

Orientation shows a low influence on the indoor temperatures in both conventional and vernacular typologies, as shown in Fig. 9 and Fig. 10. While north is taken as the base case. In the case of conventional dwelling, the east-facing orientation experiences the most heat gain (+0.1 °C), but the difference compared to the west-facing orientation with the least heat gain is negligible in comparison to the base case (north-facing) (see Fig. 9).

In the case of vernacular dwelling, east facing showed the most heat gain (+0.2 °C). South-facing showed negligible heat gain. The base case of North was nearly equal to south orientation, as shown in Fig. 10.

The impact of orientation was found to be negligible, i.e., in the range of -0.1 °C to +1.0 °C for the conventional dwelling and -0.6 °C to +0.5 °C for the vernacular dwelling. This suggests that orientation may not be a critical factor in managing indoor temperature for this specific site and climate.

# 3.2.2 Mutual shading

The conventional and vernacular dwellings were studied in isolation without neighboring building units to examine mutual shadowing. In the case of conventional dwelling, an increase of the average indoor air temperatures by +0.9 °C was observed when compared to the building with neighboring building units (see Fig. 11). The removal of the neighboring cluster in the case of vernacular typology had an overall increase in average air temperatures by +0.5 °C, as shown in Fig. 12, with the effect being most evident during summer months (Mar-May). This highlights the potential benefits of strategic building placement and the influence of neighboring structures on shading as evident from Fig. 13. The cluster shows less impact on vernacular typology due to the low U-value building envelope.

# 3.2.3 Ventilation

Window and door sizes were altered, transitioning from conventional typology (750x900 mm, 900x2100 mm) to vernacular typology (600x750 mm, 700x2000 mm) in the conventional dwelling. There was no significant difference in average temperature compared to the base case, as shown in Fig. 14). In fact, a slight warming effect (+0.1 °C) was observed when compared to the base case.





Fig. 11 - Impact of mutual shading on average indoor air temperature in Conventional dwellings

Fig. 12 - Impact of mutual shading on average indoor air temperature in Vernacular dwellings



Fig. 13 - Solar Radiance distribution, developed using Autodesk Revit®



Fig. 14 – Impact of ventilation rates on diurnal indoor air temperature in conventional dwelling



Fig. 15 – Impact of ventilation rates on diurnal indoor air temperature in vernacular dwelling



Fig. 16 – Impact of ventilation rates on monthly mean indoor air temperature in vernacular dwelling

There is an evident rise in temperature (nearly +4.5 °C) in vernacular typology for the diurnal temperatures (see Fig. 15) and monthly average temperatures (see Fig. 16) when ventilation rates were increased from 0 (infiltration only) to 1.0 ac/h (recommended ac/h for living spaces as per ("CIBSE Guides," n.d.)). The heat buffer effect of the walls and roof of vernacular type kept the indoor air cooler than ambient outdoors (Shastry et al., 2014). Contrary to the notion that ventilation contributes to keeping indoors cooler, in this case, increasing the ventilation rates makes the indoors warmer, as outdoor air was much warmer.



Fig. 17 - Roof assembly of vernacular house with attic space

## 3.2.4 Attic spaces

In vernacular typology, attic spaces serve multiple purposes beyond just storage. However, another purpose of the attic lies in its role as a thermal buffer. By creating an air gap (450 mm) between the ceiling and the roof, the attic space acts as an additional insulation layer, as shown in Fig. 17. Removing the attic space resulted in higher average indoor air temperatures of +0.3 °C throughout the year. The attic keeps the building cooler by around -0.3 °C during summer (Mar-May), as shown in Fig. 18.



Fig. 18 – Impact of attic space on monthly mean indoor air temperature in vernacular dwelling

#### 3.2.5 Roof geometry

Roof types were studied, three vernacular roof types (R1, R2, R3) and one conventional roof type (R4) were identified, as shown in Fig. 19. These roofs were modeled and simulated to see the impact of the roofs on indoor air temperatures.

Slopes of the roof are mainly facing in the northsouth direction, which are also facing the street. This facilitates the rainwater to flow into the drains rather than flowing to the narrow spaces between the building blocks, since they are closely clustered.



Fig. 19 – Roof Types (R1, R2, R3, R4)



Fig. 20 – Impact of roof geometry on monthly mean indoor air temperature in vernacular dwelling



Fig. 21 – Impact of ceiling height on monthly mean indoor air temperature in conventional dwelling

The simulations showed that R1 and R2 kept the indoors comfortable, as shown in Fig. 20.

The courtyard type and flat roof with conventional materials resulted in higher indoor temperatures, see Fig. 20. This relates well to the previous inference of higher ventilation leading to an increase in indoor temperatures, as shown in Fig. 15 and Fig. 16.



Fig. 22 - Graph representing the base case with various material assemblies and thickness (Daily variation)

#### 3.2.6 Ceiling height

The typical ceiling height found in vernacular dwellings is 2.5 m. A ceiling height reduction (from 3.5 m to 2.5 m) in the conventional dwelling resulted in a notable cooling effect on average indoor air temperature by -0.7 °C (see Fig. 21).

#### 3.2.7 Material assembly

Material assembly and thickness are crucial for achieving lower indoor air temperatures. Fig. 22 reveals that employing vernacular materials with their typical wall thickness (450 mm) proves most effective in maintaining stable, lower indoor air temperatures (-0.3 °C on an average compared to the base case). Even with a standard wall thickness (210 - 230 mm), vernacular materials outperform conventional ones in lowering temperatures with a standard wall thickness of 230 mm (-0.2 °C). Notably, a thicker wall similar to that in vernacular typology, even with the material assembly of conventional typology, provides the most benefit towards cooling (-0.3 °C). These findings show the inherent thermal benefits of vernacular materials and the importance of considering wall thickness during design.

# 4. Conclusions

Vernacular features and planning have been known to impact a dwelling's thermal performance significantly. This study examines a few buildings in a vernacular Indian setup.

On a cluster geometry level, the mutual shadowing contributed to the overall comfort in the dwelling. The vernacular building features contributing to keeping the indoors comfortable were material assembly and wall thickness, attic space, ceiling height, and specific roof geometry. The low ventilation rate in vernacular dwellings contributes significantly in maintaining the effect of these passive cooling strategies. The incorporation of these features in conventional dwellings would be beneficial in keeping indoors comfortable. This can help to reduce the dependence on insulative materials and mechanical ventilation strategies for cooling (fans, A.C.s, insulation materials), leading to less energy consumption and eventually promoting sustainability. Further, more buildings in vernacular contexts must be studied to determine their potential benefits for energy efficiency and occupant comfort.

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# Estimating Indoor TVOCs in Response to Varying Humidity Regimes in Vernacular and Conventional Dwellings

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#### Abstract

Indoor environment quality (IEQ) has emerged as a crucial factor after the COVID-19 pandemic determining the health, well-being and productivity of occupants. The current research aims to examine the buildings' ability to regulate indoor air quality, specifically looking at indoor moisture and toxicity characterised in terms of total volatile organic compounds (TVOCs). According to the United States Environmental Protection Agency (USEPA), the concentration of these compounds is two to five times greater indoors as compared to outdoors. Building materials and indoor surfaces such as paints, synthetic floorings, carpets, etc., constantly emit TVOCs. The dependence of TVOC on varying moisture regimes has been examined in this study. The climatic response of these dwellings has been examined through indoor comfort and air quality parameters. The indoor temperature, humidity and TVOC levels in conventional and vernacular residential dwellings have been examined for the warm and humid climatic zone. Concurrently, these dwellings have also been modelled (and validated with real-time data for temperature and relative humidity levels) using Design Builder. This study examines indoor moisture and toxicity (TVOCs) levels in vernacular and conventional buildings for three climate-change scenarios. Simulation studies gave an insight into how the indoor temperature, indoor humidity and indoor TVOC levels, attributed to fresh paints, could increase over the years as per different climate change scenarios. The ageing of the wall paints has been examined further to compare how power decay affects the emissions in the future. The naturally derived materials do not have any harmful chemicals and, hence, emit less TVOCs as compared to the conventional building materials, thereby, maintaining better indoor air quality for the occupants.

# 1. Introduction and Motivation

Climate change is leading to rising temperatures in an intensified manner as compared to the expected levels. The recent report by Intergovernmental Panel on Climate Change (IPCC) reports that the warming of the earth will reach 4.5 °C by the end of this century. Studies show that regional temperature changes can be more extreme than the global average. In a world with a +2 °C global temperature increase, a local area might experience a 3 °C change, which is 1°C higher than the global average. If the global temperature increase reaches +4 °C, that same local area could see a 7.5 °C change, exceeding the global average by 3.5 °C (New, 2011).

Several countries across the globe have recorded their highest temperatures in the past nine months (Pandey, 2024). In March 2024, record-breaking temperatures have been reported for Columbia, South Africa, Gabon, Kenya and South Sudan. On the other hand, in South Sudan, extreme temperatures exceeding 43 °C are usually recorded in the summer months, but this year, 41 °C was reported on March 19 in the capital city Juba. South Africa is experiencing an unusual heatwave. Rio in Brazil has experienced a record-setting heatwave since March 17, 2024, the highest in a decade. The high heat that is predicted to persist in 2024 due to both climate change and the naturally existing El Nino is confirmed by these record-breaking temperatures that occurred on March 18 and 19, 2024. Heatwave regions often experience two heat waves in a season that last five to seven days each. However, as a result of global warming, heatwave frequency, length, and maximum duration are all increasing. Over the past 30 years, the average length of heat waves in India's hotspot regions has increased by almost 2.5 days (Rajeevan et al., 2023). According to India Meteorological Department (IMD) data, India also had a 34% increase in heat-related mortality in the last decade. The number of states and union territories experiencing heatwaves in March 2023 was three, whereas, in April 2023, it rose to eleven. Many Indian cities have recorded the highest temperatures in 2023 and 2024 till now. March to May 2023 observed the highest recorded temperatures in Delhi (46.2 °C; T<sub>mean</sub> = 40.1 °C), Mumbai (39 °C; T<sub>mean</sub> = 32 °C) and Bankura (43.7 °C; T<sub>mean</sub> = 40.1 °C; T<sub>mean</sub> = 38.8 °C).

As the outdoor temperature rises, the indoor temperature also rises correspondingly. A climate change model predicts that an increase in outdoor temperature of 1 °C during the summer will result in an increase of 0.41 °C in indoor temperature (Asumadu-Sakyi et al., 2019). Recent research has also revealed the role of the building material in passively regulating indoor moisture in response to external climatic conditions for occupants' wellness in naturally ventilated buildings (Privadarshani et al., 2023). Besides, building materials constantly emit TVOCs through walls, ceilings and roofing in the case of modern buildings (D'Amico et al., 2020). VOCs are affected by the temperature and relative humidity conditions (Zhou et al., 2017). Indoor temperature, moisture, and VOCs are important factors influencing indoor air quality (Mannan and Al-Ghamdi, 2021). This can potentially deteriorate the indoor air quality and cause risks to human health and productivity. Therefore, it is crucial to examine the interplay of indoor moisture and VOCs in naturally ventilated dwellings, extended to account for possible climate change scenarios.

The present study aims to examine:

- (a) indoor temperature, humidity and TVOCs in naturally ventilated vernacular and conventional dwellings
- (b) impact of climate change on indoor air quality in terms of indoor TVOCs.

# 2. Methodology

There are three main segments in which the study has been conducted: real-time monitoring, simulation studies using Meteonorm and Design Builder, and estimation of TVOC levels indoors based on changing humidity levels based on earlier studies (Fang et al., 1999) and IA-Quest, an indoor air quality emission simulation tool. Data monitoring for temperature and relative humidity was done to validate the design-builder models. TVOCs were monitored in the conventional and vernacular dwellings to compare the emissions from the building materials. The rooms selected were similar in occupancy and activity patterns.

## 2.1 Real-Time Data Monitoring

For real-time data monitoring, one vernacular and one conventional residential dwelling have been identified in the rural village of Sugganahalli, located about 90 km from Bangalore, India. As per the National Building Code of India, the village falls under the warm and humid climatic zone. These buildings have been selected based on different building materials used. The walls of the vernacular dwelling are made up of stones and coated with mud or lime plaster as shown in Fig. 1. However, the walls of the conventional dwelling are made up of brick, mortar, cement plaster and painted with commercially available paints as shown in Fig. 2. The conventional dwelling is twelve years old, whereas the vernacular dwelling is ninety years old. The sensors have been placed outdoors and in the bedrooms of both dwellings, which have a bed and shelves.

The data for temperature and relative humidity, both outdoors and indoors has been monitored realtime using Supco LTH sensors (range: T = -40 °C to 65 °C, RH = 0 to 99.9%; accuracy:  $T = \pm 1$  °C). The indoor TVOC levels have been monitored using the Temtop LKC1000S+ 2<sup>nd</sup> generation device. This device measures the TVOC values (range: 0-5 mg/m<sup>3</sup>; resolution: 0.01 mg/m<sup>3</sup>). The frequency of the data collected is every ten minutes for one month.



Fig. 1 – Vernacular dwelling in Sugganahalli



Fig. 2 - Conventional dwelling in Sugganahalli

## 2.2 Simulation-Based Study

The selected dwellings were modelled in Design Builder v4.5. These models were calibrated using the field data for temperature and relative humidity parameters. Three climate change scenarios that are being examined as per the reports of IPCC are IPCC AR4 (Fourth Assessment Report) B1 (structured economic growth and adoption of clean and resource-efficient technologies), IPCC AR4 A1B (rapid economic growth fuelled by balanced fossil/nonfossil energy use), and IPCC AR4 A2 (regionally sensitive economic development). Since India is a developing nation where growth in rural and urban areas is dynamic, all three climate change scenarios based on the nature of future growth have been simulated. As per the different scenarios (AR4 A1B, AR4 A2 and AR4 B1), weather files for Sugganahalli were exported for the years 2020 and 2040 from Meteonorm v7. This data was integrated into the design-builder model to examine the building's climatic response using simulation. The varying humidity levels for the years 2020 and 2040 for the warm and humid climatic zone have been analysed and used for the estimation of indoor TVOC levels. The ventilation rates while running the simulations were kept to a minimum equal to infiltration rates (0.5 h<sup>-1</sup>), as observed on the field because the door and windows were kept closed. The design-builder simulations were run for the years 2020 and 2040 for all three climate change scenarios. The results for indoor temperature and indoor relative humidity levels were further used to estimate the indoor TVOC levels for freshly painted surfaces as explained in Section 2.3.

# 2.3 Estimation of TVOC Levels

The TVOC levels have been estimated for the indoor temperature and humidity conditions for the conventional dwelling for three different climate change scenarios for the years 2020 and 2040 as shown in Fig. 3. Data from Meteonorm can be obtained at tenyear intervals, hence, data from 2020 has been used as the base year. The emission factors for various building materials used in a conventional dwelling were taken from a controlled experimental study (Fang et al., 1999). This study discussed emissions from floor varnish, PVC flooring, sealant, carpet and wall paint. However, in the context of this study, the conventional dwelling used commercially available paint. The emission factors from the paint are considered for the estimation. The temperatures taken for the controlled experiment were 18 °C, 23 °C and 28 °C. The relative humidity levels taken for the same were 30%, 50% and 70%. It was observed from the controlled experiments that wall paint was a major contributor to the TVOC levels (Fang et al., 1999). This study primarily investigates whether temperature and relative humidity affect the TVOC emission concentration from the wall paint. Paints are considered the major contributors to indoor TVOCs (Mai et al., 2024; Mo et al., 2020). Testing of emission factors is complex, requiring controlled environment studies. There were no recent studies to refer to the emission factors of various building materials, therefore, study by Fang et al. is considered to estimate the impact of temperature and relative humidity on TVOC emissions. The specifications of the paint used in the study by Fang et al. might be different from the paint that is being used in the dwellings taken as case studies. But the trends of emission decay would be similar. The relation of dependency of TVOC values on absolute humidity (Equation 1) has been taken as a basis for the projection of TVOC values for climate change scenarios by best curve fitting the TVOC concentration levels at different temperatures and relative humidity values. This equation is used to estimate the TVOC concentration in milligrams per cubic metre using the humidity ratio values, where x represents the value of humidity ratio in grams of water vapour per kg of dry air (gwv/kgda). Values from Equation 1 depict the initial TVOC emissions from the wall paint at different moisture content levels in the air.

$$TVOC = -7.3456x^2 + 277.11x - 414.86$$
(1)

Temperature and relative humidity have been taken on an hourly basis for the entire year to estimate indoor TVOC levels. This has been further analysed to study the seasonal variation of the TVOC concentration for freshly painted surfaces. The simulation has been done for the present and future scenarios in the case of the conventional dwelling. The initial maximum emission factor is calculated using Equation (1). The power decay law is then used to calculate the emissions from the painted surfaces over years, provided the surfaces are not re-painted in between the duration. The coefficient values for the decay of emissions from wall paints have been taken from the material database of IA-QUEST software. It calculates the emission factors according to Equations 2a, 2b, and 2c (Sander et al., 2006) with the age of the building material. EF is the emission factor in mg m- $^2$  h-1, t is time in hours, and a, b and x0 are constants.

Power law decay model:  

$$EF = a * t^b$$
 (2a)

Peak model:

$$EF = a * \exp\{-0.5 \left[\frac{\ln(\frac{t}{x_0})}{b}\right]\}$$
 (2b)

Constant model: EF = a (2c)

The power decay function is applied to TVOC emissions calculated from a freshly painted surface at a certain moisture content. The TVOC exposure values are extrapolated from the equations used by the IA-QUEST software and presented in Table 1. However, no significant difference between exposure values has been observed in different climate change scenarios as these values lie in the constant emission range.



Fig. 3 - Study methodology

#### 2.4 Results and Discussions

# 2.4.1 Estimation of TVOCs as per various humidity regimes

TVOCs have been estimated based on humidity ratio values for all three climate change scenarios for freshly painted surfaces. It can be observed from Table 1 that the average indoor temperature from 2020 to 2040 is expected to increase from 27.95 °C, 27.92 °C, 27.94 °C to 28.41 °C, 28.35 °C, 28.27 °C, respectively for AR4 A1B, AR4 A2 and AR4 B1 scenarios. Similarly, the average indoor relative humidity is expected to increase from 74.67%, 74.58%, 74.67% to 75.41%, 75.32%, 74.99% respectively and humidity ratio is expected to increase from 15.21 gwv/kgda, 15.41  $g_{wv}/kg_{da}$ , 15.20  $g_{wv}/kg_{da}$  to 16.01  $g_{wv}/kg_{da}$ , 15.91 gwv/kgda, 15.70 gwv/kgda respectively as per three climate change scenarios. The monthly average values for indoor temperature, indoor relative humidity, humidity ratio and estimated TVOC concentrations indoors for the years 2020 and 2040 as per various climate change scenarios have been summarised in Table 1. The increase in the humidity ratio is resulting in increased overall TVOC emissions.

The seasonal variation trends of estimated TVOCs for different climate change scenarios have been shown in Fig. 4. It can be observed from these graphs that TVOC emissions are maximum in summer and monsoon seasons which means that an increase in either the temperature or the relative humidity can cause an increase in TVOC emissions. Table 2 shows the maximum and minimum values of the TVOC emissions estimated for various seasons for three climate change scenarios. It can be observed from the table that the range of TVOC exposure values increases in the summer season due to an increase in temperature. This creates a higher possibility of sudden exposure to TVOCs for the occupants of the buildings.

Table 1 – Monthly average values of indoor temperature relative humidity and estimated initial and exposure levels of TVOCs as per various climate change scenarios

	2020					2040					
Climate change scenarios	Month	T (°C)	RH (%)	HR (g wv/kg da)	TVOC (mg/cu m)	TVOC exposure levels (mg/cu m)	T (°C)	RH (%)	HR (g wv/kg da)	TVOC (mg/cu m)	TVOC exposure levels (mg/cu m)
	January	26.68	64.28	11.15	1.76	0.07	27.19	65.06	11.77	1.83	0.02
	February	27.94	66.38	12.81	1.93	0.07	28.48	67.17	13.57	1.99	0.02
	March	29.64	69.64	15.63	2.12	0.07	30.18	70.44	16.6	2.16	0.02
Α	April	31.1	74.6	19.51	2.2	0.07	31.63	75.48	20.79	2.17	0.02
R	May	30.24	77.66	19.24	2.2	0.07	30.74	78.46	20.4	2.18	0.02
4	June	27.59	77.04	15.25	2.1	0.07	28.03	77.88	16.04	2.14	0.02
	July	27.13	79.55	15.35	2.11	0.07	27.56	80.14	16.08	2.14	0.02
Α	August	26.8	80.62	15.23	2.1	0.07	27.21	81.18	15.91	2.13	0.02
1	September	27.17	83.6	16.52	2.16	0.06	27.49	84.6	17.27	2.18	0.02
В	October	27.73	79.34	16.07	2.14	0.06	28.1	79.91	16.74	2.17	0.02
	November	26.78	74.22	13.57	1.99	0.06	27.14	74.92	14.14	2.04	0.02
	December	26.57	69.11	12.14	1.87	0.06	27.11	69.72	12.82	1.93	0.02
	Average	27.95	74.67	15.21	2.06	0.07	28.41	75.41	16.01	2.09	0.02
	January	26.59	64.19	11.06	1.75	0.07	27.11	64.93	11.67	1.82	0.02
	February	27.93	66.42	12.81	1.93	0.07	28.39	67.05	13.45	1.98	0.02
	March	29.59	69.79	15.62	2.12	0.07	30.08	70.57	16.51	2.16	0.02
	April	31.04	74.45	19.35	2.2	0.07	31.54	75.19	20.5	2.18	0.02
A	May	30.3	77	19.1	2.2	0.07	30.76	77.93	20.22	2.18	0.02
K	June	27.52	77.3	15.23	2.1	0.07	28	77.91	16.01	2.14	0.02
4	July	27.2	79.55	15.44	2.11	0.07	27.55	80.08	16.04	2.14	0.02
Α	August	26.78	80.68	15.22	2.1	0.07	27.09	81.47	15.83	2.13	0.02
2	September	27.11	83.51	16.41	2.15	0.06	27.44	84.22	17.09	2.18	0.02
	October	27.69	78.99	15.92	2.13	0.06	28.1	80.07	16.79	2.17	0.02
	November	26.7	74.34	13.52	1.99	0.06	27.23	74.66	14.19	2.04	0.02
	December	26.53	68.72	12.02	1.85	0.06	26.96	69.8	12.68	1.92	0.02
	Average	27.92	74.58	15.14	2.05	0.07	28.35	75.32	15.91	2.09	0.02
	January	26.77	64.37	11.25	1.77	0.07	27.1	64.87	11.64	1.82	0.02
	February	27.94	66.41	12.81	1.93	0.07	28.28	66.78	13.25	1.97	0.02
	March	29.71	69.76	15.77	2.13	0.07	30.07	70.1	16.34	2.15	0.02
	April	31.13	74.55	19.52	2.2	0.07	31.56	74.85	20.4	2.18	0.02
A	May	30.29	77.45	19.25	2.2	0.07	30.69	77.66	20.01	2.19	0.02
K	June	27.57	77.2	15.26	2.1	0.07	27.88	77.22	15.67	2.12	0.02
	July	27.07	79.37	15.23	2.1	0.07	27.41	79.92	15.81	2.13	0.02
В	August	26.77	80.66	15.2	2.1	0.07	26.9	81.31	15.53	2.12	0.02
1	September	27.15	83.76	16.54	2.16	0.06	27.46	83.76	16.98	2.17	0.02
	October	27.7	79.03	15.94	2.14	0.06	27.9	79.7	16.41	2.15	0.02
	November	26.65	74.47	13.5	1.99	0.06	27.04	74.52	13.93	2.02	0.02
	December	26.57	69	12.12	1.86	0.06	26.92	69.14	12.49	1.9	0.02
	Average	27.94	74.67	15.2	2.06	0.07	28.27	74.99	15.7	2.08	0.02



Fig. 4 - Seasonal variation of estimated initial monthly average TVOC concentration as per various climate change scenarios

Estimated TVOC levels for different years (milligrams per cubic metre)							
Climate change scenario		AR4 A1B		AR4 A2		AR4 B1	
		2020	2040	2020	2040	2020	2040
	Minimum	1.45	1.51	1.46	1.50	1.46	1.50
Winter (January)	Maximum	2.15	2.18	2.15	2.18	2.16	2.18
	Minimum	1.38	1.47	1.37	1.46	1.39	1.44
Spring (March)	Maximum	2.20	2.20	2.20	2.20	2.20	2.20
	Minimum	1.11	0.67	0.99	0.74	1.11	0.99
Summer (May)	Maximum	2.20	2.20	2.20	2.20	2.20	2.20
	Minimum	2.00	1.98	2.06	1.83	1.91	1.76
Wonsoon (September)	Maximum	2.20	2.20	2.20	2.20	2.20	2.20

Table 2 - Minimum and maximum values of estimated TVOCs as per various seasons and climate change scenarios

# 2.4.2 Comparison of the estimated and the observed values in the conventional dwelling

The estimated values of TVOCs are the maximum initial emitted from the surface of wall paints. However, these values are further combined with the ageing effect to understand how the decay factor affects the emissions.

IA-Quest software is used to model the conventional dwelling and plot TVOC emission decay plots for the present and future scenarios. The simulated average TVOC emission value for the present comes out to be 0.063 mg/m<sup>3</sup> (as shown in Fig. 5), however, the average value from the data monitored in the conventional dwelling is 0.046 mg/m<sup>3</sup>. These emissions are further expected to decrease as per simulation for the year 2040 to 0.02 mg/m<sup>3</sup> (as shown in Fig. 6).



Fig. 5 – Simulation of TVOC in the conventional dwelling (2024)



Fig. 6 - Simulation of TVOC in the conventional dwelling (2040)

Fig. 7 shows the average values simulated for the years 2024 and 2040 along with the monitored value of TVOC emissions on the field in the conventional dwelling. For the newly constructed buildings, the initial TVOC emissions would be higher. These emissions are expected to decrease as per the decay models as the painted surface gets old (according to Equations 2a, 2b, and 2c) unless it is re-painted in between which can cause a sudden increase in TVOC emissions. The emission values are in the permissible range, however, continuous exposure to volatile organic compounds can cause chronic health impacts for occupants of the dwelling.



Fig. 7 – Comparison of simulated and monitored average TVOC values for 2024 and 2040

# 2.4.3 Comparison of the monitored values in the conventional and vernacular dwelling

The data for indoor temperature, indoor relative humidity and indoor TVOCs has been monitored in the case of conventional and vernacular dwellings as shown in Table 3.

Table 3 - Comparative indoor temperature, relative humidity and
TVOCs for conventional and vernacular dwelling

	Conventional				Vernacular		
,	T (°C)	RH (%)	TVOC (mg/m3)	Simulated TVOC (mg/m <sup>3</sup> )	T (°C)	RH (%)	TVOC (mg/m3)
Min	26	35.1	0.01	-	25.9	44.1	0.01
Max	33	68.2	0.5	-	28.9	66	0.31
Avg	29.2	51.2	0.03	0.06	27.4	55.8	0.02

TVOC concentration in the vernacular dwelling is lesser as compared to that in conventional dwelling as shown in Fig. 8. The peaks which are observed in the case of vernacular dwelling is because of burning incense stick inside the room, as reported by the residents of house, representing minimal emissions from the building material. This indicates that the naturally occurring materials do not significantly contribute to TVOCs as compared to modern building materials. It also highlights better indoor air quality in vernacular dwellings as compared to conventional counterparts.



Fig. 8 – TVOC in a conventional and vernacular dwelling for a typical week in March 2024

# 3. Conclusion

The study examines indoor moisture and air quality, characterised in terms of TVOCs. As the temperature is expected to rise over the years according to recent IPCC reports, VOCs from building materials are also expected to increase which can deteriorate the indoor air quality. This study focused on naturally ventilated buildings, taking the case of one conventional and vernacular dwelling in warm and humid climatic zone of India. The simulation results, for all three climate change scenarios, indicate that the initial concentrations of TVOCs would increase.

The simulations also indicate that the maximum average concentrations of TVOCs are found in the months of summer (May) and monsoon (September). In summers, the temperature increases and in monsoon, the humidity levels increase which results in increased values of TVOC. This suggests that higher levels of either temperature or relative humidity result in higher TVOC emissions. The emissions are expected to significantly decrease with increasing age of the paints, however, re-painting the surfaces can exponentially increase the emissions which can be harmful to the occupants of the dwelling. The vernacular dwellings are made up of earth-based materials and don't have paint coatings, hence, have lower TVOC emissions as compared to conventional dwellings. This suggests that naturally occurring materials can be used as building materials to improve indoor air quality. The emission factors used in this study are taken from the literature. However, experimental studies are envisaged to be taken up to calculate the emission factors for the presently available surface finishes including wall paints.

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# Nomenclature

Symbol	Description
RH	Relative Humidity (%)
Т	Temperature (° $C$ )
TVOC	Total Volatile Organic Compounds

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# Examining Indoor Humidity Ratio in Response to Varying Window-To-Wall Ratio and Ventilation in Indian Climate Zones for Earth-Plaster Based Dwellings

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#### Abstract

Indoor Earth-based plasters in buildings offer indoor humidity regulation through moisture buffering. This study examines the applicability of using earth-based plaster indoors as a passive strategy for regulating indoor humidity for occupant comfort, using a simulation-based approach. BESTEST model geometry was used to simulate indoor T/RH conditions with varying window-to-wall ratio (WWR) and air changes per hour (ACH) for Indian climate zones using EMPD (Effective Moisture Penetration Depth) model in DesignBuilder tool. Experimentally derived material properties of earth-plaster were used as input to the model. The results revealed that the surface area available for moisture sorption/desorption or WWR is critical in determining the moisture buffering potential. High WWR leads to low surface area available for moisture buffering, resulting in high diurnal indoor Humidity Ratio peaks. Also, air changes per hour (ACH) have a significant bearing on moisture buffering. As the ACH increases, the peaks in indoor HR increase and become closer to the outdoor HR. In this chapter, monthly mean indoor HR for the given geometry was computed for the 5 climate zones of India. These results were examined vis-à-vis indoor comfort Humidity Ratio recommendations for comfort (accounting for thermal, skin, and respiratory comfort) for occupants in the rural Indian setup as reported in our previous work. The results suggest that earth-plaster for moisture buffering can be effectively used in Warm and Humid, Hot and Dry, and Composite climate zones of India. Using this strategy in Temperate and Cold climate zones was not found effective. Earth-based plasters are derived from natural soil, and their use can avoid cementitious (energy and carbon-intensive) material and support occupants' wellness simultaneously.

#### Introduction and Motivation

Earth is a hygroscopic material used as a surface finish in many traditional architectural styles. Apart from the thermal properties of earth, it also offers excellent indoor humidity regulation (Priyadarshani et al., 2021a, 2021b, 2022, 2023). Indoor humidity is critical to occupant comfort, particularly impacting thermal, skin, and respiratory comfort. Regulating indoor humidity passively can help significantly reduce the building heating/cooling load. Depending on building typology, indoor temperature and humidity vary diurnally and seasonally in response to the external climatic conditions. Diurnal variation in indoor humidity is also attributed to moisture buffering in the case of hygroscopic surface finishes. Earth-based materials have been examined in the light of thermal performance; however, their implication on indoor humidity is often overlooked in presently available design guidelines for comfort and energy efficiency, more so in the case of naturally ventilated buildings.

This study aims

- To examine indoor Humidity Ratio in response to window-to-wall ratio and air change rates with the use of earth-based interior surface plaster.
- 2. To study the applicability of moisture buffering as a passive strategy for indoor moisture regulation in different climate zones of India.
- 3. To extend the adoption of earth-based plasters on conventional materials like fired-clay bricks masonry.

# 2. Materials and Methods

# 2.1 Hygrothermal Characterization of Earth Plaster

Earth-based dwellings in India were examined for indoor humidity regulation and plaster samples from these dwellings were collected. These samples were subjected to lab-scale tests to investigate their hygrothermal performance. Measurement of density, thermal conductivity, and dynamic vapor sorption (DVS) for the samples was conducted. The experimentally measured values were then used as input parameters to a whole-building computational for further analysis. The average density and thermal conductivity of the earth-based plaster samples were 1150 kg/m<sup>3</sup>, and 0.22 W/(m K), respectively. Further, the moisture transfer coefficients a, b, c, and d were calculated as 0.0139, 9.638, 0.025, and 0.676, respectively, based on the DVS. Material properties for the rest of the building materials were adapted from DesignBuilder material library.

## 2.2 Whole-Building Simulation

The ANSI/ASHRAE standard BESTEST (Building Energy Simulation TEST) case building was used to perform simulations using the Design-Builder tool (see Fig. 1).



Fig. 1 – Building geometry used for simulation (a) BESTEST case geometry (b) Wall assembly details

The simulation model was set up with the envelope material being a burnt clay brick wall with cement concrete plaster on the exterior side and earth plaster interiors. The floor and roof material were set as Reinforced Cement Concrete. The Moisture Penetration Depth Conduction Transfer Function (EMPD) solution method was used for computations. Multiple simulations were performed with Air change rates (ACH) varying from 0.5 (infiltration only) to 4 (highly ventilated) and with window-to-wall ratio (WWR) ranging from 0-100 were performed for five cities representing different climate zones of India as per the National Building Code of India (2005) (see Fig. 2). The results were then comfortable humidity ratio (accounting for thermal, skin, and respiratory comfort) for occupants of composite climate zone of India reported in our previous study (Priyadarshani et al., 2023).



Fig. 2 – Representative cities for different climatic zones selected for simulations

# 3. Results and Discussions

# 3.1 Comparing Humidity Ratio With and Without Moisture Buffering

Indoor humidity ratio peaks depend on the moisture buffering offered by the surface material. The diurnal peaks of indoor Humidity Ratio (HR) are regulated in the case of hygroscopic earth-based plaster material compared to the less hygroscopic cement-based plaster materials for the same outdoor conditions. The indoor HR trends resulting from earth-based and cement-based indoor plasters are shown in Fig. 3 for different months of the year. It clearly indicates dampened indoor HR in the case of more hygroscopic earth-based indoor plasters.



Fig. 3 – Indoor Humidity Ratio for earth-based (hygroscopic) and cement-based indoor plasters

# 3.2 Relationship between Outdoor and Indoor Humidity Ratio

The indoor HR variation in an enclosed space diurnally depends mainly upon the hygroscopicity of the indoor surface through moisture buffering. The extent of moisture buffering determines the amount of humidity that can be released/or adsorbed by the material in a situation of surface moisture concentration perturbation. Therefore, the difference between indoor and outdoor humidity is crucial to examine the effectiveness of moisture buffering in a given building enclosure. The difference in humidity ratio between outdoor and indoor with varying ACH for Bangalore is shown in Fig. 4. The humidity excess/deficit (Indoor HR – Outdoor HR) between outdoor and indoor changes with season, consistently being higher when the air change rates are lower. This occurs because of a moisture source (occupancy) present indoors, and the absence of air change led dilution to reduce indoor air humidity.



Fig. 4 – Variation in humidity deficit/excess (Indoor-Outdoor HR) for a typical week in Bangalore (temperate climate zone) with varying air changes per hour

The indoor humidity excess is higher during the winter (January) and monsoon (September) weeks, with a difference of ~5 g-wv/kg-da in winter and ~3 g-wv/kg-da in monsoon (low infiltration rates). As the air changes per hour become higher, the indoor humidity approaches outdoor humidity levels. Interestingly, the variations in humidity deficit/excess are higher at low ACH (say infiltration, ACH=0.5), suggesting high buffering capacity. The difference in diurnal variation in Bangalore is ~6 g-wv/kg-da. In the case of Ahmedabad, the variations are highest in May, and the differences in outdoor and indoor humidity are as high as 10 g-wv/kg-da.

Kolkata is situated in the warm and humid climate zone, and the difference in outdoor and indoor humidity is the lowest (<2 g-wv/kg-da) in most of the months. Composite climate zone is characterized by cold winters, hot summers, and humid monsoons. In the case of Delhi, the difference between outdoor and indoor humidity in winter reflects the cold indoor environment, causing very low indoor humidity (less than outdoors). The humidity difference variations in the warmer months of March, May, and September are similar with a humidity difference of ~3 g-wv/kg-da at low ACH/infiltration.



Fig. 5 – Indoor Humidity Ratio with changing Window to Wall Ratio at ACH=0.5 (only infiltration) for Bangalore during winter (low humidity) and monsoon season (high humidity)

In the cold climate zone, Shimla, with low air temperatures, the capacity of air to hold water vapor is also low. Also, the range of humidity variations in the colder conditions, specifically below 10 °C is very narrow. This is reflected in a very low moisture loading rate, correspondingly leading to less difference between the indoor and outdoor air humidity ratio (<2g-wv/kg-da) even at low air change rates.

# 3.3 Impact of Window-To-Wall Ratio

Window-to-wall ratio (WWR) is the ratio of the area of windows/openings to the ratio of the wall surface. Since wall surfaces are hygroscopic in nature, the surface area exposed to the indoor air impacts the diurnal variations of indoor humidity ratio through moisture buffering.

Table 1 – Details of Building geometry (Surface Area and Vo	-וכ
ume) for the simulation case building	

	Wall Sur face Area (m²)	-Volume (m³)	Wall Area/Volu (m²/m³)	Surface me
WWR00	75.6	129.60	0.58	
WWR10	68.04	129.60	0.53	
WWR20	54.44	129.60	0.42	
WWR30	38.1	129.60	0.29	
WWR40	22.88	129.60	0.18	
WWR50	11.44	129.60	0.09	
WWR60	4.58	129.60	0.04	
WWR70	1.36	129.60	0.01	
WWR80	0.28	129.60	0.00	
WWR90	0.04	129.60	0.00	
WWR100	0	129.60	0.00	

For the same rate of moisture generation introduced in the simulation model (occupancy), the peaks are best regulated in the case of WWR=0% and have maximum diurnal variations when WWR=100% (see Fig. 5) for the case of Bangalore. Window to wall ratio is critical for the design of buildings. A WWR that is too low can result in no natural daylighting, and a WWR that is too high can result in excessive radiative heat gains through windows, leading to high cooling loads.

Given the role of WWR in the thermal performance of buildings, the optimum WWR is suggested to be between 20-30% (Ahmed et al., 2023). Therefore, to employ moisture buffering, it is critical to examine the indoor humidity ratio levels vis-à-vis climate zones.

The higher the surface area available for adsorption/desorption for a given air volume, the higher the moisture buffering potential of an enclosure. The peaks in indoor HR are lowest in the case of low WWR. HR variation with varying ACH for WWR between 20-40% (for both daylighting and thermal comfort) is found comparable. Therefore, it is fair to consider an average of WWR 30 to examine the impact of ACH. Correspondingly, the presented results are applicable for a Wall surface/ Volume ratio of 0.18-0.42 (see Table 1).

Further, as stated previously, the impact of ACH and WWR varies as the outdoor environmental conditions vary. At lower temperatures, the air can hold less humidity when compared to higher temperatures. Therefore, this phenomenon varies with seasons.

The simulations pertaining to different climate zones for ACH=0.5,1,2,3, and 4 and WWR=30 have been shown in Fig. 7. It can be seen that the mean Humidity Ratio Levels vary seasonally. It is, therefore, critical to assess the applicability of moisture regulation as offered by the application of earth plaster for comfort in different months of the year. Fig. 7 also shows the mean indoor HR values expected vis-à-vis recommended Humidity Ratio values suggested in literature (De Dear & Brager, 2002; Kong et al., 2019; Li et al., 2019). Indoor Humidity Ratio Vis-à-vis Recommendations for Comfort

Recommendations for upper limits of HR have been viewed from both buildings' and occupants' health perspectives. In cold climates, the wall surfaces become cold frequently (with temperatures lower than the dew point temperature); therefore, the risk of interstitial condensation causing dampness on walls is higher. This is an essential reason for ASHRAE-55 standards suggesting an "upper limit" for indoor humidity ratio, focusing on preventing moisture-associated defects like surface condensation, mold growth, etc.

However, this upper limit being comfortable concurrently for occupants' health needs careful examination. Recent occupant comfort centric studies suggest a higher value of indoor HR for comfort (>17 g-wv/kg-da) (Kong et al., 2019; Li et al., 2019). Therefore, in tropical regions, the comfort standards applicable for examining humidity in buildings are unclear.

It can be observed that the applicability of hygroscopic earth plaster as a passive design strategy for indoor humidity-related comfort is dependent on the benchmarking comfort values. There is a wide variation when indoor HR is examined for prescribed recommendations.



Fig. 6 - Mean monthly indoor HR vis-à-vis comfortable HR limits based on (Priyadarshani et al., 2023)

It can be seen that with comparatively lower HR recommended by ASHRAE-55, i.e., 12 g-wv/kg-da, the indoors can be categorized as comfortable, unlike in other recommendations. Another important observation is that in a cold climate zone, irrespective of the recommendation values used, the indoor humidity is very low and mostly uncomfortable.

In temperate climate zones, the mean HR values conform to the ASHRAE-55 standards. Still, they are consistently in deficit by nearly 5-7 g-wv/kg-da with recommendations of the studies done in tropical areas. In ascertaining the applicability of the design strategy explained in this work, comparing the values with a "comfortable" indoor HR for local occupants is essential. Our previous work suggests the optimum humidity ratio levels for occupant comfort

in rural India (composite climate zone) range from 17.4-22.6 g-wv/kg-da (Priyadarshani et al., 2023). Mean monthly HR ranges using hygroscopic earthplaster indoors vis-à-vis comfortable HR values for the study participants have been shown in Fig. 6. Also, Fig. 8 shows the monthly applicability of earth-based interior plasters and illustrates the need for appropriate moisture regulation for comfort. Results indicate that it can be a potential strategy in warm and humid, hot and dry, and Composite climate zones when existing recommendations are followed; however, its use in temperate and cold climate zones needs further scrutiny. The need for a comfortable HR for local occupants is critical in proposing guidelines for using moisture buffering as a passive design strategy for indoor comfort.



Fig. 7 – Mean monthly indoor HR for different climatic zones with varying ACH vis-à-vis prescribed recommendations for optimum HR by ASHRAE-55 (Li et al., 2019) and (Kong et al., 2019)

# 4. Conclusion

The study highlights the importance of moisture buffering indoors provided by hygroscopic earth plaster and its implications on indoor Humidity Ratio. Experimentally derived hygrothermal properties of earth materials were appropriately relied on to simulate its impact at a whole-building level. The study highlights that ACH and WWR are critical parameters influencing moisture buffering as a passive strategy to regulate moisture in naturally ventilated buildings. Further, its applicability in different climate zones has been examined. Results indicate that indoor earth-based plaster can regulate in

Temperate Climate: Bangalore					
ACH	0.5	1	2	3	4
Jan	12.23	11.00	10.41	10.22	10.14
Feb	10.19	8.85	8.24	8.05	7.95
Mar	12.62	11.43	10.88	10.71	10.64
Apr	13.44	12.12	11.51	11.32	11.24
May	17.53	16.11	15.47	15.28	15.19
Jun	17.45	15.74	14.91	14.68	14.58
Jul	16.38	14.75	14.02	13.82	13.73
Aug	17.42	16.17	15.53	15.34	15.25
Sept	16.80	15.28	14.52	14.31	14.21
Oct	16.73	15.14	14.49	14.32	14.24
Nov	14.59	12.92	12.20	11.99	11.90
Dec	13.10	11.65	11.12	10.97	10.90

Hot and Dry Climate: Ahmedabad					
ACH	0.5	1	2	3	4
Jan	8.86	8.18	7.80	7.66	7.59
Feb	9.86	8.90	8.43	8.28	8.21
Mar	11.50	10.42	9.90	9.73	9.64
Apr	13.20	11.80	11.10	10.87	10.75
May	17.69	16.46	15.90	15.73	15.65
Jun	22.05	20.63	20.02	19.85	19.77
Jul	24.14	22.82	22.15	21.94	21.83
Aug	23.21	21.68	20.79	20,49	20.34
Sept	21.98	20.17	19.21	18.92	18.79
Oct	19.04	16.62	15.60	15.30	15.15
Nov	13.34	11.08	10.22	9.95	9.82
Dec	11.61	10.19	9.65	9.48	9.40

Warm and Humid Climate: Kolkata					
ACH	0.5	1	2	3	4
Jan	10.11	10.02	9.70	9.61	9.56
Feb	11.84	11.44	10.94	10.80	10.73
Mar	16.30	16.10	15.65	15.53	15.49
Apr	19.85	19.50	18.87	18.68	18.59
May	22.29	21.98	21.21	20.96	20.85
Jun	23.30	23.23	22.60	22.40	22.31
Jul	24.11	24.13	23.37	23.10	22.98
Aug	23.05	22.76	21.93	21,66	21.53
Sept	22.76	22.69	21.92	21.66	21.55
Oct	21.73	21.25	20.30	19.99	19.83
Nov	16.72	16.27	15.46	15.20	15.09
Dec	12.41	11.79	10.97	10.74	10.63

door humidity, dampening the HR peaks, which is beneficial both from energy efficiency and occupants' comfort and health (thermal, skin, and respiratory) perspective.

This strategy is most effective in warmer months in warm and humid, hot and dry, and Composite climate zones. A major challenge associated with the use of this strategy in temperate and cold climate zones corresponds to low surface temperatures leading to condensation risk. From the occupant's health and IAQ perspective, earth is naturally derived, does not pose a risk of exposure to harmful chemicals like VOCs, and ensures occupants' wellness.

Composite Climate: Delhi					
ACH	0.5	1	2	3	4
Jan	7.93	7.67	7.53	7.49	7.46
Feb	9.54	8.98	8.72	8.64	8.60
Mar	11.01	10.05	9.58	9.43	9.36
Apr	11.68	10.26	9.57	9.34	9.23
May	17.32	15.98	15.33	15.13	15.02
Jun	19.65	18.25	17.59	17.39	17.29
Jul	22.34	20.43	19.56	19.29	19.17
Aug	23.15	21.28	20.48	20.24	20.14
Sept	22.14	19.77	18.69	18.36	18.20
Oct	17.55	15.22	14.24	13.96	13.83
Nov	11.43	9.63	8.97	8.77	8.68
Dec	9.17	7.90	7.41	7.27	7.20

Cold Climate: Shimla					
ACH	0.5	1	2	3	4
Jan	4.49	4.18	3.98	3.91	3.88
Feb	4.92	4.63	4.49	4.44	4.42
Mar	5.93	5.44	5.20	5.11	5.08
Apr	7.74	7.10	6.79	6.69	6.64
May	9.10	8.06	7.53	7.36	7.27
Jun	12.53	11.83	11.56	11.49	11.46
Jul	15.31	14.57	14.20	14.08	14.02
Aug	15.84	15.28	14.94	14.82	14.76
Sept	14.87	13.96	13.40	13.21	13.11
Oct	10.54	9.40	8.77	8.56	8.45
Nov	7.74	6.71	6.20	6.04	5.96
Dec	5.51	4.84	4.52	4.41	4.36



Comfortable Humidity Ratio (17.4-22.6 g-wv/kg-da)

Excess Humidity : Dehumidification / Ventilation Required

Fig. 8 – Mean Indoor Humidity Ratio with earth-based plaster used as interior surface finish for Wall surface to volume ratio  $0.18-0.42 \text{ m}^2/\text{m}^3$  (WWR =20-40%) for different climate zones in India

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# Calibrated BEMs and LSTM Neural Networks for Indoor Temperature Prediction: A Comparative Analysis in Pre- and Post-Retrofit Scenarios

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#### Abstract

The need to mitigate the risks of overheating in buildings due to climate change has highlighted the importance of accurate models for predicting indoor temperatures and thermal comfort, particularly after retrofitting. To this end, white-box models, such as Building Energy Models (BEMs), and black-box models, such as Long Short-Term Memory (LSTM) neural networks, have been extensively used in recent decades. While BEMs provide detailed insights through physically-based simulations, requiring calibration for enhanced accuracy, LSTMs provide a datadriven approach that captures complex thermal dynamics with greater simplicity, albeit with less interpretability. Few studies have undertaken a comparative analysis of these models in terms of prediction accuracy, especially across pre- and post-retrofit conditions and different lengths of training periods. Thus, in this study, a comparison between the predicting capabilities of calibrated BEMs and LSTM in summer was carried out using two real monitored mock-ups in Northern Italy representing both pre- and post-retrofit conditions. The results show that, for the considered limited training periods (8 and 3 days), the dataset size does not significantly influence BEM accuracy, while LSTM accuracy is more affected. Moreover, BEMs show higher prediction accuracy in scenarios with higher indoor air temperature (IAT) variability, i.e. where unseen data could be less predictable, such as in pre-retrofit conditions. LSTMs, however, excel in low-variability scenarios, such as the post-retrofit conditions in this case. This study highlights the critical need for careful model selection and calibration based on the data availability and building typology to ensure prediction reliability.

# 1. Introduction

The need to mitigate overheating risks in buildings under climate change scenarios, coupled with the rise in the adoption of Model Predictive Control and fault detection and diagnosis (FDD) systems, led to the need for accurate indoor temperature and thermal comfort prediction models, especially for postretrofit conditions. To achieve this aim, white-, greyand black-box models have been widely adopted in recent decades (Shahcheraghian et al., 2024). White boxes, such as Building Energy Models (BEMs), use physically based simulations of building dynamics, providing detailed insights and good prediction, especially if a calibration procedure is undertaken. Back-box models, such as Long Short-Term Memory neural networks (LSTM), employ a fully datadriven approach to capture complex thermal dynamics, offering simplicity and adaptability but at the cost of reduced interpretability (Mtibaa et al., 2020; Lu et al., 2022; Cui et al., 2023). Given that each methodology presents its advantages and drawbacks, and that various models have shown differing performance in different scenarios, it is important to undertake a thorough comparison to guide model selection. However, to the authors' knowledge, few studies have aimed to compare the accuracy of these modeling approaches under different conditions. In Arendt et al. (2018), white-, grey- and black-box models are compared in terms of indoor air temperature (IAT) predictability, finding that black-box models outperform grey- and white-box models in quite almost the considered scenario, with grey-box models needing shorter training periods for good accuracy. In Afram and Janabi-Sharifi (2015), Cui et al. (2023), and Vivian et al. (2024), grey- and black-box models are compared, finding that, on average, LSTM outperforms grey-box models albeit grey-box models remain a valid alternative, especially in case of low data availability. In Hauge Broholt et al. (2022), the robustness of black and grey-box models of thermal building behavior against weather changes is evaluated. The authors found that the predictive performance of the grey-box models was slightly better compared to the black-box model in this case. However, not all these studies include white-box models, building envelopes, and the indoor environment, as well as different scenarios such as pre- and post-retrofit conditions.

One of the main advantages of white-box models when compared to black-box ones is that once calibrated they can be modified to reflect optimization changes in the represented object. Several Standards suggest the adoption of calibrated simulations to estimate the energy saving achievable through energy retrofit measures (EVO, 2012; ASHRAE, 2014). However, a few studies verified the accuracy of a BEM calibrated in pre-retrofit conditions in predicting the thermal and energy response of a retrofitted one (Chong et al., 2021).

For these reasons, this study has two main objectives, i.e.

- to compare the accuracy of BEMs and LSTM models in predicting the indoor thermal response of buildings considering both pre- and post-retrofit conditions and different training periods;
- to assess the ability of BEMs, calibrated in preretrofit conditions, to reproduce the post-retrofit indoor thermal response, also considering post-retrofit, i.e. second-stage, calibration.

The findings of this study can help researchers and engineers select the best model for IAT prediction based on data availability and building typology. The paper is organized as follows: Section 2 describes the methodological approach, the experimental setup, and the adopted modeling methods.

Section 3 reports the comparison between models and a critical discussion of the results. Finally, Section 5 summarizes the key findings of the research.

# 2. Phases, Materials and Methods

## 2.1 Phases

The work is subdivided into the following three phases:

- first, two identical pre-retrofit mock-ups (Cell A and Cell B) representative of Italian buildings from the 1960s were built and their thermal response was monitored and compared in preretrofit conditions to provide proof that the construction process led to the same thermal response;
- then, BEMs and LSTM models were created and calibrated, and then compared in pre-retrofit conditions in terms of model accuracy also considering different training periods, to identify the best solution and training period in this case;
- finally, a comparison between BEM and LSTM models in the post-retrofit scenarios was made (Cell A was retrofitted in the second year). In particular, the LSTM was recreated using the post-retrofit data. Conversely, to assess the capacity of BEMs calibrated in pre-retrofit conditions to predict the post-retrofit IAT after the appropriate upgrades, a post-retrofit BEM was created by modifying the pre-retrofit calibrated one and then recalibrating it only by tuning the properties of the new layer (e.g. external insulation) and modified building characteristics (e.g. infiltration rate).

# 2.2 Experimental Setup

Two identical free-running experimental test cells (Cell A and Cell B) were constructed in Malosco, Italy (1041 m a.s.l.), to allow an experimental comparison between pre- and post-retrofit scenarios considering the same outdoor conditions (see Fig. 1a and b), which is a quite rare comparison in the existing literature. The cells, designed to be representative of the construction type and size of a typical Italian room in a pre-retrofit condition, were monitored for two consecutive years. After the first year, Cell A was retrofitted with an innovative, nonintrusive, and modular timber façade system, enabling an experimental comparison between pre- and



Fig. 1 – a) Geometrical description of the experimental units and sensors placement (dimensions in centimeters). b) The two test cells before retrofit; c) Cell A after retrofit

post-retrofit scenarios under similar external conditions (Fig. 1c). In particular, a novel, prefabricated, multi-layered insulation panel made of a self-sustained wood frame filled with mineral wool and enclosed with OSB panels was applied to the walls providing an additional, nominal wall thermal resistance of 7.81 m<sup>2</sup>K/W (Callegaro & Albatici, 2023). No internal loads were present during the periods considered to solely assess environmental influences on indoor conditions, providing ground truth data for model calibration. More information on construction features, building characteristics, and monitoring systems can be found in (Callegaro & Albatici, 2023).

## 2.3 White-Box Model

## 2.3.1 Building energy modeling

The Sketchup v. 2013 was used as a graphical interface of the EnergyPlus v.22.2.0 simulation engine (DOE 2017) to create the BEM of the test cells, following modeling methods described in (Maracchini & D'Orazio, 2022). In particular, the Conduction Transfer Function (CFT) was adopted as a heat balance algorithm with 6 timesteps per hour considered for calculation. Internal and external convective heat transfer coefficients were computed by adopting an adaptive convection algorithm, since generally more reliable for calculating convective heat transfer coefficients if compared to other techniques (Costanzo et al., 2014). The Flow Coefficient model was finally implemented to model the infiltration rate (Maracchini & D'Orazio, 2022).

## 2.3.2 Sensitivity analyses and calibration

A software tool specifically developed by the authors was used for the model calibration (Maracchini, 2023). This tool integrates the Morris method for parameter screening (Saltelli et al., 2008; Tian and Wei, 2013) with the Non-dominated Sorting Genetic Algorithm (NSGA-II) for the optimizationbased calibration (Martínez et al., 2020; Vera-Piazzini & Scarpa, 2024). In particular, the Morris method is used to identify the parameters with uncertainty that mostly impact model accuracy and then those that can be discarded from the calibration process to reduce the computational burden without reducing calibration effectiveness.

All the most relevant parameters were considered for both sensitivity analysis and calibration. The parameters considered for calibration and the related range of variations are reported in Table 1 for both pre-retrofit and post-retrofit scenarios. A multiplier approach was adopted to avoid compensation errors among layers of the same building component. For example, for each component type (walls, roof, and floor), all the conductivities were grouped with a single multiplier that was varied between a range of ±20% (WALL\_COND, ROOF\_COND, etc.). Similarly, for each component, the density and specific heat capacity of all the layers were grouped using a volumetric heat capacity (VHC) multiplier, used to avoid compensation errors in terms of thermal inertia effects.

Concerning the target function used in both the sensitivity and calibration processes, different error metrics can be used (Martínez et al., 2020). In this work, the Root Mean Square Error (RMSE) was used as a target function for the sensitivity analysis while, for the calibration, a single-objective optimization approach was adopted with a target function computed as the product between the RMSE, the R2, and a novel indicator introduced in this study, named Maximum Absolute Hourly Difference (MAD) computed between simulated and measured data. This approach is considered more effective than the use of multi-objective optimization since it can provide optimized solutions with a lower computational time while being sufficiently accurate in terms of both absolute errors and inertial effect.

Concerning the post-retrofit conditions, only the parameters of the added layer and the modified building characteristics (e.g. infiltration rates, i.e. flow coefficient) are varied for model calibration (see Table 1). Due to the low number of parameters considered, a sensitivity analysis was not necessary in this case.

Table 1 – Parameters and related ranges considered in sensitivity and BEM calibration processes. Parameters with \* are multipliers. WIN: windows; VHC: Volumetric Heat Capacity; TA: Thermal Absorptance; SA: Solar Absorptance; COND: conductivity; SR: Solar Reflectance; T: Temperature. Parameters with X in the post-retrofit column are considered for calibration of new layers/modified building characteristics.

Parameters	Range	Post-retrofit
WALLS_COND*	[0.8, 1.2]	Х
WALLS_VHC*	[0.8, 1.2]	Х
WALLS_TA	[0.8, 0.95]	Х
WALLS_SA	[0.1, 0.3]	Х
ROOF_COND*	[0.8, 1.2]	
ROOF_VHC*	[0.8, 1.2]	
FLOOR_COND*	[0.8, 1.2]	
FLOOR_VHC*	[0.8, 1.2]	
ROOF_TA	[0.8, 0.95]	
ROOF_SA	[0.3, 0.8]	
DOOR_COND*	[0.2, 2.0]	
DOOR_VHC*	[0.2, 2.0]	
DOOR_TA	[0.8, 0.95]	
DOOR_SA	[0.3, 0.8]	
WIN_COND*	[0.2, 2.0]	Х
WIN_TA	[0.8, 0.95]	Х
WIN_SA	[0.3, 0.8]	Х
FLOW_COEF	[0.0001, 0.007]	Х
GROUND_T [°C]	[13.0, 17.0]	
GROUND_SR	[0.15, 0.25]	

## 2.4 Black-Box Model

Concerning black box models, pure Artificial Neural Networks such as the Long-Short-Term-Memory neural networks (LSTM) were adopted using their capacity to learn long-term dependencies in dynamic systems like buildings (Lu et al., 2022). LSTM models consist of chains of neural network modules, focusing on a cell state mechanism that manages information flow through gates, by adopting the following workflow:

- 1. First, a forget gate determines what information to discard from the cell state.
- Then, an input gate decides which new information to add to the cell state. This involves a gate that selects values to update and a *tanh* layer that generates a vector of new candidate values that could be added to the state;
- Thirdly, the old cell state is updated with the new values identified in the previous step;
- 4. Finally, the final output is generated based on the updated cell state, which is modified by an output gate that applies a *tanh* function to scale the values between -1 and 1.

In this study, LSTM was developed with the Python TensorFlow library (TensorFlow Developers, 2024) and calibrated through different steps involving generating the network, optimizing hyperparameters, and training it to assimilate system behavior. This process includes layering LSTM with a fully connected layer and a sigmoid function, normalizing input data, and adjusting hyperparameters like learning rate, hidden layer size, and optimization algorithms (see Table 2) to minimize loss, ensuring the model avoids underfitting or overfitting by regulating training iterations (epochs) (Vivian et al., 2024).

Table 2 – Hyper-parameters optimization.

Hyper-parameters	Options
Learning rate	[0.01, 0.001, 0.0001]
LSTM hidden layer size	[16, 32, 64, 128]
Optimization algorithm	Adam, RMSprop

#### 2.5 Model Accuracy Comparison

The evaluation and comparison of the performance of the models was carried out both qualitatively (graphical comparison) and quantitatively. In the latter case, reference is first made to common error indicators computed between predicted and observed data, such as RMSE, R2, and the additional MAD indicator introduced in this study.

The period considered for model calibration and comparison goes from the 21st of June to the 1st of July 2021 for both Cell A (post-retrofit condition) and Cell B (pre-retrofit condition). The hourly dataset was subdivided into training and testing datasets. For the training one, different lengths were considered for comparison purposes equal to 3 and 8 days, respectively. The test datasets instead referred to the last 3 days of the period considered.

# 3. Results and Discussion

# 3.1 Experimental Comparison

In this section, a comparison between the experimental IAT profiles obtained for the two mock-ups in pre-retrofit conditions (first summer) is reported. As can be seen from Fig. 2, a very good agreement is obtained in terms of IAT. In particular, RMSE, R2, and MAD values computed between the two datasets are equal to 0.14 °C, 1.00, and 0.20 °C, respectively. The R2 value denotes a perfect alignment of the two curves in terms of trend and inertial effect, while the two error indicators (RMSE and MAD) denote a negligible difference between the two mockups, even lower than the instrument accuracy, thus denoting a complete overlapping between the two IAT profiles. Thus, the two cells showed the same thermal response, and the two buildings can be correctly used for comparative purposes between pre- and post-retrofit conditions.



Fig. 2 – Comparison between test cells in pre-retrofit conditions

# 3.2 Pre-Retrofit Comparison

In this section, the results of the pre-retrofit comparison are reported and discussed. Fig. 3 reports the results of the sensitivity analyses in terms of the mean value of the absolute values of the elementary effect  $\mu^*$ , which is used to rank the parameters from the most to the least important in calibration processes (Tian & Wei, 2013).



Fig. 3 – Sensitivity analyses results in terms of  $\mu^*$  computed on RMSE values [°C]. Only the most parameters are reported for the sake of brevity

As can be seen, in this case, the solar absorptance of the walls (WALLS\_SA) is the most important parameter for IAT prediction, followed by door SA and window thermal conductivity. Parameters not reported in Fig. 3 have a negligible effect on the IAT, and therefore are not considered for model calibration.

In Fig. 4a, the comparison between BEM and LSTM output is provided in terms of IAT profiles, while Table 3 reports the values of the accuracy indicator. Both the BEMs calibrated with 3 and 8 training days (BEM B3 and BEM B8, respectively) show a good agreement with the experimental data in both the training and testing phases, with a strong reduction of the initial RMSE, R2, and MAD (equal to 2.74 °C, 0.59 and 3.6 °C, respectively, for the training period). The overlapping between the BEM B3 and BEM B8 model outputs indicates that, in this case, BEM models seem not to be affected by the variation in training length, thus the shorter length is considered sufficient for predicting testing data.

Conversely, as expected, LSTM models (LSTM B3 and LSTM B8) seem to be more affected by the training dataset length (see Fig. 4a), with increasing accuracy when longer periods are considered. In general, however, LSTMs outperform BEMs in the training phase, while the inverse is observed in the testing phases. This denotes the difficulty of LSTMs to predict new data points with the considered training periods and highlights the need for a larger dataset for training.
Table 3 – Accuracy indicators in pre- and post-retrofit conditions with 3 and 8 training days. RMSE and MD values in °C. tr: training; t: testing. Best results are underlined

Model	RMSEtr	$R2_{\rm tr}$	MAD <sub>tr</sub>	RMSEt	R2t	MADt
BEM B3	0.28	0.93	0.44	0.21	0.99	0.50
BEM B8	0.36	0.91	0.69	0.24	0.98	0.38
LSTM B3	0.27	0.98	0.52	0.56	0.99	1.28
LSTM B8	0.03	1.00	0.20	0.49	0.91	0.95
BEMB3up	0.44	0.74	0.82	0.70	0.80	1.26
BEMB8up	1.24	0.56	2.13	1.24	0.88	1.78
BEM A3	0.30	0.82	0.43	0.40	0.91	0.90
BEM A8	0.41	0.74	0.84	0.42	0.94	0.74
LSTM A3	0.01	1.00	0.03	0.10	0.94	0.30
LSTM A8	0.02	1.00	0.14	0.09	0.94	0.23

#### 3.3 Post-Retrofit Comparison

One of the main advantages of BEMs when compared to LSTM is that they can be modified to reflect changes in the building over its lifetime and that were not considered in the training phase. To understand the capability of BEMs calibrated on preretrofit conditions to predict the thermal response of a retrofitted building, BEM B3 and BEM B8 were updated to reflect the energy retrofit modifications that occurred in Cell A.

In Fig. 4b, the comparison between BEM and LSTM output is provided in terms of IAT profiles, while Table 3 reports the values of the accuracy indicator. As expected, despite the improvement, the obtained model (BEM B3up and BEM B8up in Fig. 2b) provides accuracy indicators lower than that previously achieved for BEM B3 and BEM B8 (see Table 3).

This can be traced back to:

- the different construction features that are not considered in the model upgrade (e.g. infiltration);
- the uncertainty related to the thermal properties of the newly added materials;
- iii) overfitting/compensation errors that may have occurred during the calibration phase of B3 and B8 models.

To reduce the impact of the two first error categories, a recalibration of B3up and B8up was carried out by fine-tuning building infiltration parameters



Fig. 4 – Comparison between predicted and observed IAT in both training and testing phases considering (a) pre- and (b) post-retrofit conditions

and thermal properties of the added wall layers, obtaining two "two-staged" calibrated BEMs BEM A3 and BEM A8. The obtained profiles show an accuracy higher than that previously observed (Fig. 4b) but still lower than that obtained through a full calibration with all relevant parameters involved (as in BEM B3 and BEM B8 cases, see Table 3). This may be caused by the presence of overfitting/compensation errors in the pre-retrofit calibration phase, which is also stressed by the different output profiles obtained for B3up and B8up (which were identical in Fig. 4a). Concerning LSTMs (LSTM A3 and LSTM A8), better performance is obtained, even better than that achieved in the pre-retrofit phase (LSTM B3 and LSTM B8) in both training and testing phase. Moreover, a lower dependence of LSTM on the training period can be observed. This can be due to the lower variability and dependence of observed indoor data on outdoor predictors in this case (postretrofitted Cell A), which makes this scenario easier to predict than a pre-retrofit one, even with shorter training datasets.

# 4. Conclusions

This study investigated the accuracy of calibrated BEMs and LSTM models in predicting IATs in summer, in both pre- and post-retrofit scenarios. The results showed that in pre-retrofit conditions BEMs have consistent accuracy regardless of the training dataset size. Post-retrofit updates to pre-retrofit calibrated BEMs decreased their accuracy due to unaccounted changes and uncertainties. Recalibration of new parameters improved the performance, although it did not reach pre-retrofit accuracy levels, probably due to overfitting/compensation errors in the pre-retrofit phase. Therefore, particular attention should be paid to this aspect or compensation errors when using calibrated simulations should be reduced. LSTMs increase accuracy with longer datasets in pre-retrofit conditions while performing better in post-retrofit, benefiting from reduced data variability and external dependencies, indicating shorter training datasets could be sufficient in this scenario.

The main limitation of this study lies in the use of: a) a single and limited monitoring period, b) a single construction system, and c) a specific building geometry and location for carrying out the comparisons. Therefore, future studies should be carried out to extend this work and make the results more generalizable. Further studies will also investigate the accuracy of calibrated BEMs in predicting other important output variables not considered in this study, such as relative humidity and heat fluxes.

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# Impact of Different Radiation Decomposition Models and ERA5 Dataset on Building Energy Simulation Results: A Case Study in Brazil

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#### Abstract

This study compares three different radiation decomposition models (Erbs, DIRINT, and DISC) for estimating direct normal radiation to the data from the reanalysis dataset ERA5. It also evaluates the impact of considering these different models and datasets on building energy simulation outcomes for three locations in Brazil (Brasília, Salvador, and São Paulo). As the simulation study case, we analyzed a typical residential building in the Brazilian context. This building model was analyzed in three different cases (Brazilian standard building characteristics reference, low solar absorptance values, and considering a 0.80 m overhang). Regarding radiation datasets, the Erbs model exhibited the lowest RMSE for direct and diffuse radiation compared to the monthly values provided by the Brazilian Solar Atlas. By analyzing the RMSE values, we demonstrated that ERA5 overestimated direct normal radiation while significantly underestimating diffuse values compared to the Solar Atlas. Concerning simulation results, we observed differences of up to 14% higher cooling load values when comparing the results using ERA5 data with the DISC model ones. However, maximum operative temperatures did not show such significant differences, with a maximum deviation of 1%. Also, the three cases tested demonstrated the sensitivity of the building simulation to the different radiation datasets. These results are important for advancing the understanding of the impacts of using reanalysis datasets, which is becoming an increasingly common approach.

# 1. Introduction

The impact of solar resources directly influences the outcomes of building energy simulations (BES). However, measurements are frequently restricted to global radiation, with limited data on its components: direct and diffuse. While global radiation can be readily and cost-effectively measured, obtaining data on the more expensive measurements of direct and diffuse components is less common (Schlager et al., 2023). Henceforth, various models for decomposing direct and diffuse radiation have been developed since the 1960s (Liu et al., 1960). These models may rely on global radiation values, solar elevation, apparent solar time, air temperature, and cloudiness.

In recent years, reanalysis data has been employed to develop weather files for BES. Reanalysis datasets combine historical observations into global estimates using advanced modelling and data assimilation systems (ECMWF, 2024). The ERA5 dataset from the European Center for Medium-Range Weather Forecasts is among the extensively utilized reanalysis datasets.

Researchers have been analyzing the impact of different decomposition models on simulation outcomes. Zweifel and Zelenka (2007) assessed that improvements in radiation data modelling could significantly affect BES results in Switzerland. They found a 34% increase in cooling load values when comparing different datasets with different radiation decomposition models. However, these datasets also exhibited temperature modifications. Lupato et al. (2017) compared 33 different split algorithms with data measured over ten years in Trieste, Italy. In this case, the Perez model (Perez et al., 1992) performed significantly better than the other models. When considering simulation results, errors of up to 4% were found for cooling and heating loads for this model compared with the case considering the ground measurements.

Copper and Sproul (2013) compared various models to estimate both global irradiance and its direct and diffuse components using data collected in Australia. The authors also assessed the impact on BES results. This study suggests that bias and uncertainty in simulation results were minimal when global irradiance was measured, and only diffuse and direct irradiance were estimated. However, when global irradiance was unknown, bias and uncertainty levels notably increased.

Some studies have also examined how ERA5 data compare to measurements. Sianturi et al. (2019) evaluated the ERA5, and MERRA-2 datasets compared to ground observations in Indonesia. The authors reported that ERA5 tends to overestimate monthly solar radiation. Additionally, they noticed that both reanalysis models tend to overestimate values, especially on cloudy days. Cao et al. (2022) conducted a similar study in China, considering ERA5 and MERRA-2, along with two satellitederived datasets, compared to 98 solar radiation measurement stations. Their findings revealed that the ERA5 data overestimated the direct normal component. Additionally, they observed that daily global radiation data exhibited greater accuracy than direct, diffuse, and hourly global solar radiation products.

In the Brazilian context, a widely used data source for solar resources is the Brazilian Solar Atlas (Pereira et al., 2017). The atlas has a horizontal spatial resolution of 0.09° x 0.09° (approximately 10 x 10 km at the satellite's zenith axis). The Solar Atlas was developed based on the satellite radiation model BRASIL-SR (Martins et al., 2007), derived from the GKSS model (Stuhlmann et al., 1990) and adapted to the typical Brazilian climate and seasonal atmospheric conditions. As a validation step for the development of the atlas, a statistical comparison was made with 503 surface meteorological stations from INMET (National Institute of Meteorology) and INPE (Brazilian Institute for Space Research), considering the period from 2005 to 2015.

This study aims to compare different radiation decomposition models for estimating direct normal radiation (DNI) with data from the ERA5 and evaluate the impact of these different datasets on BES results.

# 2. Method

The method of this study consists of the development and analysis of different weather files, considering three DNI estimation models compared to radiation data obtained from ERA5 reanalysis. Afterwards, these files were used as inputs for the BES of a reference building, and the resulting cooling load and internal operative temperature values obtained were compared among themselves. In this way, we structured the method section into two primary components: (1) the development and analysis of the weather files and (2) the Building Energy Simulation method by itself.

# 2.1 Development and Analysis of the Weather Files

We employed the TMYx.2007-2021 weather files developed by Dru Crawley and Linda Lawrie as a basis for comparison (Climate OneBuilding, 2024). The solar resource in these files is derived from ERA5 reanalysis data; thus, global horizontal (GHI), direct normal, and horizontal diffuse radiation (DIF) all come from the same source.

We employed three distinct DNI estimation models, using the GHI data from these weather files for calculation. The DNI estimation models utilized in this study were Erbs (Erbs et al., 1982), DISC (Maxwell, 1987), and DIRINT (Perez et al., 1992). The Erbs model estimates diffuse horizontal radiation (DIF) from GHI using an empirical relationship between DIF and the ratio of GHI to extraterrestrial irradiation. The DISC algorithm derives DNI from GHI through empirical relationships between global and direct clearness indices, accounting for absolute (pressure-corrected) airmass. The DIRINT model enhances the DISC model by incorporating time-series GHI data and dew point temperature information. To implement these models, we used the pylib python v0.10.3 library (Anderson et al., 2023). It is important to note that various estimation models are available, such as the Boland-Ridley-Laurent (BRL) model used in certain radiation studies in Brazil (Lemos et al., 2017). However, for this study, we chose to limit the comparison to these three traditional models, with future research aiming to expand the comparisons to include additional models and ground-based data.

Using the estimates of DNI and DIF fractions obtained from each method employed, we modified the TMYx.2007-2021 EPW files for the following Brazilian locations: São Paulo (latitude: 23.56° S), Salvador (latitude: 12.97° S), and Brasília (latitude: 15.79° S). Table 1 summarizes the sites, including their Köppen-Geiger climate classification (with the corresponding ASHRAE 169/2006 climate zone in parentheses).

Table 1 - Characterization of the considered locations

Location	Lat., Long.	Altitude (m)	Climate
Brasília	-15.8°, -47.9°	1060	Aw (2A)
Salvador	-12.9°, -38.3°	19	Af (0A)
São Paulo	-23.4°, -46.4°	749	Cfa (2A)

Lastly, the obtained results were calculated for monthly and annual resolutions and compared to the values provided by the Brazilian Solar Atlas (Pereira et al., 2017), which presents monthly weather data for DNI, DIF and GHI. We used the root-mean-square error (RMSE) indicator for this comparison, considering the Brazilian Solar Atlas monthly data as the reference.

#### 2.2 Building Energy Simulation

For the BES part, we used a single-family reference building based on the Brazilian building characterization conducted by Triana et al. (2015). The model represents an affordable one-story house with two bedrooms, a living room integrated with the kitchen, and one bathroom, totaling approximately 40 m<sup>2</sup>. The model was simulated using EnergyPlus (version 23.2) with the basic thermal properties for walls, ceilings, floors, and windows in accordance with the reference values of the Brazilian Residential Building Performance Standard (NBR 15575:2021) (ABNT, 2021). Table 2 presents these thermal properties for each type of building component.

The transparent elements have a solar heat gain coefficient of 0.87 and a thermal transmittance of  $5.70 \text{ W/(m^2-K)}$ . The GroundDomain:Slab object was employed to simulate the ground contact with the floor properties according to the NBR 15575 standard. This floor properties compare to a 10 cm con-

crete slab featuring a thermal conductivity of  $1.75 \text{ W/(m\cdot K)}$ , a specific heat of  $1000 \text{ J/(kg\cdot K)}$ , a solar absorptance of 0.65, and a 2,200 kg/m<sup>3</sup> density.

Table 2 – Thermal properties of the building components

Component	U* (W/m²K)	TC** (kJ/m²K)	Solar absorptance (-)
Internal walls	3.37	220	-
External walls	4.84	220	0.58
Roof	2.42	220	0.65

\*U = Thermal Transmittance (U-Factor with Film from EnergyPlus' outputs)

\*\*TC = Thermal capacity

To better understand the effects of decomposition models on simulation results, we considered three cases for the selected typology: (1) case 0 - reference, (2) case 1 - low absorptance, and (3) case 2 - shading. Case 0 considers absorptance values required by NBR15575 for walls (0.58) and roof (0.65). Case 1 modifies these values to 0.30 for both walls and roof. Finally, case 2 adds a 0.80-meter overhang around the perimeter of the building. Fig. 1 shows the model of the considered cases.



The simulation was carried out in two stages. In the first scenario, the living room and bedrooms were conditioned, while in the second scenario, all rooms were naturally ventilated. For the conditioned scenario, the air-conditioning model was configured as an Ideal Loads system, with a heating setpoint of 21 °C and a cooling setpoint of 24 °C. The outputs included the heating and cooling thermal loads, measured in kWh. In the naturally ventilated scenario, the Air Flow Network system was employed, considering a slider window with a maximum opening factor of 0.45 operated according to the inside and outside temperatures. The windows are always opened when the space is occupied, and the indoor temperature is 19 °C or higher and exceeds the external temperature. The output consisted of the operative temperature for each room, which was then utilized to calculate the thermal autonomy (percentage of occupied hours within a specific temperature range). The method considers different maximum operative temperature limits based on the weather file of each location for thermal autonomy calculation and thermal load consideration, with thresholds set at 26 °C for São Paulo and Brasília and 28 °C for Salvador. To simplify the presentation of results, we will analyze the indicators of cooling thermal loads and inside maximum operative temperature in this work.

#### Results

We noticed a consistent trend in our results: the annual DNI values obtained from ERA5 were consistently higher than those from the Solar Atlas. At the same time, the other models showed lower values except for the Erbs model in São Paulo, as shown in Table 3. On the other hand, the DIF consistently shows lower values in ERA5 compared to the Solar Atlas. Meanwhile, the decomposition models consistently yielded higher values than those in the Atlas.

Table 3 – Annual DNI and DIF values (kWh/m² per day) for each location and model

Model	Brasília		Salvad	Salvador		São Paulo	
	DNI	DIF	DNI	DIF	DNI	DIF	
ERA5	5.577	1.554	5.783	1.518	4.381	1.640	
DIRINT	3.954	2.791	4.149	2.732	2.765	2.772	
DISC	3.968	2.831	3.947	2.935	3.096	2.744	
Ersb	4.301	2.424	4.189	2.573	3.926	2.340	
Solar Atlas	5 4.895	2.088	4.666	2.099	3.657	2.002	

\* The highest values for each location are highlighted in red bold and the lowest in blue italic.

Fig. 2 summarizes each method's DIN and DIF monthly values for each city. Upon analyzing the distribution of monthly values for each location, we observe that the ERA5 values and decomposition models follow the trend of the Solar Atlas. All three locations show a reduction in diffuse values during the Southern Hemisphere winter. Regarding DNI, Brasília exhibits peak values between August and September, the dry season in the region, while Salvador shows higher values during the summer months (December to February), and São Paulo presents more constant values during the year. Overall, there is a tendency for higher DNI values considering ERA5 data in all cases except for Brasília from May to August. The Solar Atlas values exceeded those of other datasets, possibly due to variations during the measurement period, which did not coincide with the other values. For DIF, the ERA5 values are consistently lower across all periods and locations.

When assessing the RMSE results at the monthly resolution, the Erbs model consistently demonstrated the lowest values for both DNI and DIF across all studied locations, except for DIF in São Paulo, where ERA5 exhibited the smallest RMSE value (Table 4). Notably, for DNI, ERA5 yielded the highest RMSE values in Brasília (32.79 kWh/m<sup>2</sup>) and Salvador (36.07 kWh/m<sup>2</sup>), while in São Paulo, it ranked as the second highest, falling below the DISC model (26.06 kWh/m<sup>2</sup>).

Table 4 – RMSE of the monthly DNI and DIF values (kWh/m<sup>2</sup> per month) for each location and model

Model	Brasíl	Brasília		Salvador		São Paulo	
	DNI	DIF	DNI	DIF	DNI	DIF	
ERA5	32.79	16.65	36.07	17.79	25.86	11.71	
DIRINT	31.30	23.58	19.42	19.47	25.80	20.71	
DISC	30.61	24.85	24.81	25.85	26.06	21.83	
Ersb	24.27	11.51	17.96	14.64	20.03	12.29	

\* The highest values for each location are highlighted in red bold and the lowest in blue italic.

Simulation results revealed variations in cooling loads, with those derived from ERA5 data showing the lowest values, while the DISC model exhibited the highest values for all locations (Table 5).



Fig. 2 - Monthly irradiation (DNI and DIF) values for each location

Table 5 – Cooling load values (kWh) with the percentage differ-
ence from ERA5 case in parentheses

Location	Model	Case 0	Case 1	Case 2	
Location	widdei	(ref.)	(low abs.)	(overhang)	
	ERA5	4,825 (-)	1,589 (-)	3,683 (-)	
Provília	DIRINT	5,201 (8%)	1,768 (11%)	4,025 (9%)	
Drasilia	DISC	5,240 (9%)	1,784 (12%)	4,062 (10%)	
	Ersb	5,054 (5%)	1,688 (6%)	3,889 (6%)	
	ERA5	10,327 (-)	5,445 (-)	8,867 (-)	
Colvedor	DIRINT	10,691 (4%)	5,694 (5%)	9,215 (4%)	
Salvauoi	DISC	10,777 (4%)	5,769 (6%)	9,291 (5%)	
	Ersb	10,558 (2%)	5,616 (3%)	9,102 (3%)	
	ERA5	2,630 (-)	804 (-)	1,908 (-)	
ção Daulo	DIRINT	2,845 (8%)	904 (12%)	2,100 (10%)	
Sao Paulo	DISC	2,878 (9%)	914 (14%)	2,122 (11%)	
	Ersb	2,749 (5%)	855 (6%)	2,017 (6%)	

The largest relative differences in cooling load results occurred in case 1 (lower absorptance), reaching values of up to 14%. This case also exhibited the lowest absolute thermal load values. When comparing these results with those obtained using the Erbs model (which demonstrated the lowest RMSE values compared to the Solar Atlas), relative differences with ERA5 ranged from 5 to 6% for Brasília and São Paulo and from 2 to 3% for Salvador. This variation can be attributed to the greater influence of the temperature on cooling load estimation in Salvador due to its warmer climate.

Regarding maximum operative temperature, the results mirrored the trend observed in cooling thermal load values; however, differences remained within 1% compared to the ERA5 results. The Erbs model and ERA5 results were very close to each other (with differences below 0.1%), whereas the largest disparities were noted when compared to the DISC model (approximately 1.0%).

# 4. Conclusion

This work aimed to assess the impact of different radiation decomposition models and datasets on estimating DNI in BES results. Three decomposition models were compared to data obtained from ERA5 for DNI and DIF. As previously reported in the literature, our results also showed that when comparing ERA5 data with the Brazilian Solar Atlas data, there is a tendency to overestimate DNI values. Furthermore, we found that DIF values are notably underestimated compared to other decomposition models and monthly data from the Brazilian Solar Atlas.

The more traditional radiation decomposition models returned similar values, consistently lower than those from the Brazilian Solar Atlas. Compared to the Atlas, the Erbs model showed the lowest RMSE values for all locations and radiation components, except for DIF in São Paulo. Regarding simulation results, they exhibited differences of up to 14% higher cooling load values when compared to results using ERA5 data with the DISC model. However, maximum operative temperatures did not show such significant differences, with a maximum deviation of 1%. The influence of thermal properties on the sensitivity of building simulations to differences in DIN and DIF decomposition was also demonstrated, as illustrated by the three cases analyzed.

These results are important to advance the understanding of the impacts of using reanalysis model data, which is becoming an increasingly common alternative. Additionally, it highlights the importance of developing and validating estimation models to reduce the uncertainties inherent in building simulations.

Further comparisons with ground measured DNI and DIF data, as well as other estimation models, are necessary to enhance the analyses. Nevertheless, the study already indicates that when using ERA5 data directly, cooling loads tend to be underestimated compared to traditional radiation decomposition models. Furthermore, a limitation of the study is that the period of measured data for the development of the solar atlas differs from that considered for weather file generation.

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# Effects of Different Wind Speed Databases on the Performance of a Vertical Axis Micro Wind Turbine Integrated With a Typical Residential House: A Comparative Simulation Analysis for Five Italian Cities

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#### Abstract

Renewable energy technologies represent a promising option to cover the building sector energy needs. In particular, micro vertical axis wind turbines are emerging as a viable solution thanks to their ability to capture wind from all directions and efficiently convert wind energy into electric power. In this study, the performance of a 2.2 kW commercial vertical axis micro wind turbine serving a typical residential building located into five different cities in Italy (Naples, Rome, Milan, Palermo, Alghero) has been analysed by means of the TRaNsient SYStems simulation tool (TRNSYS) allowing us to evaluate the effects of climatic conditions (including wind velocity). Simulations have been performed by considering three different sources of long-term wind speed data for each city: (a) the Typical Meteorological Year version 2 weather database (TMY2), (b) the NASA LaRC POWER database, and (c) the Open-Meteo database. The results highlighted that (a) the selected wind speed datasets significantly affect the assessment of wind turbine performance, as well as (b) the proposed micro wind turbine can reduce the electric energy imported from the grid, the equivalent global CO2 emissions and the operating costs up to 43.46%, 43.50% and 95.62%, respectively.

# 1. Introduction

Small-scale wind turbines (SSWTs) with power outputs less than 50 kW are gaining considerable attention from scientists because of their low maintenance costs, excellent dependability, broad operating range, and minimal environmental effect (Calautit & Johnstone, 2023; Kalashani et al., 2023). According to the International Commission of Electrotechnics (iea50, 2024), SSWTs are usually

classified into 3 different categories depending on the rated power: (a) pico wind turbine with rated power not larger than 1 kW; (b) micro wind turbines with rated power between 1 kW and 7 kW; (c) mini wind turbines with rated power between 7 kW and 50 kW. There are basically two types of wind turbines (Calautit & Johnstone, 2023; Kalashani et al., 2023): (a) horizontal axis wind turbines, and (b) vertical axis wind turbines. The performance of horizontal axis wind turbines is dependent on wind direction, while vertical axis SSWTs can use wind from all directions (Calautit & Johnstone, 2023; Kalashani et al., 2023). Vertical axis SSWTs have a significant potential to be utilized and integrated into residential urban environments to limit the corresponding energy demand currently covered by fossil fuels. The challenge of estimating the feasibility of vertical axis SSWTs based on the local wind resource, which is very site-specific and less predictable than other renewable sources, is one of the obstacles to their widespread diffusion in urban settings (Calautit & Johnstone, 2023; Kalashani et al., 2023), also taking into account that the wind flow can be disturbed by the surrounding trees and buildings. This challenge can be addressed by means of dynamic simulation platforms allowing to accurately take into account the boundary conditions (Calautit & Johnstone, 2023; Kalashani et al., 2023). With reference to this point, the TRaNsient SYStems simulation tool (Klein et al., 2007) is recognized in the scientific community as one of the most detailed dynamic modelling and simulation environments because it considers the fluctuating nature of occupant-driven loads, the part-load features of generating systems,

and the relationship between climate and system output (Rosato et al., 2020). In particular, climatic conditions (including wind speed) can greatly affect the performance assessment of vertical axis SSWTs and several databases have been developed in the last decades with the aim of accurately representing the real meteorological data of installation sites.

In this study, the performance of a 2.2 kW commercial vertical axis micro wind turbine (VAMWT) serving a typical house located into 5 different cities in Italy (Naples, Rome, Milan, Palermo, Alghero) has been analyzed by means of the TRNSYS platform (version 16) (Klein et al., 2007). Taking into account that this software platform allows us to evaluate the effects of climatic conditions (including wind velocity), simulations have been performed by considering 3 different sources of long-term wind speed data for each city: (a) the Typical Meteorological Year version 2 weather database (TMY2) (Marion and Urban, 1995; Klein et al., 2005), (b) the NASA LaRC POWER database (NASA LaRC POWER, 2003), and (c) the Open-Meteo database (Historical Weather API, 2024; 2023). The building-integrated Zippenfenig, VAMWT's energy, environmental, and financial performance has been compared to that of the same building when it is only fed by the central grid. To the knowledge of the authors no scientific studies are available in the literature with reference to the effects of different wind speed databases on the performance of a VAMWT integrated with a typical residential house upon varying the Italian cities. The main goals of the paper are: (a) assess the potential energy, economic, and environmental benefits associated with the use of a VAMWT compared to a traditional scenario for an electric demand profile typical of a residential house; (b) evaluate the effects of climatic conditions associated to different Italian cities; (c) analyze the impact of different wind speed datasets on energy, environmental and economic advantages; (d) support the use of wind energy via VAMWTs.

# 2. Building Electric Demand and Wind Turbine Characteristics

It is commonly recognized that a wide range of factors influence how much electricity residential structures use. For this purpose, the daily electric energy demand profiles connected to the operation of home appliances and lighting systems (excluding cooking devices as well as heating/cooling systems) have been modelled by using a novel tool created by the Loughborough University based on a stochastic method (McKenna et al., 2015). The tool enables the creation of random profiles (without a detailed definition of the building) based on a variety of parameters, including the maximum number of people, the day of the week, the month of the year, the number and kinds of household/lighting appliances. A maximum of four people is assumed in this study, together with typical household appliances (1 fridgefreezer, 1 fridge, 1 clock, 1 phone, 1 iron, 1 vacuum, 1 personal computer, 1 printer, 2 TVs, 1 microwave, 1 dish washer, 1 washing machine) and lighting systems. By merging 365 distinct daily electric load profiles with a time step of 1 minute, a reference yearly stochastic electric demand profile of the building has been defined. The electric loadduration diagram is displayed in Fig. 1, with the values arranged in descending order. This figure shows that the electric demand has a maximum of 4383 W and a minimum of 21 W; the corresponding annual electricity demand is 2408.96 kWh.

A commercial Savonius vertical axis micro wind turbine has been analyzed in this study (FLTXNY\_FS\_Model, 2024). The wind turbine has 2 blades, a start-up wind speed (minimum wind speed required to starts spinning, without providing electric power) of 1.5 m/s, a cut-in wind speed (speed at which a wind turbine starts generating electricity) of 2.0 m/s, a cut-off wind speed (maximum wind speed at which the wind turbine can produce usable power) of 14.0 m/s, a maximum power output of 2200 W, a rotor diameter of 0.8 m, a turbine length of 2.0 m, and a capital cost of 675.22 €. This model has been selected because it has a one power rating consistent with that required by a typical Italian house and it represents a good compromise between cost and performance.



# 3. Simulation Model and Weather Data

The TRNSYS simulation tool (version 16) (Klein et al., 2007) has been used in this study to model the wind turbine operation as well as the related load and climatic conditions. Each physical piece of a thermodynamic equipment is modelled in TRNSYS via a mathematical tool (named "Type") that is a FORTRAN source code. In this case, the TRNSYS Type 90 has been used to model the performance of the selected wind turbine. This model requires the definition of 6 parameters (site elevation, data collection height, hub height, turbine power loss, number of turbines, logical unit of the containing power data) as well as 6 inputs (control signal, wind velocity, ambient temperature, site shear exponent, barometric pressure, performance curve of the wind turbine) to obtain 3 outputs (power output, turbine operating hours, power coefficient). The turbine power loss has been assumed equal to 0. The shear exponent determines the rate of wind speed increase as a function of height; in this study a value of 0.26 has been considered (because the fluctuations in wind resource evaluations are typically not large enough to induce significant mistakes into the estimates, it is frequently assumed to be constant). The performance curve of the selected wind turbine, which shows the power output as a function of wind velocity, is reported in Fig. 2 according to the manufacturer data in the case of the turbine is installed at a height of 9 m. Site elevation, wind velocity, ambient temperature and pressure (required as input by the TRNSYS Type 90) have been established by utilizing the TRNSYS Type 15-6 according to the selected databases. This particular Type serves as a weather data processor, facilitating the

utilization of one-year-long datasets at regular intervals from an external weather data file. By utilizing this Type, it becomes feasible to incorporate climatic conditions tailored to individual cities.



Fig. 2 – Performance curve of the selected wind turbine

In greater detail, the following five distinct Italian cities have been considered to account for the diverse climatic conditions prevalent across Italy: Naples; Rome; Milan; Palermo; Alghero. In this study three different sources of long-term wind speed data for each city have been considered: (a) the TMY2 database (Marion & Urban, 1995; Klein et al., 2005), (b) the NASA LaRC POWER database (NASA LaRC POWER, 2003), and (c) the Open-Meteo database (Historical Weather API, 2024; Zippenfenig, 2023).

The TMY2 weather data files are derived from the National Solar Radiation Data Base (NSRDB) containing hourly values of measured or modelled meteorological data for the 30-year period from 1961-1990. The Sandia method, an empirical technique for choosing certain months from many years to be concatenated in order to construct a whole year, is the foundation upon which the reference year is built. The choice of months is based on data derived from five parameters: wind speed, dew point temperature, dry bulb temperature, global horizontal radiation, and direct normal radiation. Around 1000 global locations are included, which correlate to over 150 nations. In particular, the following stations are considered in this study with reference to the selected cities: Alghero (40.63° N, 8.28° E, 40 m); Milano/Malpensa (45.62° N, 8.73° E, 211 m); Napoli (40.85° N, 14.30° E, 72 m); Palermo/Point Raisi (38.18° N, 13.10° E, 34 m); Rome/Fiumicino (41.80° N, 12.23° E, 3 m). The NASA LaRC POWER database was obtained from

the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project funded through the NASA Earth Science/Applied Science Program. Long-term climatologically averaged estimates of meteorological quantities and surface solar energy fluxes are included in this data. The information is available from 1981 up to a few days ahead of actual time. The dataset uses a variety of observation types, such as remotely sensed data from satellites, sea level winds inferred from backscatter returns from space-borne radars, land surface observations of surface pressure, ocean surface observations of sea level pressure and winds, and upper-air data (from pilot balloons, aircraft winds, dropsondes, and rawinsondes). In this study, weather data have been derived via the Data Access Viewer Enhanced (DAVe) system v. 2.3.1 (NASA POWER, 2024) with reference to the year 2023 according to the following weather stations: Alghero (40.56° N, 8.32° E, 37.84 m); Milano/Malpensa (45.47° N, 9.18° E, 209.03 m); Napoli (40.84° N, 14.25° E, 264.43 m); Palermo/Point Raisi (38.12° N, 13.36° E, 221.69 m); Rome/Fiumicino (41.90° N, 12.50° E, 198.41 m). In particular, hourly temporal levels averaged wind speed data at an elevation of 10 meters above the earth's surface have been used. The Open-Meteo database partners with national weather services to create open data with high resolution. It leverages a powerful combination of global (11 km) and mesoscale (1 km) weather models; weather data are presented in hourly resolution, including detailed past measurements from 1940 onwards based on various sources such as airplanes, buoys, radar systems, and satellites. In this research, the data corresponding to the year 2023 according to the following latitudes, longitudes and altitudes of the selected cities have been used: Alghero (40.53° N, 8.39° E, 19 m); Milano (45.45° N, 9.17° E, 145 m); Napoli (41.86° N, 12.54° E, 54 m); Palermo (38.14° N, 13.34° E, 38 m); Rome (41.89° N, 12.51° E, 20 m). In particular, hourly wind speed data referring to an elevation of 10 meters above ground have been considered.

Fig. 3, 4, 5, 6 and 7 report the annual wind velocityduration diagrams (with values sorted in descending order) as a function of the long-term wind speed datasets for the Italian cities of Naples,

Rome, Milan, Palermo and Alghero, respectively. These figures also report the differences between the wind velocities associated to the databases NASA LaRC POWER and Open-Meteo with respect to the values associated the TMY2 dataset (representing one of the most used climatic datasets). The data in these figures indicate that these differences are significant, varying from minimum values of -12.33 m/s, -13.80 m/s, -8.52 m/s, -17.15 m/s and -13.01 m/s up to maximum values of 10.32 m/s, 10.52 m/s, 12.22 m/s, 12.27 m/s and 14.46 m/s for Naples, Rome, Milan, Palermo and Alghero, respectively. Table 1 reports the mean annual wind speed  $\mu$  and the mean standard deviation  $\sigma$  upon varying the city and the database. This table indicates that the TMY2 dataset provides the lowest mean annual wind speed with reference to the cities of Naples, Milan and Alghero; the database NASA LaRC POWER is characterized by the largest mean annual wind speed in the cases of Naples, Rome and Alghero. In addition, it can be noticed that, whatever the dataset is, Milan has the lowest mean annual wind speed.

# 4. Simulation Results

Simulations have been performed over a full year, employing a simulation time step of 1 minute. It should be underlined that the proposed model does not adjust the wind velocity data derived from the selected databases because representing a real dense urban context is challenging and out of the scopes of this paper. In addition, it has been assumed that the turbine is installed at a height of 9 m (that is the installation height of the wind turbine associated with the manufacturer performance curve reported in Fig. 2).

This section discusses the simulation findings. Fig. 8 reports the annual electric energy generated by the wind turbine as a function of both city and wind speed dataset. This plot highlights that, within a given city, the electric generation strongly depends on the database. In particular, the maximum energy generation corresponds to the TMY2 dataset for Rome and Palermo, while the Open-Meteo database provides the highest values for Milan. Additionally, it is noteworthy that the annual electric energy generation is highest in Palermo in the cases of both the TMY2 and NASA LaRC POWER datasets, while the lowest values are obtained in the case of Milan (whatever the wind speed dataset is).



Fig. 3 - Annual wind velocity-duration diagrams for Naples



Fig. 4 – Annual wind velocity-duration diagrams for Rome



Fig. 5 – Annual wind velocity-duration diagrams for Milan



Fig. 6 – Annual wind velocity-duration diagrams for Palermo



Table 1 – Comparison among the selected weather databases.

		TMY2	NASA LaRC POWER	Open- Meteo
Naplas	μ (m/s)	2.48	2.93	2.75
Napies	σ (m/s)	2.06	1.85	1.74
Domo	μ (m/s)	3.19	3.25	2.59
Kome	σ (m/s)	2.35	1.90	1.56
2.61	μ (m/s)	1.10	2.10	2.16
willan	σ (m/s)	1.14	1.21	1.34
Dalarma	μ (m/s)	4.24	3.98	2.52
Palermo	σ (m/s)	2.93	2.39	1.82
Alghero	μ (m/s)	3.19	4.99	3.63
	σ (m/s)	2.35	3.13	2.38

Specifically, the annual energy generation ranges from a minimum of 138.50 kWh (in Milan) up to a maximum of 3712.13 kWh (in Alghero). For a given city, the percentage difference between the values associated to the NASA LaRC POWER dataset with respect to the values corresponding to the TMY2 database range from a minimum of -20.08% (in case of Palermo) up to a maximum of 140.80% (in case of Milan); the percentage difference between the values associated to the Open-Meteo dataset in comparison with the values corresponding to the TMY2 database range from -71.02% (in Palermo) to 183.84% (in Milan).

When the electric power generated by the wind turbine exceeds the building's electric demand, the surplus is sold to the electric central grid. Fig. 9 reports the annual electric energy sold to the grid as a function of the city and the wind speed dataset. The plot indicates that, for a given city, annual electric energy sold to the central grid significantly varies depending on the wind speed database. In particular, the maximum values correspond to the TMY2 dataset in the cases of Rome and Palermo, while the Open-Meteo database provides the highest results for the city of Milan. In addition, it can be noticed

that the annual electric energy sold to the central grid is highest in Palermo in the cases of both the TMY2 and NASA LaRC POWER databases, while the lowest values are obtained in the case of Milan (whatever the wind speed dataset is). Specifically, the annual electric energy sold to the central grid is in the range between 55.76 kWh (in Milan) and 2665.23 kWh (in Alghero). For a given city, the percentage difference between the values associated to the NASA LaRC POWER dataset with respect to the values corresponding to the TMY2 database range from a minimum of -24.78% (in Palermo) up to a maximum of 199.74% (in Alghero); the percentage difference between the values associated to the Open-Meteo dataset in comparison with the values corresponding to the TMY2 database range from -77.37% (in Palermo) to 206.09% (in Milan).





Fig. 8 – Annual electric energy production

Fig. 9 - Annual electric energy sold to the central grid

If the electric power generated by the wind turbine falls short of the building's electric demand, the shortfall must be procured from the central electric grid. Fig. 10 reports the annual electric energy purchased from the grid as a function of both the city as well as the long-term wind speed data. This plot underlines that, for a given city, the influence of wind speed database on annual electric energy purchased from the central grid is relevant.



Fig. 10 - Annual electric energy purchased from the central grid

In particular, the largest values are associated to the Open-Meteo database in the cases of Naples, Rome and Palermo, while the TMY2 dataset corresponds to the highest data in Milan and Alghero. In addition, it can be noticed that the annual electric energy purchased from the grid is highest in Milan (whatever the wind speed dataset is), while the lowest values are obtained in the case of Palermo for the databases TMY2 and NASA LaRC POWER. In greater detail, the annual electric energy purchased from the grid varies from a minimum of 1362.06 kWh (in Alghero) up to a maximum of 2325.36 kWh (in Milan). For a given city, the percentage difference between the values associated to the NASA LaRC POWER dataset with respect to the values corresponding to the TMY2 database range from a minimum of -22.08% (in Alghero) up to a maximum of 6.31% (in Palermo); the percentage difference between the values associated to the Open-Meteo dataset in comparison with the TMY2 dataset range from -5.97% (in Milan) to 34.88% (in Palermo).

# 5. Energy, Environmental and Economic Comparison between Proposed and Reference Scenarios

A comparison between the performance of the proposed scenario, where the building is connected to both the central grid and the wind turbine, and the reference scenario, where the building is solely connected to the central grid (without the wind turbine) is carried out from energy, environmental, and economic perspectives.

The percentage difference  $\Delta E_{el}$  between the annual electric energy  $E_{el,imp}^{PS}$  imported from the grid in the case of the proposed scenario (including the wind turbine) and the annual electric energy  $E_{el,imp}^{RS}$  imported from the grid in the case of the reference scenario (without the wind turbine) has been calculated as follows:

$$\Delta E_{el} = \frac{E_{el,imp}^{PS} - E_{el,imp}^{RS}}{E_{el,imp}^{RS}}$$
(1)

Fig. 11 reports the values of  $\Delta E_{el}$  as a function of both city and wind speed dataset. All the values reported in this figure are negative, meaning that the proposed scenario allows to reduce the electricity imported from the grid with respect to the reference scenario, whatever the city and the wind speed dataset are. In greater detail, this figure indicates that, for a given city, the utilization of the wind turbine allows to reduce the imported electric energy from a minimum of -3.47% in Milan (city characterized by the lowest annual average wind speed) based on the TMY2 dataset, up to a maximum of -43.46% in Alghero (city with the highest annual average wind speed) considering the NASA LaRC POWER dataset.



Fig. 11 –  $\Delta E_{el}$  as a function of the city and wind speed dataset

In this study, the environmental impact has been evaluated utilizing the energy output-based emission factor approach proposed by Chicco and Mancarella (2008). In particular, the percentage difference  $\Delta CO_2$  between the global equivalent  $CO_2$  emissions  $CO_2^{PS}$  of the proposed scenario (including the wind turbine) and the global equivalent  $CO_2$  emissions  $CO_2^{RS}$  of the reference scenario

(without the wind turbine) has been derived as follows:

$$\frac{\Delta CO_2 = \frac{CO_2^{PS} - CO_2^{PS}}{CO_2^{RS}} =}{\sum_{i} u_{CO_2,i}^{E_{d_i}} \cdot P_{el,imp,i}^{PS} \cdot STS - \sum_{i} u_{CO_2,i}^{E_{d_i}} \cdot P_{el,imp,i}^{RS} \cdot STS} \frac{\sum_{i} u_{CO_2,i}^{E_{d_i}} \cdot P_{el,imp,i}^{RS} \cdot STS}{\sum_{i} u_{CO_2,i}^{E_{d_i}} \cdot P_{el,imp,i}^{RS} \cdot STS}$$
(2)

where  $u_{CO_2,i}^{E_{el}}$  is the i-th CO<sub>2</sub> emission factor corresponding to the i-th electric power imported from the grid in the case of the proposed scenario  $(\,P^{\text{PS}}_{el,\text{imp},i}\,)$  or in the case of the reference scenario  $(\,P^{\text{RS}}_{el,\text{imp},i}\,)$  at the same simulation time, while STS is the simulation time step (assumed constant and equal to 1 minute). The values of CO2 emission factor  $u_{CO_2}^{E_{el}}$  associated to the electricity consumption in Italy depends on the location, the day as well as the time of the day. Fig. 12 indicates the values of this factor used in this study as a function of time in the cases of the selected Italian cities according to (Electricity Maps, 2024). Fig. 13 reports the values of  $\Delta CO_2$  as a function of both city and wind speed dataset. All the values reported in this figure are negative; this means that the proposed scenario reduces the CO2 emissions with respect to the reference scenario, whatever the city and the wind speed dataset are. In greater detail, this figure underlines that, for a given city, the utilization of the wind turbine allows to reduce the CO2 emissions from a minimum of -3.44% in the case of Milan (city with the lowest annual average wind speed) based on the TMY2 dataset, up to a maximum of -43.50% when the wind turbine operates in Alghero (city with the highest annual average wind speed) considering the NASA LaRC POWER database.

The percentage difference  $\triangle OC$  between the operating costs  $OC^{PS}$  (due to the electricity imported from the grid) reduced by the annual revenue REV<sub>el,sold</sub> obtained thanks to the electricity sold to the central grid  $E_{el,sold}^{PS}$  in the case of the proposed scenario (including the wind turbine) and the operating costs  $OC^{RS}$  (due to the electricity imported from the grid) of the reference scenario (without the wind turbine) has been calculated via this formula:

$$\Delta OC = \frac{\left(OC^{PS} - REV_{el,sold}\right) - OC^{RS}}{OC^{RS}} = \frac{\left(UC_{el,imp} \cdot E_{el,imp}^{PS} - UC_{el,sold} \cdot E_{el,sold}^{PS}\right) - UC_{el,imp} \cdot E_{el,imp}^{RS}}{UC_{el,imp} \cdot E_{el,imp}^{RS}}$$
(3)

where UCel,imp is the unit cost of electricity purchased from the grid (assumed constant and equal to 0.26 €/kWh), while UCel,sold is the unit price of electric energy sold to the grid (assumed constant and equal to 0.19 €/kWh) according to the current Italian market scenario (GME, 2024; ARERA, 2024). Fig. 14 reports the values of  $\triangle OC$  as a function of both city and wind speed dataset. All the values in this graph are negative and, therefore, the proposed scenario reduces the operating costs with respect to the reference scenario, whatever the city and the wind speed dataset are. In more detail, this figure underlines that, for a given city, the utilization of the wind turbine allows to reduce the operating costs from a minimum of -5.16% in the case of Milan (city with the lowest annual average wind speed) considering the TMY2 dataset, up to a maximum of -95.62% when the wind turbine operates in Alghero (city with the highest annual average wind speed) based on the NASA LaRC POWER database.

The integration of the wind turbine leads to a reduction in operating costs, albeit accompanied by an additional investment cost. The simple payback period SPB, i.e., the time needed to recoup the supplementary initial investment through savings in operating costs and revenue generated from electricity sold to the grid, can be calculated via the following formula:

$$SPB = \frac{WT^{CC}}{(OC^{PS} - OC^{RS}) + REV_{el,sold}} = \frac{WT^{CC}}{(OC^{PS} - OC^{RS}) + E_{el,sold}^{PS} \cdot UC_{el,sold}}$$
(4)

where WT<sup>CC</sup> is the capital cost of wind turbine (675.22  $\in$ ). Fig. 15 reports the SPB as a function of both wind speed dataset and city. This plot indicates that SPB ranges from a minimum of 1.1 years (in Alghero according to the NASA LaRC POWER dataset) up to a maximum of 21.2 years (based on the TMY2 database for Milan); it indicates that the selected win turbine is suitable from an economic point of view (i.e., SPB is lower than the expected wind turbines' lifetime, that is equal to about 20÷25 years), whatever the city and the weather dataset

are. The influence of wind speed dataset is still, not negligible also in terms of SPB.



Fig.  $12 - CO_2$  emission factor as a function of city and time



Fig.  $13 - \Delta CO_2$  as a function of the city and wind speed dataset



Fig. 14 –  $\Delta OC$  as a function of the city and wind speed dataset



Fig. 15 - SPB as a function of the city and wind speed dataset

# 6. Conclusion

The effects of 3 wind speed databases on the performance of a vertical axis micro wind turbine serving a typical house have been assessed via a detailed dynamic simulation platform upon varying 5 Italian cities. The simulation outputs indicated that, whatever the Italian city and the wind speed dataset are, the selected wind turbine reduces the electric energy imported from the grid, the equivalent global CO2 emissions and the operating costs up to 43.46%, 43.50% and 95.62%, respectively. This study also underlined that the influence of both the city and the wind speed dataset is relevant. In particular, the best results have been obtained for Alghero (city with the highest annual average wind speed) according to the NASA LaRC POWER database, while the worst data have been achieved in Milan based on the TMY2 database. A minimum simple pay-back period of 1.1 years has been obtained for Alghero in the case of the NASA LaRC POWER dataset.

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# The Challenge of Archetypes Representativity for Wide Scale Building Investigation in Italy

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#### Abstract

The recent focus on new strategies towards the achievement of smart cities and energy community goals has required a massive use of urban scale tools for building energy modelling. The main aim is to support decision makers to address urban energy policies allowing the development of energy scenarios combining multiple actions. Despite some exceptions of simplified input datasets, urban scale simulation tools commonly require a large amount of input data to describe the building stock investigated, depending on the tool and the modelling purpose. Several literature studies explained the building stock modelling challenge, enhancing the current lack of complete databases describing the national building stock. The regional datasets of energy performance certificates are not fit for purpose and are often not available for research or statistical analysis. To tackle this issue, a hybrid approach combining different sources of information can be implemented; however, large quantities of data belonging to heterogeneous datasets must be updated, harmonized, integrated, potentially reducing the available data or reducing the accuracy. For these reasons, a possible way is the definition of archetype and prototype buildings, defined as ideal buildings described by sets of characteristics considered as representative of certain clusters of the building stock. However, a major challenge still must be solved: how is it possible to properly distribute archetype properties respecting the real presence of buildings within the considered location? In this work the last Italian population and housing census has been used to determine the distribution of building typologies according to the Italian building stock. Statistical analysis allowed for the clustering of the available information to deal with the lack of information for urban scale modelling tools, providing useful data for the representativity of available information within the national building stock. Future applications will apply the methodology to other case studies.

#### 1. Introduction

The building and construction sector, which is responsible for 36% of global final energy consumption and 37% of energy-related CO<sub>2</sub> emissions in 2020 (GBC, 2021), holds a pivotal role in the global energy transition. To tackle the pressing issue of climate change, the World Energy Transition Outlook report by IRENA<sup>1</sup> emphasizes the urgent need for drastic reductions in global CO2 emissions, aiming for net zero by 2050 to meet the 1.5 °C climate target. A significant portion, up to US 963 billion \$/year, is earmarked for building interventions, focusing on boosting renewable energy usage and adopting energy-efficient technologies<sup>1</sup>. The European Union (EU) lead this commitment, allocating a quarter of its budget's financial resources to tackle climate change. With the European Green Deal, targeting climate neutrality by 2050, member states are urged to incorporate sustainability principles, cleaner construction practices, and a cleaner and less emissive building sector into decisions regarding energy-related policies and investments (EU, 2019).

Upgrading the current building stock to a zero-carbon-ready standard stands out as a critical priority in meeting the decarbonization goals set for the sector by 2030 and 2050. However, retrofitting the building stock to a zero-carbon-ready standard poses a tough challenge, given that a minimum of 40% of developed economies' building floor area

<sup>1</sup> Available at https://irena.org/publications/2021/Jun/World-Energy-Transitions-Outlook (Apr 23rd, 2024).

predates modern energy-efficiency standards, including the Rio Conference of 1992 and the Kyoto protocol of 1997. Attaining this objective requires a robust annual deep renovation rate of over 2 %, spanning the period from the present to 2030 and beyond (Teres-Zubiaga et al., 2020). Given that the rates of building retrofits have not reached the set targets for many years, and that these rates need to speed up drastically, the switching from a single building renovation approach to a district scale perspective is the most effective, considering the potential connections among buildings and the achievable share of renewable energy sources. However, the need to shift from the idea of single buildings retrofit to that of entire districts requires the support of large amount of data on buildings' characteristics, HVAC properties, and user profiles to fully hold the retrofit needs and potentials. The conceptualization of urban-level strategies requires the creation of building archetypes to broaden the perspective beyond individual buildings and capture the prevailing building typologies for effective modelling (Carnieletto et al., 2021) and retrofit technologies definition. However, gathering information on large building stocks often relies on census data due to the limited availability of extensive datasets. Typically, this data is anonymized and does not go beyond a province or municipal scale nor provide detailed characteristics that may be useful for the purpose of the archetypes. Therefore, the development of comprehensive archetypes requires a combination of a diverse set of data obtained from various sources (Mata et al., 2014).

The use of census data is an essential approach for researching and developing applications in multiple areas concerning the built environment.

Census data can be used for extrapolating information regarding the frequency of building characteristics in terms of materials, geometry, end uses, etc. This approach is normally used to achieve a good characterization of building stocks without validating the dataset at single building scale, supporting the definition of important indicators for socioeconomic weaknesses. By integrating data gathered from surveys or local datasets, it is possible to better characterise groups of buildings or areas according to the intended goals of the analyses. For example, questionnaires are used to document the habits regarding the use of household appliances (Duman et al., 2023), energy consumption of decentralised sources (Marigo et al., 2021), or economic characteristics of households and how these affect their spending and well-being (Perchiunno et al., 2020).

Despite the wide application range of census data, the databases are often not easily accessible, if not even closed to consultation. This is the case for Italy. Various studies attempting to develop strategies for the energy renovation of the Italian building sector have faced countless difficulties in obtaining the necessary data due to this fragmentation of databases (Agugiaro, 2016). The use of data made available by the National Institute of Statistics (ISTAT) databases represents a necessary and fundamental solution to cope with the shortcomings. When it comes to the residential real estate sector, the quantities of data offered by ISTAT are useful for characterising buildings by age, construction type and building systems. Although not always fully representative, due to the lack of updates since 2011, the outcomes obtained represent a significant baseline for any work saving time-consuming analysis and for the development or national archetypes for urban scale energy simulations.

# 2. Method

In 2011 ISTAT released the 15th Census of the national population. Data was collected and grouped at municipal level, with algorithms able to check the reliability of each group of individual data, as described by the detection strategies (Carbonetti, 2023).

Since the main goal of this analysis is to statistically represent the national building stock to provide useful information for urban scale analysis and energy retrofit scenarios, the main outcomes concern a set of minimum information characterizing buildings in order to develop detailed archetypes to perform energy simulations. The geometric layout has been excluded from the analysis. In general, there is a lack of datasets regarding the geometrical layout of building footprints; when available, they can be uploaded from georeferenced tools.

Italy is divided in five different areas, as the

location and the related historical development and cultural differences may influence the installed building technologies:

- North West: Piemonte, Liguria, Valle d'Aosta, Lombardia
- North East: Veneto, Trentino Alto Adige, Friuli
  Venezia Giulia, Emilia Romagna
- Centre: Toscana, Umbria, Marche, Lazio,
- South: Campania, Calabria, Puglia, Basilicata, Abruzzo, Molise
- Islands: Sicilia and Sardegna

Nationwide, a total of 14,452,680 buildings were surveyed in 2011. The database can be divided in two main categories: residential and non-residential buildings. The work focused on the residential sector which represents the largest share of the surveyed buildings (around 12,187,698 constructions). The analysis is based on the 110 Italian provinces grouped by geographic area. Based on the defined pertinence area (from north to south), the average surface areas and user related variables, such as the typical occupancy ratio, have been discussed. Furthermore, buildings have been grouped according to the period of construction and to the main building technology adopted (bricks, concrete, or other materials). The last subsection describes the main energy sources for space heating and domestic hot water.

# 3. Results

The 12,187,698 residential buildings include about 31,208,161 housing units surveyed in 2011; 77.3% were occupied by at least one resident person, with the remaining 22.7% being vacant or occupied only by non-residents. Probably due to the intense presence of tourism and the related services, Valle d'Aosta had about 50.1% of homes unoccupied by residents, followed by Calabria (38.8%) and Molise and the province of Trento (37.1%). On the contrary, the province of Bolzano (88%), Lombardy (85%) and Campania (83%) has the highest ratio of units occupied by residents. The outcomes presented in the following paragraphs can be considered as distinctive features for the description of national archetypes, outlining some fundamental characteristics

in terms of structural typology, generation systems, and usage type based on climatic zone, region, and year of construction. These results can be used to complement existing databases or serve as a framework for the construction of national archetypes.

#### 3.1 Building Use

About 84.3% of the total buildings investigated belong to the residential sector (Table 1), among which 51.8% are single dwellings. The same trend can be seen at regional scale, excluding Valle d'Aosta (about 73.6%).

Table	1 –	Building	stock	division	based	on	end	uses
lable	. –	Dununig	SLOCK	uivision	Daseu	UII	enu	uses

	Italy	NW	NE	Centre	South	Island
N. blds [Millions]	14.4	3.32	2.78	2.44	3.63	2.32
Resid.	84.3%	83.9%	85.9%	83.8%	84.3%	83.6%
Product	2.0%	2.7%	2.6%	2.0%	1.3%	1.3%
Comm.	1.7%	1.8%	1.7%	1.8%	1.6%	1.4%
Tertiary	0.4%	0.5%	0.4%	0.4%	0.4%	0.4%
Tourism	0.4%	0.4%	0.5%	0.5%	0.4%	0.3%
Service	1.2%	1.4%	1.3%	1.3%	1.2%	1.0%
Other	4.8%	5.1%	4.1%	6.1%	4.0%	4.8%
Non defined	5.1%	4.2%	3.4%	3.9%	6.8%	7.2%

Figure 1 shows the share between non-residential buildings (16% at national scale), which include constructions for productive use (18.9%), followed by commercial (16.2%) and services (11.7%). The smallest share belongs to tourism/reception and of-fice/tertiary use (about 4% each).



Fig. 1 – Building stock representation based on end uses (residential excluded)

# 3.2 Geometry and User Related Variables

Italy has a fairly even distribution of residential building types. Small (31%) and medium to large apartment blocks (40%) are the most frequent dwellings (Table 2). A significant difference can be seen within the northern regions: on the east side, the prevalent housing solution is the condominium with three to ten units (29%), while on the west side and central area almost half of the residential building are apartment blocks with more than 11 internal units. This trend can be linked to the massive industrial development after the world wars, which gathered groups of people to find employment (Salvati et al., 2017). Several districts of the bigger cities underwent urban development based on wide blocks intended for less affluent people and owned by the municipality or local authorities.

The southern area traces the same national share, while islands prefer small condominiums; the reason could be related to the highest building density in the main cities, while the countryside is mostly left for activities related to agriculture and animal farms. Single family houses are almost equally spread nationwide, with a slightly higher presence in the islands.

A.m.o.a	Number of units						
Area	1	2	3-10	>11			
Italy	17%	13%	31%	40%			
North West	17%	10%	25%	48%			
North East	17%	16%	39%	29%			
Centre	13%	12%	31%	44%			
South	17%	13%	32%	39%			
Islands	20%	17%	35%	28%			

Table 2 - Residential building per number of internal units

Looking at the average surface of dwellings (Table 3), similar shares can be distinguished. The interval of 80-99 m<sup>2</sup> is the most evenly distributed; this size is compatible with an apartment for a family of three or four people, which represents 14% (northwest) to 21% (centre) of the typical user occupancy (Table 4). The share of the smallest area is not representative; similarly, dwellings with more than six users have a share of less, except in the southern regions where it is 2.3%.

Although around 30% of the buildings in each area are inhabited either by one or two people, the smallest dwelling areas are less frequent.

The census investigated is the last complete database describing the national building stock but it dates back 2011, thus an updated version would probably present some differences. In the past 13 years, part of the buildings could have been retrofitted according to the retrofit targets imposed by standards promoting strict policies on energy efficiency. Furthermore, the average occupancy density of buildings per area may have changed due to the continuous evolution of the population. However, considering that the number of new buildings decreased (from 54,664 in 2018 to 49,100 in 2020<sup>2</sup>), the national renovation rate was about 0.85% per year until 20203, and the occupancy density profile will be attributed based on the area of interest in case of urban scale analysis, the information reported can still be considered as a baseline for the representation of the Italian stock when validating for example urban scale energy models.

Dwelling area [m <sup>2</sup> ]	Italy	NW	NE	Centre	South	Island
29	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%
30-39	1.9%	2.1%	1.4%	2.0%	2.0%	1.9%
40-49	4.6%	5.6%	3.9%	4.8%	4.2%	4.2%
50-59	6.7%	8.2%	5.8%	7.1%	5.7%	5.6%
60-79	21%	24%	19%	22%	18%	17%
80-99	25%	25%	24%	25%	27%	24%
100-119	17%	15%	18%	17%	19%	21%
120-149	12%	10%	13%	11%	13%	15%
>150	11%	10%	15%	10%	11%	11%

Table 3 – Share of the residential building per dwelling area

<sup>2</sup> https://www.istat.it/storage/ASI/2021/capitoli/C18.pdf (May 10th)

<sup>3</sup> Ministero dello Sviluppo Economico (MISE), Strategia per la Riqualificazione energetica del parco immobiliare Nazionale, Nov. 2020

Table 4 – Share of the residential building per number of occupants

Number of users	Italy	NW	NE	Centre	South	Island
1	30%	32%	30%	31%	25%	28%
2	28%	30%	29%	28%	24%	25%
3	20%	20%	20%	21%	20%	20%
4	16%	14%	15%	15%	21%	19%
5	4.5%	3.2%	3.8%	4.0%	6.9%	5.4%
>6	1.6%	1.1%	1.6%	1.6%	2.3%	1.6%

# 3.3 Construction Technologies

The history of the Italian state significantly influences both the construction rate, and the technologies applied. A large fraction of the building stock belongs to the period before World War I (i.e., before 1918), with values ranging from 10.5% in the South to 14.6% in the Northwest of the country (Figure 2). The islands have the lowest share (about 5.7%). The decline visible between the two world wars is recovered in the period immediately following: 60-61% of the building stock was built between 1946 and 1990, in the North, about 64% in the central area, and 67 to 70% within southern Italy and Islands, respectively. This phase of high building intensity can be attributed to the historical period, corresponding to industrial development and the urgent need for building reconstruction. A consequence of this rather driven development, a downward trend began in the 1990s and ended with the financial crisis that occurred between 2008 and 2011, when the share of building constructions ranges on average between 4% and 3.5%. At regional scale, the behaviour can differ from the national trend. The most intense period in the north-west area (Piemonte and Lombardy) was the decade 1961-1970, driven by the emerging industrial and manufacturing growth. Veneto and Friuli Venezia Giulia on the east side has on average the same share until the 1980. Lombardy and Tuscany still have around half a million buildings belonging to the period before 1918. This building category is particularly relevant in Tuscany, which holds a high density of historic buildings preserved as cultural heritage that represents 20% of the regional stock. The lowest share of historic constructions is registered in Sardinia, with less than 5 %.



Fig. 2 – Number of residential buildings per period of construction

According to Figure (3 a-e) brick structures have been the most common construction technology until 1970 throughout the country. Later, the share of buildings material changed for each area, following the different growth of the industrial development. Since the early 1960s, concrete has become dominating over masonry construction in the north-west of the country (Figure 3a); a similar trend can be seen in the southern and central areas (Figures 3c, 3d, 3e), although from early 1970s. Within the north-eastern regions (Figure 3b), bricks and concrete have been used almost equally from 1980, with a significant and contemporary increase of other materials (mostly wood).



Fig. 3 – Building share per construction material and geographic area: North West (a), North East (b), Centre (c), South (d), Islands (e)

#### 3.4 Energy Sources for Space Heating

Some information was collected concerning the energy source used for space heating. Natural gas is still the main source (Figure 4), supplying on average more than 70% of the buildings, as can be seen from the national statistics. Islands have a significantly lower share due to a less developed distribution grid. For the same reason, a notable fraction of diesel boilers and solid fuels, mostly wood, are still used for space heating.

On average electricity was supplying 5% of space heating systems; however, due to the lack of distributed natural gas pipelines, increased solar radiation and windy areas, electric energy is the heating source for 22% of the buildings in the two main islands (Sicily and Sardinia).



Fig. 4 - Distribution of energy sources for space heating

The same system is used for space heating and domestic hot water in about 69% of the dwellings in the country. When looking at smaller areas, this solution has been adopted in 85.6% of the buildings located in the north-east, 69.6% on the north-west and 74.2% in the central regions. Southern areas are closed to the national median (65.2%), while the Islands area covers only 35.5%, mostly due to the lack of methane pipelines, thus gas fired boilers. According to the report on the national energy system provided in 2023 by the national agency for new technologies, energy and sustainable economic development (ENEA, 2023), gas is still the most used fuel; although the demand in 2023 decreased by 2% compared to 2022, ENEA attributes the main reason to favourable climatic conditions. A decline was estimated also for other commodities, in particular petroleum products and electricity from the grid.

The different distribution of generation systems depends also on the location and the related climate zone. The distribution of the climatic zones (from A to F, classified based on DPR 412 (1993) has been studied at municipal scale, thus grouped for the representation at regional scale. In figure 5, zone A is almost not represented since it is attributed only to two locations (Lampedusa and Porto Empedocle), thus the geographical representation is negligible. Zone F is typical of mountain areas; thus, it is present in the Alps and Apennines. Zone B can be found only in the South, while C and D commonly describe the coastal area. Climate zone E is the vastest area throughout the Italian peninsula.



Fig. 5 – Climate zone distribution (municipality share per climate)

# 4. Discussion and Conclusion

The present work represents a first analysis of the building census provided by ISTAT in 2011, aiming to obtain a reliable statistic to be applied for urban scale energy simulations. Due to the lack of complete databases describing the national building stock, the outcomes obtained can complete other partial datasets, allowing the development of representative building archetypes for specific periods of construction and geographical areas. Within this framework, this paper provides a first description of the Italian building stock, mostly focused on residential dwellings that cover the majority of the buildings. In the last 13 years, the situation has

partly changed due to the policies concerning energy savings and the improvement of energy efficiency. However, the renovation rate up to 2022 was about 0.85% per year; after that a massive incentive policy supporting refurbishment actions partly increased the renovation rate, which is still far from the goal (1.2%, with respect to a goal of 2.1%). Therefore, the resumed information can still be used as a valid statistic for a baseline validation of urban scale building energy models while updated information are not available. In fact, some input parameters used in a modelling or simulation process are defined by specific tools (like georeferenced tools that provide geometric data), while others are based on average values derived from standards or from randomized distributions. This means that instead of using precise local data for every input, the model relies on statistical averages that represent typical conditions for specific input categories. This approach helps to smooth out the effects of localized variations, ensuring that the simulation reflects broader trends rather than specific local conditions. Moreover, large scale models (i.e., wider than small district level) aim to represent the overall performance rather than the single building calibration. Furthermore, the outcomes obtained can be used for the calibration of national case studies. In conclusion, the methodology used and the variables investigated, based on statistical analysis, could serve as key indicators for defining national archetypes, highlighting essential characteristics such as structural typology, generation systems, and usage patterns according to climatic zones, regions, and construction years. These findings can enhance existing databases or provide a foundation for developing national archetypes. A realistic view of building performances allows the development of more tailored policies, thus more achievable goals, according to the regional outcomes. Future research will focus on collecting data at a more localized level (province or municipality), incorporating more research findings as they become available, and applying these outcomes to various case studies to assess their potential utility, such as studying the building stock distribution to design case specific energy strategies with policymakers or urban planners.

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# Comparison between Real Energy Consumption, Italian APE and Dynamic Energy Simulation

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#### Abstract

The most important challenge of energy modelling is certainly to guarantee that the energy consumption predicted by the simulation during the Design phase reflects the real consumption of the building once built. With the increase in energy consumption monitoring, in recent years it has been realized that there is often a substantial difference between expected and actual energy consumption; this difference is called the "Performance Gap" or "Energy Gap". Furthermore, the energy classification of buildings according to methodologies recognized by Italian regulations is becoming increasingly important, in order to have access to economic benefits or building bonuses. The scope of this work is to compare the energy consumption estimated through dynamic energy simulations and through the Italian regulation-based software with the real consumption of the building, evaluating the reliability of the calculation procedures and calibrating the dynamic model with the real usage schedules (post occupancy evaluation). This study is based on a large recent office building, with high national and international energy performance standards (LEED certified).

# 1. Introduction

The building sector is a major contributor to the emission of greenhouse gases into the atmosphere since it consumes about 30% of the world's energy to which corresponds the emission of about 40% of direct and indirect CO<sub>2</sub> globally (IEA, 2022). Energy consumption by buildings is also continuously increasing. Although all phases of a building's life produce carbon dioxide, 80-90% of the building sector's emissions occur during the "operational" phase, thus, they mainly depend on the energy used for heating, cooling, ventilation, pumping, lighting, and power appliances.

From these premises, it can be deduced that the building sector is by far the sector with the greatest potential for improvement in reducing greenhouse gas emissions.

A building is a complex system, and the energy phenomena that develop within it are different and continuously related to each other. Simulating the performance of such a system makes it possible to analyse the energy consumption of buildings according to their actual use.

However, it has been noted that these simulations often do not reflect the actual performance once the building is constructed (Turner et al., 2008) and they differ from the energy consumption estimates derived from calculations according to the Italian regulations.

# 2. Calculation Methodologies

Simulating the behaviour of a building and its energy needs creates a level of awareness that leads to a transparent real estate market geared toward improving the energy efficiency of our heritage.

Dynamic energy simulations are an advanced calculation methodology used to analyse and optimize the energy efficiency of buildings. This technique is based on the use of mathematical models to simulate the thermal behaviour of a building over time, considering dynamic variations in external and internal environmental conditions.

Unlike a static system, which can be described by direct, instantaneous equations that are not affected by time, a dynamic system evolves over time and therefore must be described by equations that link past variables with present variables, since the state of the system depends on the previous state.

Therefore, this article aims to analyse the impact

these methodological differences have in the evaluation and prediction of a building's energy consumption.

#### 2.1 Building Description

The building subject of this article is located in the northwestern of Italy; it has a sinuous shape that stretches along the north direction and is mainly for office use; it has an area of 15,000 m<sup>2</sup> and houses about 600 employees. The building has seven floors on one side, while on the other floor it reaches 4 floors.

A portion of the building is also dedicated to reception, gymnasium, relaxation room, cafeteria and open spaces.

The façade of the building is entirely composed of glazed surfaces alternating with opaque "spandrel" panels. The glazed surfaces are composed of two types of frames: one used for the flat surfaces, and one used for the curved surfaces of the building. The glazing surface used in the flat facades is triple glazing with double chamber of 22 mm filled with 90 percent argon gas; the total thickness is thus 74 mm. In contrast, the glazing surface used in the curved facades has a triple glazing with 12 mm double chamber filled with 90% argon gas, reducing the total thickness therefore to 54 mm.

The facade of the building's elevated floors features a series of shading both inside and outside to reduce incident solar radiation in summer and avoid the phenomenon of Glare (glare from the sun). On the exterior facade there are vertical and horizontal baffles of about 30 cm for the entire extent of the wall. The main thermophysical characteristics of the building's envelope are shown in the Table 1.

Table 1 – Thermophysical characteristics of the building's envelope

Description	Thermal Trasmittance	Solar Factor (for windows)
Opaque exterior wall	0.19 W/m²K	-
Opaque panel	0.3 W/m <sup>2</sup> K	-
Roof	0.186 W/m <sup>2</sup> K	-
Window	0.75 W/m <sup>2</sup> K	0.26

Within the building there are activities and machinery that, in addition to consuming energy electricity, generate, along with people, a certain amount of heat and thus affect the energy balance and heat load of a building.

Table 2 shows the main values considered.

Table 2 - Internal loads, lighting power density and occupancy

End Use	Plug Loads	Lighting Power Density	Occupancy
Office	12 W/m <sup>2</sup>	11 W/m <sup>2</sup>	14 m²/persona
Meeting Room	12 W/m <sup>2</sup>	11 W/m²	14 m²/persona
Stairs and Toilets	2 W/m <sup>2</sup>	7 W/m <sup>2</sup>	unoccupied
Data Room	120 W/m <sup>2</sup>	5 W/m <sup>2</sup>	unoccupied

The building is also equipped with a daylighting control and dimmable artificial lights according to the following set points:

- Office and meeting room: 500 lux
- Corridors, stairs and toilets: 200 lux
- Reception: 300 lux.

The building uses multipurpose groundwater heat pumps for its conditioning.

# 2.2 Real Energy Consumption

Knowledge of actual building consumption was possible through the monitoring of the simulated building (in this case, the reference report is related to the year 2019). One of the main difficulties comes from the fact that the measurement of electricity consumption was carried out on cabins common to several buildings in the complex, and therefore some of the meters represent not only the consumption of the modelled building but also those of two adjacent buildings. To compare the results, it was necessary to estimate the share attributable solely to the modelled building through information present in the monitoring report.

The report divides consumption into the following items: Air conditioning, lighting, FEM (electrical

equipment), Fans, Pumping, ACS (domestic hot water), UPS (lighting), UPS (FEM) and CED (Data Room). UPS (lighting) and UPS (FEM) are the consumption related to lighting and electrical equipment connected to a UPS (Uninterruptible Power Supply) system, i.e., a system of batteries that manage to power these loads even in the event of a power failure, e.g., in the event of a blackout; since the batteries themselves do not consume any current other than that required by the loads, the consumption of these two items was added up to those of lighting and FEM, respectively.

The following figures show the monthly trends (Fig. 1), the energy use intensity (Fig. 2) and the percentage distributions of the main electric consumption items (Fig. 3).



Fig. 1 – Monthly consumption trends





Fig. 2 - Energy Use Intensity for different items



Fig. 3 - Percentage distributions of electric consumption items

#### 2.3 Dynamic Energy Simulation

The tool used to simulate the building is the simulation software in DesignBuilder version v7 that uses the simulation engine EnergyPlus but with a userfriendly interface that allows users to enter geometry and useful data for simulation intuitively and quickly.

The weather data comes from the software Meteonorm, a global standard and a powerful tool for solar energy applications and building design.

As mentioned, one of the main problems (and at the same time one of the main challenges) of dynamic energy simulations is the energy gap, i.e., the difference between estimated and actual energy consumption.

This project also showed this issue, and by monitoring real consumptions, it was possible to calibrate the energy model to make it as closely aligned as possible with real usage conditions.

The Fig. 4 shows the difference between pre and post occupancy simulation.



Fig. 4 - Pre and post occupancy simulation results

The main discrepancies between the two models were:

- The evaluation of the internal loads
- The occupancy profiles
- The real set point temperature in the building
- The value of the temperature of the air supplied by the Air Handling Units
- A more accurate calculation method of the energy consumption of the ground water pumps, thanks to a new version of the simulation software. With this new approach, it was possible to recreate the actual operation of groundwater (Fig. 5) heat pumps by "simulating" with district cooling/heating the effect of groundwater in summer operation (condensation) and winter operation (evaporation).



Fig. 5 - Detailed simulation of the groundwater loop

The EUI for different items of the post-occupancy simulation is reported in Fig. 6, while Fig. 7 shows the percentage distributions of the electric consumption items.







Fig. 7 - Percentage distributions of the electric consumption items

Fig. 8 highlights the gap between the two simulations and real consumptions.



Fig. 8 - Gap between real and simulated consumptions

## 2.4 Italian Regulation

When assessing energy performance to ensure compliance with current regulations, it is crucial to use a standardized calculation method. This involves a clear procedure with standardized values, as outlined in the UNI TS 11300 standards (transposition of the European ISO 13790). Such calculations are mandatory for new constructions and are required for property transactions like buying, selling, or renting. The results are documented in an Energy Performance Certificate. This calculation should be streamlined, efficient, and accessible to a wide range of professionals with foundational knowledge of energy principles.

The current regulation uses a semi steady-state calculation method based on monthly evaluations (also in terms of weather conditions), then adding up the relative consumption to obtain annual or seasonal value.

The compilation of an energy performance certificate leads to a consumption index per unit area of non-renewable primary energy; however, it is possible to derive from the calculation software the relative electricity consumption necessary for the comparison in this article.

This consumption, broken down by the different items, is shown in Fig. 9.



Fig. 9 - Energy Use Intensity for different items

# 2.5 Comparison of the Results

Two figures summarizing the results of the three different calculation procedures are shown below, first highlighting the ratio for each consumption item (Fig. 10) and then the overall results (Fig. 11).



Fig. 10 - Comparison between EUI for different items





# 2.5.1 Comparison between Post-Occupancy Simulation and Real Data

From an energy simulation, one should not expect an exact prediction of consumption, since the behaviour of a building is influenced by many factors that a simulation necessarily cannot predict and simulate accurately.

The Fig. 12 underlines how the calibration of the energy model as a result of the data provided after the occupancy of the building and the more accurate implementation of system part related to the groundwater system, leads to an overall difference between the two cases of 11 %, a result that can be considered satisfactory.



Fig. 12 - Comparison between Energy Use Intensity

However, the inevitable residual difference is mainly due to a series of factors such as:

- weather file: it probably represents the major impacts on building energy consumption, and the one used in the simulation is based on a TRY (Test Reference Year) that often fails to represent the large climatic variations that can occur from year to year and recent weather changes.
- <u>habits of the occupants</u>: people regulate their comfort level by interacting with the indoor environment and facility control systems. These interactions between individuals and the building influence both energy consumption (also for the interior equipment) and thermal/visual comfort. However, although the simulation was performed on a post-occupancy situation, it was not possible to obtain accurate information about people's actual behaviours.
- <u>real data</u>: as mentioned above, since electricity consumption was derived from values including other buildings, it is inevitable to expect a margin of error in estimating actual consumption as well.

# 2.5.2 Comparison between Post-Occupancy Simulation and Italian Regulation

Different reasons, on the other hand, underlie the difference between the consumption derived from the energy calculation according to the Italian standards and that obtained by the dynamic simulation. Below are the main factors:

- <u>Weather data:</u> it is important to remember first of all that the monthly semi steady-state method implies that in the calculation of heat loss/input, the reference values are monthly averages, without taking into account the hourly variations that actually happen. In addition, the weather conditions used in the calculation according to the Italian standard is derived from UNI 10349:1994, since the building practice is prior to 2016 and therefore does not contemplate the updated data more similar to 2019, the reference year of real consumption.
- <u>Software limitations</u>: the calculation software according to the Italian regulations <u>has</u> limited possibilities to represent the actual system plant configuration; specifically in the software

used, while in the heating plant it is possible to enter the real number of heat pumps, for the cooling plant it is possible to enter only one machine, with consequent inaccuracy in the calculation of the efficiency at partial loads; even the water pumps related to groundwater can be considered only as auxiliary consumption of the heat pumps, forcing a simplification that brings considerable inaccuracies with respect to the real operation.

- <u>Operating period:</u> the heating system is considered to be on 24 hours a day only during the period between October 15 and April 15, not considering any demands outside this time frame; similarly, the cooling system is operational only from April 15 to October 15, while the dynamic simulation shows demands outside this period since the high value of the Window to Wall Ratio of the building.
- Operation of the Air Handling Units: unlike heating/cooling systems, AHU are considered to operate for only 8 hours a day, unlike in reality; since energy consumption related to air handling is a major consumption item for office buildings, this aspect leads to a relevant divergence in consumption estimation; moreover, in the calculation according to the national standard, only the pre-heating coil is considered and the post-heating coil is left out, which could also be operational in summer; furthermore, the cooling coil cannot be implemented, resulting in the non-assessment of this consumption.
- <u>Lighting system</u>: lighting follows regulatory timetables and does not reflect the actual operating hours; furthermore, it is not possible to include a dimming system for lights according to the daylighting control as actually happens.
- <u>Internal equipment:</u> internal gains due to occupancy and different equipment, are normed according to UNI TS 11300 based on cadastral category and have well-defined time profiles. This represents one of the main critical issues since the real specific power is much higher and has a significantly different operating profile; however, these values do not contribute to the determination of the energy class of the building and consequently do not appear in the total energy consumption.

# 3. Conclusion

The building sector significantly contributes to global greenhouse gas emissions and energy consumption. While various phases of a building's life cycle emit carbon dioxide, the operational phase is responsible for the majority of the emissions, highlighting the importance of improving energy efficiency in buildings.

Through this paper, we wanted to share a comparative analysis between real consumption and estimated consumption at the design stage, with both a dynamic (pre- and post-occupancy) and semi steady-state analysis required by the regulations.

The results showed the importance of calibrating the dynamic model according to the real building use and at the same time its validity: the comparison between post-occupancy simulation and real data revealed a satisfactory alignment after calibrating the energy model, though residual differences persisted due to factors like weather variability and occupant behaviour; dynamic energy simulation could become a tool that can be used for energy analyses and evaluations of improvement interventions. This paper also shows how the current method of calculation according to national regulations should be outdated because it cannot be a valid reference for estimating the real energy consumption of a building (because of weather data limitations, software constraints, operational periods, and assumptions about system operation and occupant behaviour), something that is increasingly required in the real estate field and in a view to the progressive and urgent decarbonization of the building stock.

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- Turner, C., M. Frankel, and U. Council. 2008. "Energy performance of LEED for new construction buildings." *New Buildings Institute* 4(4): 1–42.
# Simulation Tests for the Determination of the U-Value of Walls by Using Response Factors Theory with Noisy Boundary Conditions

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#### Abstract

The thermal behaviour of buildings' opaque components is still one of the most important aspects in the overall energy performance of a building. In the framework of the reduction of greenhouse gas emissions and global energy consumptions, the optimization of the walls' composition can lead to more sustainable and highlyefficient buildings, both for new and existing constructions. One of the parameters describing the thermal performance of a building's wall is the thermal transmittance or U-value. The determination of the U-value is usually done through analytical methods according to the Standard UNI EN 6946, especially when components are characterized by simple geometries and uniform layers. However, when such a hypothesis does not stand anymore, experimental procedures in controlled environments must be adopted, e.g., climatic chambers. Stationary methodologies, like the ones suggested either by the standard UNI 1934 or the UNI EN ISO 8990, are extremely accurate and reliable, but the main drawback is the long-time procedure required, especially for highlyinsulated walls with larger thicknesses. To overcome this issue and to save both time and energy required to run the experiment, techniques based on the response factors theory have been recently gained interest with the aim of finding an alternative methodology to the standard timeconsuming one, without compromising the accuracy of results. The simple application of a triangular temperature solicitation at one side of the wall, allows the determination of the thermal response of the wall in time, as well as, the assessment of the U-value, within a significant shorter time. Besides, such dynamic methods are capable of considering also the thermal capacity of the wall, which also influences its thermal performance. Nevertheless, the technique relies on very strict experimental conditions, e.g., high signal to noise ratios.

For this reason, this work investigates the effect that noisy boundary conditions, in terms of temperature, have on the determination of the thermal transmittance of walls. To do this, simulation tests in dynamic regime were developed in a COMSOL Multiphysics® environment. By applying multiple levels of noise to the boundary conditions, simulations are run and results in terms of perturbated heat fluxes and computed U-values are analysed. Results are then compared to the reference U-value obtained through a steady-state simulation. The main outcomes of this research can lead to practical guidelines for an alternative experimental technique aimed at measuring thermal transmittances of opaque buildings' components in controlled ambient conditions.

# 1. Introduction

The opaque envelope of a building plays a pivotal role in its energy performance, particularly during winter when the minimization of the heat loss is crucial. Due to the important impact that buildings have on energy consumptions (Eurostat, 2022; González-Torres et al., 2022), an effective thermal insulation within the envelope reduces heating demands, ensuring indoor thermal comfort. Conversely, in summer, the envelope must not only prevent heat from entering but it also acts as a thermal reservoir, absorbing and releasing heat to regulate indoor temperatures and reduce cooling needs, according to the thermal capacity of the component.

The design of an optimized thermal envelope is a fundamental step in energy efficient and sustainable buildings, like in new constructions, but also in buildings' retrofitting. One of the main thermal properties describing the buildings' thermal performance is the thermal transmittance, or the U-value. The current procedure to assess such a property is through an analytical way according to the EN 6946:2018 (CEN, 2018) where the thermal transmittance is computed by either knowing or assuming thermal conductivities and thickness of the composing layers of the wall. Nevertheless, often this information is not known, e.g., in retrofit design, or even if data are known, the analytical procedure cannot be applied because of significant irregular geometries and not-uniform layers, e.g., prefabricated walls with frames.

For this reason, experimental procedures in controlled environments, like laboratories, are preferable. The most adopted and extremely reliable techniques to measure the U-value of a building's envelope components are hot-boxes according to the Standards EN ISO 8990: 1996 (CEN, 1996), UNI EN 1934:2000 (Ente nazionale italiano di unificazione, 2000). These procedures rely on the stabilization of two chambers, where a sample is interposed, and steady-state variables like surface temperatures and heat flux are recorded and elaborated to compute the U-value of the wall. Despite the extremely accurate and reliable procedure, the main disadvantages that can be pointed out by adopting hot-boxes are, at first, the absence of other information related to the components' behaviour in non-stationary regime, like dynamic ones. In addition, such procedures often require a considerable amount of time to be concluded according to the thermal inertia of the wall. As a matter of fact, thick walls characterized by a significant thermal inertia may require more than one week to stabilize itself.

In order to reduce test time and to gain additional information on the tested wall, recent unconventional procedures have appeared based on the Response Factors theory of Mitalas & Stephenson (1967). Wall response factors describe the response of the wall when it is excited by a triangular unitary pulse in temperature on one side, and on both the excited and non-excited sides, the heat flux is obtained (Davies, 2004). Some authors like Sala et al. (2008) have exploited such technique in order to measure experimentally response factors of a hollow brick wall in laboratory conditions, which later on, they could be exploited in dynamic energy simulations. Other authors like Rasooli et al. (2016) implemented the response factors method with the aim to compute the in-situ thermal resistance of existing buildings' walls in order to overcome the difficulty of keeping constant boundary conditions. Satisfactory results were obtained in terms of accuracy with respect to stationary methods, i.e., less than 2%. Martín et al. (2010) developed a methodology for the calculation of response factors through experimental tests which was validated through simulations. They proposed a methodology in which response factors of a wall can be obtained without requiring the corresponding material properties. Besides this, they assessed the Uvalue, showing an accuracy of the procedure of about 10%.

According to the literature, impulsive procedures (or, dynamic procedures) have been investigated and adopted in order to overcome stationary methods, which require a long time and which they do not add anything more to the simple stationary characterization of the wall. However, studies focus either on just experimentally determining response factors or on in-situ measurements.

For these reasons, this research work aims to propose an alternative methodology for the determination of the U-values of walls by adopting the Response Factors theory, which has been tested by running simulation tests of two wall typologies with opposite thermal characteristics. Results in terms of U-values obtained with the dynamic method are compared with the stationary one, with and without noisy boundary conditions. Results show how the proposed methodology can be adopted to assess the U-value of walls with errors lower than 1%, and it was also possible to characterize the wall in a transient regime. The noise does not affect the method in a significant way when adopted on walls with a lower thermal resistance and a high thermal capacity (e.g., brick walls), while, for walls with a higher values of thermal resistance and lower thermal capacities (like cross laminated timber walls), in order to determine the U-value through a dynamic way with an error below 10%, internal boundary conditions must not

oscillate more than  $\pm 0.4$  K of the average value. The work points out the efficacy of the dynamic procedure, as well as its resilience against noisy boundary conditions that can be further adopted in real experimental procedure in hot-box apparatuses.

# 2. Methodology

# 2.1 Geometrical Model

The two components adopted for testing the proposed methodology are two walls, with different characteristics in terms of thermal resistance and thermal capacity, that are a 25 cm of clay brick masonry wall and a 10 cm cross-laminated timber (CLT) wall. Their thermal-physical properties are: *(i)* the density equal to 1840 kg m<sup>-3</sup> (clay bricks) and 420 kg m<sup>-3</sup> (CLT), *(ii)* the thermal conductivity equal to 0.80 W m<sup>-1</sup> K<sup>-1</sup> (clay bricks) and 0.12 W m<sup>-1</sup> K<sup>-1</sup> (CLT) and, *(iii)* the specific heat equal to 1800 J kg<sup>-1</sup> K<sup>-1</sup> and 1600 J kg<sup>-1</sup> K<sup>-1</sup>, for the clay brick masonry wall and the CLT walls, respectively.

The geometrical model of the two analyzed walls was developed in a COMSOL Multiphysics<sup>®</sup> environment (v. 5.6). The space domain of each element was discretized according to the default size settings with an extremely fine mesh (maximum size of 1.05 cm and minimum size of 0.002 cm:), chosen after a preliminary sensitivity analysis conducted on each wall where results showed that the numerical model of the time-dependent problem required a finer mesh than the normal one.

# 2.2 Simulation Tests

For each wall, two sets of simulations were run. At first, a stationary simulation for determining the U-value of the wall by imposing constant boundary conditions at the two surfaces equal to 20 °C (internal air temperature) and 0 °C (external air temperature). The thermal transmittance, named  $U_{s}$ , expressed in W m<sup>-2</sup> K<sup>-1</sup>, was determined according to Eq. 1.

$$U_s = \frac{\Phi}{(T_i - T_e)} \tag{1}$$

Where  $\Phi$  is the heat flux across the wall in W m-²,  $T_{\rm i}$  and  $T_e$  are respectively the internal and external air

temperatures (°C). The stationary numerical model was solved by means of the Backward differentiation formula with a relative tolerance equal to 10<sup>-3</sup>. The second regime that was simulated is a timedependent simulation called "dynamic", in which a triangular profile was applied to the external temperature of each wall, where the temperature followed a first increasing ramp from the initial temperature of 16 °C to 26 °C in one hour (+10 K of temperature increase). Then, the first step was followed by a second decreasing ramp till the initial temperature of 16 °C, with duration of one hour (i.e., -10 K h-1). The third and last part of the temperature profile was kept constant equal to 16 °C. At the opposite side, the internal temperature was maintained constant equal to 16 °C. The simulation time-step was equal to 1 minute and the total duration of the simulation was set equal to four days. Such a value was chosen to be sufficient to the heat flux of the non-excited side to return to zero, for both walls. For the resolution of the timedependent problem, it was necessary to change solver and choose a more suitable one for nonstationary problems. For this reason, the numerical model was solved by means of the Runge-Kutta method, where the relative and the absolute tolerances were set equal to 10-4 and 10-5. In order to compute the U-value of the wall by exploiting the dynamic test, the heat flux at the non-excited side was obtained and divided by the magnitude of the temperature increase of the triangular ramp (i.e., 10 K) in order to obtain a unitary heat flux  $\Phi_u$ , expressed in W m<sup>-2</sup> K<sup>-1</sup>. The Response Factors theory adopted in this work relies on a unitary impulse applied to one surface, but since the theory is derived from the Fourier Conduction Equation and the Laplace Transform (Hittle, 1992), the superimposition principle is valid and it was possible to apply a higher pulse in order to obtain a significant response on the opposite side that otherwise would be negligible.

The unitary heat flux  $\Phi_u$  was then fitted as a function of the time *t* (min) in MATLAB<sup>®</sup> environment using the fitting function reported in Eq. 2. Parameters a, b, c and d were determined by minimizing the root-mean-square error between simulation results and the fitting function.

$$\Phi_u(t) = \begin{array}{cc} 0 & \text{if } t < d \\ a \cdot e^{-b \cdot \ln \frac{t-d}{c}^2} & \text{if } t \ge d \end{array}$$
(2)

After that, the U-value of each wall, i.e., U<sub>d</sub>, was computed by performing the integral of the unitary heat flux in time, obtaining Eq. 3.

$$U_d = a \cdot c \cdot \pi^{\frac{1}{2}} \cdot b^{-\frac{1}{2}} \cdot e^{\frac{1}{4 \cdot b}}$$
(3)

This value was then compared to the stationary Uvalue. In both simulation regimes the internal surface thermal resistance was set equal to 0.13 m<sup>2</sup> K W<sup>-1</sup>, while the external equal to 0.04 m<sup>2</sup> K W<sup>-1</sup>, according to the Standard EN 6946: 2018 (CEN, 2018).

# 2.3 Analysis of Noisy Boundary Conditions

In order to evaluate the effect that noise applied to the temperature boundary conditions can have on the determination of the U-value with a dynamic test, the same time-dependant simulations described before were run as before but applying a random noise function to the temperature profiles. In particular, the noise function was initially defined as a random trend with mean equal to zero and maximum intensity equal to ±1.0 K, and then, different intensities were applied to it by scaling the random profile in order to obtain different noise magnitudes, which were equal to  $\pm 0.2$ ,  $\pm 0.4$ ,  $\pm 0.6$ ,  $\pm 0.8$ , and  $\pm 1.0$  K. The noise was applied at first on the external boundary condition ("External" case), after that, at the internal one (named "Internal" case) and finally on both sides ("Both" case). The previously described procedure was repeated, and the dynamic U-value was determined for each noise level.

#### Results and Discussion

Fig. 1 and Fig. 2 show results in terms of unitary heat flux obtained at the non-excited side from dynamic simulation tests and the fitted trend for the clay brick masonry wall and of the cross laminated timber wall (CLT wall), respectively. It can be pointed out that the fitting function expressed in Eq. 2 accurately represents the trend of the simulation test. As a matter of fact, root mean square errors are 0.06 and 0.08 W m<sup>-2</sup> K<sup>-1</sup> for the clay brick masonry wall case and for the CLT wall case, respectively. In the case of the CLT wall, it can be noticed that the peak of the unitary heat flux is poorly fitted with respect to the other wall. This could be explained by the sharper shape of the CLT wall thermal response. Fitting parameters for the unitary heat flux at the internal side of the clay brick masonry wall are equal to a = 0.184, b = 0.944, c =4.811 and d = 1.369. While, as regards the CLT wall, parameters are equal to a = 0.250, b = 1.515, c =2.336 and d = 0.719.

By exploiting Equation (3) for the determination of the thermal transmittance by means of the dynamic test, results of  $U_d$  are reported for the clay brick masonry wall and the CLT wall, as well as the percentage deviation of such value than the stationary U-value, i.e., U<sub>s</sub>.

#### Clay brick masonry wall

 $U_d$  = 2.098 W m<sup>-2</sup> K<sup>-1</sup> (+0.34%, U<sub>s</sub> = 2.091 W m<sup>-2</sup> K<sup>-1</sup>)

#### <u>CLT wall</u>

 $U_d$  = 0.994 W m<sup>-2</sup> K<sup>-1</sup> (-0.77%, U<sub>s</sub> = 1.001 W m<sup>-2</sup> K<sup>-1</sup>)

Results in terms of "dynamic" U-values show extremely good agreement with the stationary values, with deviations lower than 1%, a threshold that is definitely lower than the maximum standard measurement uncertainty of U-values (around 10%). A slightly higher deviation is shown for the CLT wall, but this is due to the poorer fitting procedure the proposed methodology relies on (see Equation 3). Probably, the narrower shape of the unitary heat flux of the CLT wall results more difficult to be fitted by the optimization algorithm than the one of the Clay Brick Masonry walls.



Fig. 1 – Unitary heat flux at the internal side  $\Phi_u$  expressed in W m<sup>-2</sup> K<sup>-1</sup> as a function of the time t, expressed in hours. The yellow line represents the simulation test, while, the dashed purple line represents the fitting function with parameters equal to a = 0.184, b = 0.944, c = 4.811 and d = 1.369. Root mean square error equal to 0.06 W m<sup>-2</sup> K<sup>-1</sup> (clay brick masonry wall)



Fig. 2 – Unitary heat flux at the internal side  $\Phi_u$  expressed in W m<sup>-2</sup> K<sup>-1</sup> as a function of the time t, expressed in hours. The yellow line represents the simulation test, while, the dashed purple line represents the fitting function with parameters equal to a = 0.250, b = 1.515, c = 2.336 and d = 0.719. Root mean square error equal to 0.08 W m<sup>-2</sup> K<sup>-1</sup> (CLT wall)

Moving forward to the analysis of noise, which means how the noise applied to the temperature boundary conditions affects the dynamic methodology for determining the U-value of walls, Fig. 3 and Fig. 4 are given. They show the percentage error compared to the case without noise of the thermal transmittance U<sub>d</sub> computed with the dynamic method, obtained at different noise levels applied at the external side (blue dot), internal side (yellow hexagram) and on both sides (black asterisk).



Fig. 3 – Error in the evaluation of the thermal transmittance  $U_d$  in percentage terms as a function of the noise level applied at the external side (blue dot), internal side (yellow hexagram) and on both sides. (black asterisk). Case of the clay brick masonry wall



Fig. 4 – Error in the evaluation of the thermal transmittance Ud in percentage terms as a function of the noise level applied at the external side (blue dot), internal side (yellow hexagram) and on both sides. Case of the CLT wall

As expected, the results show how noise does have an effect on the methodology for the estimation of the U-value of both walls. Nevertheless, the maximum deviation reached in the computation of the U-value with the proposed dynamic method is about +5% than the case without noise and this occurs for the CLT wall with semi-amplitude of the noise equal to  $\pm 1.0$  K. In the other cases analyzed, deviations stay below this level.

As regards the side of the application of the noise, it can be noticed that when the noise is applied to the external air temperature, errors are the lowest ones registered. For instance, the maximum error reached is -1.0% than the case without noise in correspondence to the highest semi-amplitude of the noise for both walls. A slightly higher deviation is obtained for the CLT wall in the "External" case, and this could be due to the poorer fit of the unitary heat flux discussed before. However, such differences can be considered negligible with respect to other sources of uncertainty present when performing such tests in real conditions. When the noise is applied at the constant internal temperature, results show a different behavior. In particular, it can be noticed that by increasing the noise magnitude, the error increases more than the case without noise but with a more significant impact, especially for the CLT wall. The U-value is overestimated with a +4.6% than the zero-noise case when the noise-amplitude reaches the maximum value. However, when focusing on the clay brick masonry wall, the error on the U-value with the same noise conditions is comparable with the "External" case. This result can be explained by the specific shape of the unitary heat flux adopted as input of the optimization algorithm. The heat flux on the non-excited side of the CLT wall is sharper and it is characterized by a higher and narrower peak than the one of the clay brick masonry wall, because of the lower thermal capacity of the former than the latter. This makes it more difficult for the optimization algorithm to estimate the fitting's parameters under noisy boundary conditions. The last analysis performed in this work focuses on the noise applied on both sides of the walls. Results show how by applying the same noise on both sides there is a summation effect in the clay brick masonry wall, where the two errors of the "Internal" and "External" cases, both negative, are summed showing a maximum deviation of -1.5%

than reference U-value obtained without noise. On the contrary, the summation effect in the CLT wall causes a slight decrease in the noise effect on the results of the optimization algorithm, obtaining results still closer to the "Internal" case.

# 4. Conclusion

The research presented herein focuses on the determination of the U-value of walls using the Response Factors theory. The study aimed to assess the efficacy and resilience of a dynamic methodology in comparison to traditional stationary methods, particularly in the presence of noisy boundary conditions. Through simulation tests conducted in the COMSOL Multiphysics® environment, the research investigated the impact of varying levels of noise on the determination of thermal transmittance.

Results of this study revealed promising outcomes in terms of accuracy and efficiency. The dynamic methodology demonstrated the capability to assess U-values with errors lower than 5%, highlighting its potential for practical applications in experimental procedures. By applying a triangular temperature solicitation at one side of the wall, the methodology allowed for the determination of thermal response over time and the assessment of U-values, which duration is usually lower than a standard test. This dynamic approach not only provided accurate results but also offered insights into the transient behaviour of walls, which is crucial for understanding the thermal performance of building components.

Furthermore, the work examined the resilience of the dynamic methodology against noisy boundary conditions applied on both sides in terms of temperature. Simulations showed that for both walls with lower thermal resistance and higher thermal capacity, such as brick walls, as well as, for those walls with slightly higher thermal resistance and lower thermal capacity, the method was acceptably robust against noise, with minimal impact on the accuracy of U-value determination, especially for the clay brick masonry wall. Higher deviations were obtained for the CLT wall when the noise is applied at the internal side and errors relative to the zero-noise case reached about +5.0%, depending on the specific shape of the response heat flux at the non-excited side, which is directly determined by the thermo-physical properties of the analysed wall. Still, the magnitude of the impact is not significant compared to the sources of uncertainty present under real ambient conditions.

Overall, research findings provide valuable insights and practical guidelines for measuring the thermal transmittance of opaque building components. The dynamic methodology based on Response Factors theory offers a promising alternative to traditional stationary methods, offering a more efficient and time-saving approach without compromising accuracy. The study's results pave the way for the adoption of dynamic procedures in real experimental settings, such as hot-box apparatuses, enhancing the understanding of building thermal performance and contributing to the design of more sustainable and energy-efficient buildings. The dynamic methodology presented in this research holds great potential for advancing the field of building energy performance assessment, offering a reliable and efficient approach for determining the U-value of walls in the presence of noisy boundary conditions, like in real experimental procedures. Additionally, this methodology can support decision-making procedures when it comes to a more detailed building component design by enabling faster thermal characterization of components.

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# Nomenclature

# Symbols

CLT	Cross Laminated Timber
e	Euler's number
Φ	Heat flux (W m <sup>-2</sup> )
$\Phi_{\mathrm{u}}$	Unitary heat flux (W m <sup>-2</sup> )
ln	Natural logarithm
t	Time (min)
Т	Temperature (°C)
U <sub>d</sub>	Thermal transmittance obtained with
	the dynamic test (W m <sup>-2</sup> K <sup>-1</sup> )
Us	Thermal transmittance obtained with
	the steady-state test (W m <sup>-2</sup> K <sup>-1</sup> )

# Subscripts/Superscripts

a	Parameter 1
b	Parameter 2
c	Parameter 3
d	Parameter 4
e	External

i Internal

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# Calibrating a Clothing Insulation Model for Thermal Comfort Assessment in Educational Buildings

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#### Abstract

Thermal comfort assessment in buildings usually relies on the calculation of Predicted Mean Vote (PMV) which is determined by four environmental variables, such as air temperature, air humidity, air velocity and mean radiant temperature, and by two personal factors, namely the metabolic rate and the clothing level. The latter factor is fundamental in determining the thermal sensation since it can be changed and adapted in response to the indoor conditions, thus allowing an extension of the neutral temperature range. Moreover, the uncertainty of clothing level in simulated models can affect the reliability of results in terms of thermal comfort and overall IEQ assessment. This study aims to calibrate existing models on an extensive set of data collected in an Italian high school located near Rome and to build a new clothing model. The outdoor and indoor environmental conditions in 22 natural ventilated classrooms were monitored during the school years 2020-2022. Students' thermal sensation votes and the corresponding clothing levels were surveyed during regular lessons. First, the physical variables used in the literature to predict clothing insulation were at first analyzed to highlight the significant ones based on the collected data. Second, the significant physical variable (i.e., operative temperature) was used as input to feed existing models and to predict clothing insulation; the predicted values were then compared with the observed mean clothing insulation of the students in each classroom. Third, a calibration of a clothing linear model based on operative temperature was carried out and a new linear model based on the indoor running mean temperature was set. Finally, to explore to which extent the linear clothing model based on Top can affect the thermal comfort simulation, the Predicted Mean Vote (PMV) was calculated.

# 1. Introduction

In building energy simulation (BES) the possibility of predicting people behavior is fundamental when the objective is the accurate calculation of the energy demand during the operating phase. It is acknowledged that people usually behave in such a way to maintain comfort conditions. Regarding thermal comfort, people usually adopt personal strategies, such as adapting their clothing (i) or making interventions on the system control (ii) or operating the windows (iii). Regardless of the adopted strategy, the more accurate the thermal comfort prevision, the more reliable is also the estimated energy demand. However, there are some indoor environments, such as classrooms in educational buildings, where the system regulation is not possible, and the operation of windows is not effective in guaranteeing the thermal comfort of all the students. In this kind of building, clothing adaptation can play an important role in providing students' thermal comfort. According to Fanger's model, thermal comfort clothing insulation is one of the personal factors which determines thermal comfort, together with the metabolic rate, and the four environmental variables (i.e., air temperature, air humidity, air velocity and mean radiant temperature (Fanger, 1970). Predicted Mean Vote (PMV) can be calculated using (i) standard clothing based on the reference season (i.e., 1 clo for winter and 0.5 for summer), (ii) observed clothing insulation collected through questionnaires or (iii) predicted clothing values derived from environmental physical parameters.

As highlighted in the literature, clothing adjustment according to the variation of environmental parameters is evidence of the behavioral adaptation (Torriani et al., 2023). The relationship between clothing insulation and environmental parameters has been investigated in different studies to identify simulation models able to predict occupants' clothing insulation levels, avoiding data collection through questionnaires that could be time-consuming.

Several research studies have focused on adult workers in office buildings, highlighting that occupants seem to choose their daily clothing according to the outdoor conditions, such as the daily mean outdoor temperature (Morgan & de Dear, 2003; Haldi & Robinson, 2011) and the outdoor temperature at 6 am (De Carli et al., 2007; Schiavon & Lee, 2013). A few authors present clothing models based on field campaigns in educational buildings, reporting different clothing adaptation behaviors adopted by students according to outdoor and indoor conditions. Table 1 reports a summary of the most recent studies presenting clothing insulation models based on dataset collected in educational buildings. The study conducted by Mors et al. (2011) in primary school reported Linear Regressions (LR) between the mean clothing insulation and external temperatures, namely the daily minimum (Text,min), the mean (Text,mean) and running mean outdoor temperature ( $\Theta_{mr}$ ). The study by Carvalho et al. (2013) based on university students revealed that clothing insulation levels are linked to a recent thermal memory of the external conditions. Particularly, clothing is predicted from the mean outdoor temperature of the previous day (Text, dayx-1) and the maximum value of the current day (Text,max dayx), through Multi Linear Regression model (MLR). Studies focusing on secondary and high school students highlighted the relationship between clothing and indoor conditions (i.e., operative temperature, Top). Torriani et al. (2023) and Wu & Wagner (2024) implemented a linear regression (LR) model using binned operative at 0.5 °C and obtaining a similar slope but a different intercept term. In addition to LR model, Nakagawa et al. (2020) also developed a logistic model with 1 °C intervals of Top.

When models rely on data collected in real build-

ings, it is useful to validate them in different buildings and locations. Therefore, the present work aims to (i) train and test new linear model on sets of real data in an Italian high school during the two-year period 2020-2022 in order to predict clothing insulation, (ii) compare the model with existing linear models, and finally to (iii) evaluate the effect of a detailed clothing model on the thermal comfort evaluation.

Table 1 –List of studies on clothing insulation models in educational buildings based indoor and outdoor temperatures

Ref.	Method	Model(s)	R <sup>2</sup>
Mors et al. 2011	LR	Icl=0.816-0.029*Text,min Icl=0.93-0.024*Text,mean Icl=0.934-0.028*Omr	0.85 0.91 0.91
Carvhalo et al. 2013	MLR	Icl=1.48-0.04272*Text, dayx-1 - 0.009827*Text, max dayx	0.90
Nakagawa et al. 2020	LR Logit	$\begin{split} I_{cl} = & 1.204 - 0.027 * T_{op} \\ I_{cl} = & 0.339 + (0.781 - 0.339) / \\ & (1 + exp((T_{op} - 23.42) / 2.54)) \end{split}$	0.20 0.91
Torriani et al. 2023	LR	Icl=1.0718-0.0136*Top	0.88
Wu and Wagner 2024	LR	Icl=1.44 -0.0252*Top	0.86

# 2. Methodology

# 2.1 Data Collection

Data were collected in five field campaigns conducted in 22 naturally ventilated classrooms of a high school located near Rome (Italy) during the school years 2020-2022. Onsite measurements and subjective surveys were carried out simultaneously, while students were attending regular classes. During the campaigns, students could adjust their clothing insulation. For the short-term monitoring during questionnaire administration, globe temperature, air temperature, relative humidity and air velocity were recorded with a 1-minute timestep in the middle of the room at a height of 1.1 m by means of a DeltaOhm HD32.1 multilogger, in agreement with the Standard EN ISO 7726 (CEN 2001), so that it could be possible to calculate the operative temperature. However, the long-term measurements were carried out using one Hobo MX1102A sensor installed inside each selected reference room. Sensors' specifications are reported in Table 2. The planimetry with sensors' location and the internal view of one of the monitored classrooms are shown in Figure 1 and 2, respectively.

Table 2 – List of instruments used in indoor thermal monitoring: monitored parameters and measurement accuracy

Sensor	Parameters	Accuracy [Range]
DeltaOhm HD32.1	Globe Temperature Ambient Temperature Relative Humidity Air Velocity	±0.01 °C [±199.99°C] ± 0.1 °C [> 199.99°C] ±0.1% [< 80%] ±3% [> 80%] ±0.2 m/s [0 -0.99 m/s] ±0.4 m/s [1-9.99 m/s]
Hobo MX1102A	Ambient Temperature Relative Humidity	± 0.2 °C [0-50°C] ± 2% [1-90%]

With the help of a questionnaire, students were asked to report their actual clothing insulation using a checklist with a selection of garments. Clothing insulation  $I_{cl}$  was attributed to each garment according to the ISO 7730 (CEN 2005) standard. Questionnaires were filled out by students, after being exposed for a suitable period (i.e., min 1 h) to the indoor environmental conditions.

# 2.2 Data Analysis

2.2.1 Significance of independent variables Physical parameters used in existing clothing models (Table 1) were tested through regression analysis to identify possible independent variables



Fig. 1 – Planimetry of a classroom involved in the project with instruments location: red and blue dots indicate the sensor used for short-term and long-term monitoring, respectively



Fig. 2 - Internal view of one of the monitored classrooms

to build new clothing models based on the collected dataset. The physical parameters tested were the minimum, maximum and mean outdoor temperatures, namely,  $T_{ext,min}$ ,  $T_{max}$ ,  $\Theta_{mr}$ ,  $T_{ext,mean}$ , the running mean temperature  $\Theta_{mr}$  of the 7 previous days, the average value of outdoor temperature of the day before,  $T_{ext, dayx-1}$  and the indoor operative temperature. Moreover, the indoor running mean temperature,  $T_{rm,in}$ , of the 5 previous days was included in the analysis. Regressions with p-value below 0.05 were considered significant.

# 2.2.2 Clothing model calibration and validation based on operative temperature

Before testing the linear clothing model based on operative temperature, the collected data were processed (i.e., data binning) and sampled into two groups (i.e., training and testing sets). Specifically, in order to consider subjects exposed to similar conditions, data were binned into 0.6 °C intervals as suggested by EN ISO 7726 (CEN 2001) and then randomized. Linear regression was implemented using a portion of data as a training set to predict the clothing insulation based on the operative temperature, Top, calculated with the equation suggested by EN ISO 7726 (CEN 2001). The model has been validated using the rest of the data as a set and compared with existing models. The metrics used to assess calibration and validation accuracy are the Mean Absolute Error (MAE) and the Rooted Mean Squared Error (RMSE).

# 2.2.3 New clothing linear model based on indoor running mean temperature

Linear regression was also carried out to forecast the clothing insulation based on the running mean indoor temperature,  $T_{\rm rm\ in}$ , considering the 5 previous school days.  $T_{\rm rm\ in}$  was calculated for a limited dataset (i.e., Dataset II) according to the EN 16798-1:2019 (CEN 2019) standard as follows:

 $\Theta_{mr,in} = (1-\alpha)^{*} (Tday_{x-1} + \alpha Tday_{x-2} + \alpha^{2}Tday_{x-2} + \alpha^{3}Tday_{x-3} + \alpha^{4}Tday_{x-4}) (1)$ 

with  $\alpha$  = 0.8. As for the model based on T<sub>op</sub>, the metrics used to assess the calibration accuracy are MAE and RMSE.

#### 2.2.4 Thermal comfort simulation

Predicted clothing insulation, I<sub>cl</sub>, derived from the linear model based on operative temperature was used to calculate the Predicted Mean Vote (PMV) and evaluate thermal comfort inside the monitored classrooms. PMV calculated with predicted I<sub>cl</sub> and PMV calculated using the standard values (i.e., 1 clo for the heating season and 0.5 for the cooling season), were compared with the one calculated using the mean observed I<sub>cl</sub>, and the discrepancy were evaluated in terms of MAE and RMSE.

# 3. Results

A number of 825 questionnaires were collected during 50 regular classes. The analysis focuses on two different subsets: Dataset I includes all the interviewed subjects (i.e., 825), while Dataset II refers to those who attended lessons in the classrooms equipped for a long-term monitoring (i.e., 511 subjects), and it was used to calculate the indoor running mean temperature (section 3.3). Students were aged from 13 to 20 years old, and the female-to-male ratio was 55%-45%. Table 3 summarizes the mean value of the parameters monitored during short-term monitoring. The daily mean outdoor measured during the 50 campaigns ranged between 6.0 and 22.4±3.6 °C. The average indoor air temperature (Ta) varied from 19.5 to 24.5±1.2 °C. The mean clothing insulation level worn by students varied from 0.34 to 1.65 clo ± 0.23.

Table 3 – Statistical summary of measurements collected during the short-term monitoring and clothing insulation (Dataset I)

	Text [°C]	RHext [%]	Ta [°C]	Tmr [°C]	RH [%]	Va [m/s]	Icl [clo]
Min	6.0	28	19.5	19.5	16	0.00	0.34
Max	22.4	88	24.4	24.6	68	0.06	1.65
Mean	14.4	69	22.3	21.8	47	0.01	0.85
SD	3.6	16	1.2	1.3	14	0.01	0.23

#### 3.1 Statistical Analysis

Table 4 reports the results of the linear regression analysis carried out using the mean observed clothing insulation as dependent variable and (i) the outdoor temperatures, i.e., the outdoor temperatures of the current day, namely, Text,min, Tmax, Text,mean, and of previous days, namely running mean temperature  $\Theta_{mr}$ , and the average value of the outdoor temperature of the day before, and (ii) the mean indoor temperature of the current day, i.e., operative temperature and indoor running mean temperature. All the variables, except the outdoor minimum temperature, are significantly related to the clothing insulation (p-value < 0.05) but the coefficient of determination referred to external temperatures is very low. As a consequence, models were trained considering only the indoor operative temperature and running mean temperature.

Table 4 – Statistical analysis of the effect of outdoor and indoor parameters on clothing insulation

Independent variable	p-value	R² adj.
Text,min	0.524	0.00
T ext,mean	0.000*	0.03
$\Theta_{mr}$	0.000*	0.08
Text, (day x-1)	0.000*	0.04
Text,max	0.000*	0.14
Top	0.000*	0.30
Tmr, in	0.000*	0.46

\**p-value* < 0.05

# 3.2 Clothing Model Calibration and Validation Based on Operative Temperature

First, in order to consider the clothing insulation worn by groups of students exposed to similar indoor thermal conditions, the operative temperatures were binned into 0.6 °C intervals as suggested by EN ISO 7726 (CEN 2001). Second, data were randomized and divided into training (i.e., 414 samplings) and testing (i.e., 411 samplings) sets to calibrate and validate the linear model. Results of model calibration and validation are reported in Figure 3 and Table 5-6.



Fig. 3 – Relationship between clothing insulation (I<sub>cl</sub>) and operative temperature ( $T_{op}$ ): full blue markers refer to model calibration while empty orange markers to model validation

Table 5 – Statistical analysis of the effect of operative temperature on clothing insulation

	Regression	p-value	R² adj.	
Bins 0.6° C	$I_{cl} = 1.573 - 0.0354^*T_{op}$	0.000*	0.58	
*p-value < 0.05				

Based on the dataset, there is a significant correlation (p-value < 0.05) between clothing level of students and operative temperature, with a decrease of clothing insulation when  $T_{op}$  rises. This result is consistent with previous studies conducted in high school (Torriani et al., 2023; Wu and Wagner, 2024). The model validation on the testing set and using existing models is reported in Table 6 through RMSE and MAE. The lower the errors, the better the model performs. Considering these two metrics, the validated model led to RMSE and MAE equal to 0.03 clo.

Testing the dataset with existing models, the worst performance is given by the model proposed by Nakagawa et al. (2020) with RMSE and MAE equal to 0.20 clo. Conversely, the models that better fit with the data collected during the present field campaign are those proposed by Torriani et al. (2023), i.e., RMSE = 0.06 clo, MAE = 0.05 clo, and Wu and Wagner (2024), i.e., RMSE = 0.08 clo, MAE = 0.07 clo.

Validation performance is reported also in the scatterplot between observed and predicted clothing insulation (Figure 4) which show that the clothing insulations forecasted by the model proposed by Torriani et al. (2023) and Wu and Wagner (2024) remain within the  $\pm 20\%$  tolerance intervals from the bisector.



Fig. 4 – Relationship between predicted and observed clothing insulation (IcI). Solid red line and dashed gray lines represent the bisector, ±20% tolerance intervals, respectively

Table 6 – Summary of metrics for measuring the distance between the predicted and the observed clothing insulation

	Model #1	Nakagawa et al. 2020	Torriani et al. 2023	Wu and Wagner 2024
RMSE [clo]	0.03	0.20	0.06	0.08
MAE [clo]	0.03	0.20	0.05	0.07

# 3.3 New Clothing Model Based on Indoor Running Mean Temperature

Since the statistical analysis highlights an effective relationship between the clothing insulation worn by students and indoor conditions, rather than the outdoor temperatures, a focus analysis was carried out to explore possible thermal memory based on indoor conditions monitored through the longterm onsite measurements. This analysis considers Dataset II, namely students attending lessons in the classrooms equipped for a long-term monitoring. Only school hours and only school days were considered to calculate the mean indoor temperature and the running mean temperature. For this analysis the same procedure adopted for the operative temperature model was carried out, namely data binning (i.e., 0.6 °C step intervals), randomization and sampling into training (i.e., 248 subjects) and testing (i.e., 243 subjects) sets.



Fig. 5 – Relationship between clothing insulation ( $I_{cl}$ ) and mean indoor running temperature ( $T_{rm \ in}$ ): full blue markers refer to model calibration while empty orange markers to model validation

Table 7 – Statistical analysis of the effect of indoor running mean temperature on clothing insulation

	Regression	p-value	R² adj.
Bins 0.6° C	$I_{cl} = 1.482 - 0.037^*T_{rm}$	0.000*	0.74
* 1 0	0.5		

\*p-value < 0.05



Fig. 6 – Relationship between predicted and observed clothing insulation ( $I_{cl}$ ): full blue markers refer to model calibration while empty orange markers to model validation

Table 8 – Summary of different metrics for measuring the distance between observed and predicted clothing insulation

Metrics	Model#1	Model#2
RMSE [clo]	0.03	0.06
MAE [clo]	0.03	0.05

The linear regression model between clothing insulation and indoor running mean temperature, i.e., Model#2, is shown in Figure 5 and Table 7. The intercept term and the slope are similar to those found with the model based on operative temperature (i.e., Model#1), while the coefficient of determination is higher (i.e.,  $R^2$ =0.74).

Validation performance of Model#2 is reported in Figure 6 and Table 8 in comparison with the results obtained for Model#1. It can be seen that the RMSE and MAE calculated for Model#2 are similar to those calculated for Model#1, meaning that indoor running mean temperature can be used to predict students' clothing insulation.

#### 3.4 Thermal Comfort Simulation

Figure 7 and Table 9 report the results of the thermal comfort simulation in terms of Predicted Mean Vote (PMV). The scatter plot shows the relationship between PMV calculated with the observed clothing insulation (x axis) and PMV obtained using Icl derived from the linear model based on operative temperature and PMV calculated using standard clothing. It can be seen that PMV that consider the predicted Icl is quite a good proxy of PMV calculated with observed clothing insulation (RMSE=0.13, MAE= 0.10), while there is an overestimation or underestimation if the PMV which uses standard seasonal clothing (RMSE=0.32, MAE= 0.29).



Fig. 7 – Relationship between PMV calculated with predicted and standard clothing insulation (I\_{cl}) and PMV based on observed I\_{cl}

Table 9 – Summary of different metrics for measuring the distance between PMV calculated with observed  $I_{cl}$  and PMV obtained with Top and using standard clothing

Metrics	PMV Model#1	PMV standard
RMSE	0.13	0.32
MAE	0.10	0.29

# 4. Conclusion and Further Development

This study focused on the calibration and validation of linear models for predicting the clothing insulation of students in real classrooms based on an extensive set of data collected in an Italian high school located near Rome. Linear regression models have tested using operative temperature and indoor running mean temperature of the previous 5 school days. Based on the collected data and the presented analysis, this study shows that:

- Linear models in the literature based on indoor operative temperature can predict clothing insulation of students with a Mean Absolute Error lower than 0.07 even when applied to different datasets/conditions
- 2. When developed or tuned on monitoring data are available, this error can be decreased (0.03 for Model#1)
- Based on collected data, indoor running mean temperature (Model#2) can be used instead of operative temperature to predict clothing insulation (MAE = 0.05).
- PMV with detailed clothing (Model#1) reduces the over/underestimation of thermal comfort, which could be beneficial in BES IEQ evaluation

As a future development, it could be interesting to extend the research including other educational stages (i.e., primary school or university). This could also allow for the further validation of the models, improving their reliability. Moreover, multi linear regressions considering different independent variables and different type of regressions will be explored.

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# Alternative Affordable Solutions in Reducing the Number of Hours with Heat Strain Inside Buildings

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#### Abstract

Challenges of climate change affect various aspects of human life. This research focuses on the health implications resulting from climate-induced alterations and underlines the vulnerabilities experienced by specific demographic groups, notably the elderly and socioeconomically disadvantaged. These individuals frequently suffer the impact of extreme heat events due to their limited access to cooling technologies, such as air conditioning units, thus exacerbating their vulnerability to heat-related illnesses and diminishing their overall quality of life. Relying on air conditioning systems causes various limitations, including increased energy consumption, exacerbation of greenhouse gas emissions, and the risk of power outages. Moreover, rules and financial problems such as initial and operational costs block widespread adoption, particularly among low-income households.

In response to these problems, this study promotes an affordable alternative strategy focused on utilizing practical yet effective methods, electric fans, window coverings, and natural ventilation to alleviate indoor heat stress and to evaluate their efficacy in enhancing thermal comfort and protecting the well-being of occupants. Numerical simulations were conducted using EnergyPlus and Design Builder software. The simulations focused on a prototypical building, reflecting the common architectural features, representative of multi-family housing built from 1961 to 1975, using the Tabula web tool. The simulations were executed for three cities, Palermo, Pisa, and Trieste in Italy. The analytical framework of this study extends beyond historical weather data, including datasets covering future projections. This comprehensive approach enhances analysis by integrating changing climate conditions.

The findings reveal a significant reduction in hours with heat strain with electric fans emerging as a key tool in mitigating them, even under worst-case scenarios. Natural ventilation and window shading also play significant roles in reducing heat strain hours within apartments. In conclusion, the study emphasizes the urgent need to address the multifaceted impacts of climate change on public health. It advocates for affordable solutions such as electric fans, window coverings, and natural ventilation to combat high internal temperatures and to contribute to broader environmental sustainability goals.

#### 1. Introduction

The ongoing change in climate patterns has led to a consistent rise in ambient temperatures, resulting in notable social and health implications for occupants within built environments. Recent findings from the 2021 Sixth Assessment Report of the IPCC underscore this escalating temperature trend (IPCC, 2021), emphasizing the urgent need to integrate climate considerations into effective building energy policies (Robert & Kummert, 2012). Authorities must prioritize these effects when conducting risk assessments (Manzan et al., 2022), especially given the heightened risk of heat-related health issues stemming from increased temperatures and more frequent heatwaves over the past three decades (Attia et al., 2021).

In response to these challenges, many industrialized countries have usually turned to air conditioning systems to maintain indoor comfort levels and mitigate health risks. However, this approach presents drawbacks, notably regarding energy consumption and infrastructural limitations. The growing demand for space cooling, as highlighted in the 2018 IEA report (IEA, 2018), underscores the need for more sustainable alternatives.

Low-income households, in particular, face significant financial barriers to accessing traditional air conditioning solutions, prompting a shift towards more energy-efficient options like simple electric fans. Research by Haddad et al. (2022) underscores the prevalence of fans in low-income housing, offering a cost-effective means of alleviating indoor heat stress. Health concerns, especially in hightemperature environments, further underscore the importance of exploring alternative cooling methods (Manzan et al., 2023).

Studies by Tadepalli et al. (2021) emphasize the potential of ceiling-mounted fans to enhance indoor comfort while reducing reliance on air conditioning. Similarly, the work of Morris et al. (2021) and Tartarini et al. (2022) highlights the safety and efficacy of electric fans, providing valuable insights into their widespread applicability across various climatic conditions by applying the Gagge model (Gagge et al., 1971). They also developed a web platform to assess the usefulness of electric fans (Tartarini et al., 2020).

While fans offer a promising solution for indoor cooling, concerns remain regarding their effectiveness in extreme heat conditions. Research efforts, such as those by Jay et al. (2015), seek to address these concerns and enhance guidelines for fan usage during heatwaves.

In summary, addressing the challenges posed by rising temperatures requires a multifaceted approach that prioritizes energy efficiency, affordability, and public health considerations. By exploring alternative cooling solutions like fans, window shades, and natural ventilation, and integrating climate-responsive design principles, policymakers can mitigate the adverse effects of climate change on indoor environments while promoting sustainability and resilience.

# 2. Simulation

# 2.1 Methodology

The efficacy of ventilators in alleviating heat stress caused by elevated temperatures was validated through numerical simulations conducted on a typical building using weather files of three distinct Italian cities: Palermo in the south, Pisa in the central region, and Trieste in the north of Italy (as described in Table 2). The building's geometric properties and thermal attributes were accurately replicated using DesignBuilder software, with simulations executed via EnergyPlus version 9.4. These simulations utilized three climate datasets for each city, including current climate conditions TMY and two projections for future weather patterns, with a specific focus on the summer months of June, July, and August.

# 2.2 Building Description

The primary characteristics of the building were acquired through the Tabula web tool (TABULA WebTool s.d.), indicating its construction period between 1961 and 1975. It demonstrates qualities of low thermal mass and high transmittance, constituting a five-floor structure described by Lupato & Manzan (2019). Modifications to the geometry were made to show staircases and two apartments per floor. The building encompasses a volume of 3074 m<sup>3</sup> and a total usable surface area of 848.6 m<sup>2</sup>, with each apartment occupying 76 m<sup>2</sup>. Please see Figure 1 presents the floor plan, which depicts two apartments. The building situated facing south and apartment 1 is oriented towards the east, while apartment 2 has a westward-facing wall. For clarity, each apartment will be denoted by the floor number, beginning with 0 for the Ground floor, followed by the direction, with A1 representing eastward and A2 westward. Hence, the two ground-floor apartments are identified as F0\_A1 and F0\_A2, respectively. The opaque and transparent structures, along with internal loads, align with those utilized by Lupato & Manzan (2019). Corresponding structures for the uninsulated building are detailed in Table 1. Ventilation considerations include an air change rate of 0.3 ACH, incorporating natural ventilation through window openings. Adjustments to internal loads, opaque and transparent surface characteristics, output variables, and post-processing of results were performed using Python scripts with the Eppy library (2022).



Fig. 1 – Floor plan with the position of two apartments and stairs

	U	Mass	$U_{\mathrm{w}}$	SHGC
	$[W/m^2K]$	[kg/m <sup>2</sup> ]	[W/m <sup>2</sup> K]	[-]
Walls	1.15	194	-	-
Roof	1.10	406	-	-
Floor	0.94	478	-	-
Windows	-	-	2.2	0.7

Table 1 – Opaque and transparent surface characteristics

#### 2.3 Simulated Weather and IDF Files

The simulations utilized three distinct weather files for each city. The first weather file employed was a standard Typical Meteorological Year (TMY), generated from monitored data collected during specific periods: between 1999 and 2008 for Trieste, between 1990 and 2009 for Pisa, and between 2002 and 2009 for Palermo. The geographic coordinates of these cities are reported in Table 2. These TMY files were created following the procedures outlined in the EN ISO 15927-4 technical standard and represent the average climate behavior for each location.

Considering the predicted increase in temperatures and the expected rise in the frequency and severity of heatwaves, for the second and third files two Future Meteorological Year (FMY) were also developed. These FMY were crafted applying the morphing method (Manzan et al., 2023; Belcher et al., 2005), which involves using the TMY data with climate projections obtained from models such as HadGEM2-ES RACMO22E, which for the sake of clarity will be called M1, and MPI-ESM-LR REMO2009 that will be called M2 (Manzan et al., 2023). The two models were selected among five (Manzan et al., 2022) for having the higher and lower increase in temperatures. For both methods the RCP 8.5 scenario was considered, and future weather data was obtained for the period between 2036 and 2050. Giving rise to a worst-case scenario (M1), and another with a less intense temperature rise (M2).

For each city, we employed two IDF files. The first file outlines the building's configuration without window shades, relying solely on natural ventilation. In contrast, the second IDF file, along with ventilation, considers also that the persons are able to close the external shutters to protect the interior from excessive radiation. To ease recalling each file, the first one will be called NV and the second one SHV. During the post-processing stage, we analyzed these files under two conditions: with and without fans, across three different weather files.

Table 2 - Geographic coordinates of the cities

City	Latitude	Longitude	Altitude
Trieste	45.65	13.78	2
Pisa	43.70	10.40	4
Palermo	38.12	13.35	14

#### 2.4 Biophysical Model

The primary aim of this study is to evaluate the efficacy of a ventilator in improving indoor conditions within a building during high external temperatures. Various biophysical models have been developed by researchers, including Jay et al. (2015) and Morris et al. (2021). However, for this study, we adopted the Gagge model (Gagge et al., 1971) in combination with the methodology proposed by Tartarini et al. (2022), which has been implemented in the Python library pythermalcomfort (Tartarini & Schiavon, 2020). Specifically, our analysis utilized the `fans\_heatwaves` function within this library, which returns several biophysical parameters across different air velocities, providing insights into the impact of fans on the human body.

Solving a balance equation for a system comprising an inner core and an outer skin layer, the Gagge method assesses how environmental factors—such as dry bulb temperature ( $t_{db}$ ), mean radiant temperature ( $t_r$ ), air velocity (V), and relative humidity (RH)—as well as clothing level ( $I_{cl}$ ) and activity (M), influence the sensible and latent heat exchanges between the body and the environment.

Moreover, the *pythermalcomfort* library assists in the acquisition of biophysical parameters that can help in identifying heat strain. Specifically, three parameters—namely, the rate at which regulatory sweat is generated ( $m_{rsw}$ ), skin wettedness (w), and skin blood flow ( $m_{bl}$ )—can be compared to thresh-

old values to detect hazardous situations. According to Gagge et al., m<sub>rsw</sub> depends on the deviation of skin and core temperatures from the minimum regulatory effort values, with an upper limit of 500 mL/h. Skin blood flow is associated with the vasodilation regulatory mechanism, with the threshold set at 80 L/(h m<sup>2</sup>), as determined by Tartarini. Skin wettedness (w) serves as an indicator of thermal stress, signaling an occurrence when sweating necessitates more surface area for evaporation than what is available. The maximum allowable value for skin wettedness (w<sub>max</sub>), according to Gagge, is dependent on air velocity and clothing levels, and this parameter is also provided as output by the `*fans\_heatwaves*` function.

# 2.5 Simulation and Post-Processing

The simulations were conducted for each weather file, each IDF file, and each city, and afterward, the results underwent automated analysis using the eppy and pythermalcomfort library. Utilizing the fans\_heatwaves function, the time distribution of internal temperature, mean radiant temperature, and humidity, facilitated the extraction of physiological parameters under fan-off and fan-on conditions. These parameters, including  $m_{rsw}$ ,  $m_{bl}$ , and w, were then compared against respective limit values to identify potential heat strain conditions. Fan speeds were adjusted accordingly to achieve fan-off (Va = 0.1 m/s) and fan-on (Va = 0.8 m/s) conditions in each space and then the number of hours with heat strain was calculated for each apartment. In the post-processing stage, we also checked the PMV on different floors and apartments as an indicator of internal thermal comfort conditions.

# 3. Discussion and Result Analysis

All simulations were conducted specifically during the summer months of June, July, and August, a period characterized by elevated external temperatures that can significantly exacerbate internal heat stress conditions. Upon meticulous analysis of the data, consistent trends were observed across all three cities under investigation. However, due to limitations of space within this document, we have chosen to present only a subset of the results through thoughtfully selected tables and graphs.

Table 3 reports the maximum operative temperature (Tmo) and the number of hours with heat strain for Palermo in four different conditions: with and without a fan, with and without window shades, all projected for the future model HadG-EM2-ES RACMO22E for RCP 8.5 between the years 2036 and 2050 (the worst-case scenario, M1). It's quite clear that integrating electric fans into the environment can effectively decrease the hours of heat strain, and similarly, the installation of window shades also contributes to this reduction. The utilization of electric fans and window shades appears to play a significant role in mitigating heatrelated discomfort, highlighting their importance in promoting thermal comfort within the space. In the condition without shade and without a fan (NV) in apartment F3\_A2, we had 996 hours with heat strain (nhs), which decreased to 282 hours by adding a fan (Fnhs). Similarly, within the same apartment, the presence of window shades (SHV) contributed to a considerable reduction in heat strain hours, from 661 hours (nhs) to 161 hours (Fn<sub>hs</sub>) with the addition of a simple electric fan.

Table 3 – Maximum operative temperature and number of hours with heat strain for M1, NV and SHV, with/out fan\_ Palermo

	NV			SHV			
Flat	Tmo	nhs	Fnhs	Tmo	nhs	Fnhs	
F0_A1	37.13	62	20	36.36	39	17	
F0_A2	38.36	137	23	36.81	60	20	
F1_A1	40.87	330	60	39.98	241	42	
F1_A2	42.14	513	106	40.42	278	51	
F2_A1	42.60	573	133	41.69	400	86	
F2_A2	43.81	806	211	42.07	478	104	
F3_A1	43.56	766	186	42.69	576	124	
F3_A2	44.50	996	282	42.86	661	161	
F4_A1	44.17	465	78	43.44	363	52	
F4_A2	45.49	634	121	43.98	403	54	

In scenarios without window shades (NV), adding a fan led to an average reduction of 406.2 hours in heat strain across all ten apartments. Conversely, in situations where window shades were present, the average decrease in heat strain hours upon fan installation increases to 278.8 hours. Thus, using a fan proved advantageous in both scenarios, with its effectiveness notably pronounced in conditions without window shades.

The same variables are presented in Table 4 for Trieste in the future weather dataset MPI-ESM-LR\_REMO2009, RCP 8.5 for the years 2036-2050 (M2). It is immediately apparent that apartment F3\_A2 exhibits the highest number of hours with heat strain across all scenarios: without shade and with shade, and also without a fan and with a fan, respectively, with values of  $n_{hs} = 1115$ ,  $n_{hs} = 665$ ,  $Fn_{hs} = 558$ , and  $Fn_{hs} = 202$ . Thus, we observe that the use of window shades decreases the number of hours with heat strain, as does the use of electric fans.

Table 4 – Maximum operative temperature and number of hours with heat strain for M2, NV and SHV, with/out fan\_ Trieste

	NV			SHV		
Flat	Tmo	nhs	Fnhs	Tmo	nhs	Fnhs
F0_A1	36.07	81	0	33.94	8	0
F0_A2	39.91	416	57	35.4	64	0
F1_A1	39.42	472	75	37.1	253	12
F1_A2	43.43	853	367	38.63	419	66
F2_A1	40.97	650	199	38.5	436	64
F2_A2	44.97	1036	501	40.08	566	143
F3_A1	41.69	753	271	39.42	509	106
F3_A2	45.21	1115	558	40.7	665	202
F4_A1	42.05	497	56	40.24	315	8
F4_A2	46.33	826	274	41.68	440	38

Another notable observation is that across all three cities and scenarios, apartment F3\_A2 consistently registers the highest number of hours with heat strain. Additionally, in all apartments facing westward (A2), the number of hours surpasses those in apartments facing eastward (A1) on the same floor. Referring to Table 5, which illustrates the maximum temperature and operative temperatures experienced in each apartment in the simulated building for Pisa for the situation NV and without a fan in scenario M1, it is observed that the maximum temperature (51.06) occurred on July 10th at 20:00 in apartment F4\_A2. However, the highest operative temperature (50.88) within the same day was recorded for apartment F2\_A2, with a very similar operative temperature (50.82) reached in

apartment F4\_A2 seven days later, on July 17th. Notably, all these maximum temperatures were observed during the late evening, between 19:00 and 22:00.

Table 5 – Maximum temperature and operative temperature for M1\_NV without a fan, the time and date of reaching them\_ Pisa

Flat	Tmo	time	Tmp	time
F0_A1	38.01	07/10 20:00	38.34	07/10 20:00
F0_A2	45.06	07/10 20:00	45.48	07/10 20:00
F1_A1	41.64	07/10 20:00	41.84	07/10 20:00
F1_A2	49.35	07/10 21:00	49.49	07/10 20:00
F2_A1	43.15	07/10 20:00	43.29	07/10 20:00
F2_A2	50.88	07/10 21:00	50.99	07/10 20:00
F3_A1	43.65	07/10 20:00	43.76	07/10 20:00
F3_A2	50.68	07/10 22:00	50.65	07/10 22:00
F4_A1	43.25	07/10 20:00	43.36	07/10 20:00
F4_A2	50.82	07/17 19:00	51.06	07/10 20:00

Figures 2 and 3 illustrate the temporal evolution of physiological variables within Apartment F3\_A2 under SHV conditions in Pisa, where high summer temperatures prevail, as outlined in Table 6. Figure 2 depicts the scenario without fans, while Figure 3 represents the situation with fans. Notably, the variables  $m_{rsw}$  and  $m_{bl}$  exhibit minimal changes with fan utilization, remaining comfortably below their respective thresholds of 500 mL/h and 90 mL/(h m<sup>2</sup>). Conversely, the parameter *w*, denoting skin wettedness, shows a significant decrease in value with increased air velocity, as evident in Figures 3e) and 2b). Specifically, *w* attains its maximum of 0.7 in the absence of fans, while it reduces to 0.6 when fans are operational.

Table 6 reports the maximum values of these physiological parameters with and without fan intervention in Apartment F3\_A2, alongside the corresponding occurrences of heat strain (nhs). Heat strain predominantly arises from elevated skin wettedness, reaching its peak across all apartments, particularly affecting centrally located units and those facing westward. The use of fans substantially changes this dynamic.

An additional facet of the analysis examines the Predicted Mean Vote (PMV), revealing that across both future weather scenarios (M1 and M2) outlined earlier, a notably high percentage of hours demonstrate a PMV value equal to or greater than 2.

		N	V	SHV		
F3_A2		No fan	fan	No fan	fan	
	m <sub>rsw</sub>	63.77	55.13	58.91	50.35	
λV	W	0.70	0.41	0.50	0.27	
<b>VI</b>	ты	24.04	21.64	22.69	20.39	
	nhs	0	0	0	0	
	m <sub>rsw</sub>	157.07	191.44	124.63	135.56	
11	w	0.70	0.60	0.70	0.60	
2	ты	ты 80		75.13	58.25	
	nhs	1484	881	779	204	
	m <sub>rsw</sub>	m <sub>rsw</sub> 156.53		129.87	142.62	
2	w	0.70	0.60	0.70	0.60	
2	ты	80	80	80	80	
	nhs 1376		1007	948	356	

Table 6 – Maximum values for physiological parameters and number of hours with heat strain for the apartment F3\_A2\_ Pisa



Fig. 2 – The temporal evolution of physiological variables within apartment F3\_A2 under SHV conditions in Pisa with no fan

This suggests a significant probability of occupants experiencing considerable thermal discomfort, primarily due to an excessively warm sensation (Fanger, 1972).



Fig. 3 – The temporal evolution of physiological variables within apartment F3\_A2 under SHV conditions in Pisa with fan

Across all three cities, we observed a consistent trend of PMV escalation in M1 (HadGEM2-ES RACMO22E for RCP 8.5) surpassing that in M2 (MPI-ESM-LR\_REMO2009, RCP 8.5). However, both scenarios exhibit a significant spike, surpassing that of TMY.



Fig. 4 – Percentage of PMV >=2 in each apartment for all scenarios without a fan\_ Trieste

Figure 4 illustrates the variation in three distinct weather files under two conditions, NV and SHV, without the use of a fan in Trieste. It is evident that the percentage of PMV values equal to or exceeding two shows a notable increase in future models, indicating a substantial dissatisfaction with the internal thermal comfort among occupants. This trend in PMV behavior is consistent across all cities, as observed in the other findings.

# 4. Conclusion

The multifaceted challenges posed by climate change necessitate urgent action to safeguard public health and enhance the resilience of built environments. This study has shed light on the health implications of climate-induced changes, particularly focusing on vulnerable demographic groups such as the elderly and socioeconomically disadvantaged individuals. By delving into the impacts of extreme heat events, it has become evident that limited access to cooling technologies, such as air conditioning units, exacerbates the vulnerability of these groups to heat-related illnesses, thereby compromising their overall well-being.

However, the reliance on air conditioning systems presents its own set of limitations, including increased energy consumption, greenhouse gas emissions, and the risk of power outages, not to mention the financial barriers hindering widespread adoption, especially among low-income households.

In response to these challenges, this study advocates for the adoption of affordable alternative strategies, such as electric fans, window coverings, and natural ventilation, to alleviate indoor heat stress and enhance thermal comfort. Through numerical simulations conducted using Design Builder and Energy Plus software, the efficacy of these methods has been evaluated across different climatic conditions, providing valuable insights into their potential to protect the well-being of building occupants.

The findings of this study underscore the significant role of electric fans in mitigating heat strain, even under worst-case scenarios, along with the complementary benefits of natural ventilation and window shading. On average, the use of electric fans can reduce heat strain hours by 480 hours in M1 NV and 315 hours in SHV across three cities. By reducing the number of hours with heat strain, these strategies contribute to enhancing indoor comfort and promoting broader environmental sustainability goals.

In conclusion, addressing the complicated impacts of climate change on public health requires a holistic approach that integrates affordable and sustainable solutions into building design and policy frameworks. By prioritizing energy efficiency, affordability, and public health considerations, policymakers can effectively mitigate the adverse effects of rising temperatures on indoor environments while fostering resilience and sustainability for future generations.

# Nomenclature

#### Symbols

$Fn_{hs}$	n <sub>hs</sub> in FAN_ON situation
$\mathbf{I}_{cl}$	clothing level
М	activity
M1	HadGEM2-ES RACMO22E
M2	MPI-ESM-LR_REMO2009
mы	skin blood flow
m <sub>rsw</sub>	regulatory sweat
n <sub>hs</sub>	number of hours with heat strain
NV	only natural ventilation
RH	relative humidity
SHV	window shade and natural ventilation
TMY	typical meteorological year
t <sub>db</sub>	dry bulb temperature
Tmo	operative temperature
Tmp	temperature
tr	mean radiant temperature
V	air velocity
w	skin wettedness
Wmax	maximum allowable value for $w$

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# An Attempt to Model Ventilation Rate in Classrooms Based on the Measurement of Relative Humidity

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#### Abstract

Indirect CO<sub>2</sub>-based measurement of the ventilation rate is a well-established method based upon a balance equation of the CO<sub>2</sub> generated by people and dispersed by infiltration and ventilation. In principle, ventilation rate can also be estimated by water vapour mass balance when storage terms are properly modelled. This work aims to benchmark the CO2-based model and the water vapour-based model to estimate of ventilation rate in classrooms. The case study is a secondary school in Morlupo, Rome. Here, four naturally ventilated classrooms and the adjacent spaces were monitored for a two-week period (indoor temperature and relative humidity RH, CO2 concentration, occupancy, outdoor temperature and RH). The ventilation rate for each classroom was estimated using the indirect CO<sub>2</sub>-based method and then fed to an energy model developed in TRNSYS. Buffer effects for moisture were estimated using a single-layer Equivalent Penetration Depth Model. The simulated humidity ratio was compared to the measured one and input parameters for the storage models were tweaked until convergence using an optimization algorithm. Such process was repeated for 2 of the 4 classrooms. Then, the tuned parameters identified for the storage model were used as input on the remaining 2 classrooms and the ventilation rate obtained using the watervapour based method was compared to the results of the CO2-based method. Results show that the water vapourbased method significantly underestimates the air changes per hour, calling for an in-depth analysis of storage buffer terms

### 1. Introduction

Several school buildings in Italy are not equipped with mechanical ventilation systems, as ventilation is guaranteed by window operation. In those cases, an accurate estimate of ventilation rate is relevant to allow for a proper energy modelling. Among the most used methods to estimate ventilation rate, indirect CO2-based measurement is a well-established approach based upon a balance equation of the CO2 generated by people and dispersed by infiltration and ventilation. CO2 sensors are largely available on the market, but their cost is not as low. Therefore, in the present work, alternative methods are explored to model ventilation rates in naturally ventilated environments.

# 1.1 Methods for Estimating Ventilation Rates

Ventilation rate is often indirectly measured using the indirect method based on the monitoring of CO<sub>2</sub> levels (Batterman, 2017). The governing balance equation is (Lu et al., 2011):

$$V\frac{dC_{in}}{dt} = G_{CO2} + Q \cdot (C_{out} - C_{in}) \tag{1}$$

where C denotes the CO<sub>2</sub> concentration measured indoors ( $C_{in}$ ) and outdoors ( $C_{out}$ ),  $G_{CO2}$  the CO<sub>2</sub> generation rate, V the room volume, and Q the ventilation rate. Integrating by parts and assuming constant boundary conditions, which can be acceptable for short reference time, the equation can be written in a form that allows for a straightforward implementation:

$$C_{in}(t) = C_{out} + \frac{G_{CO2}}{Q} \cdot \left(1 - e^{-\frac{Q}{V}t}\right) + (C_0 - C_{out}) \cdot e^{-\frac{Q}{V}t}$$
(2)

If the CO<sub>2</sub> concentration is measured indoors and the room characteristics are known, the only unknown is represented by the ventilation rate. Eq. 2 can then be solved by iteration.

Another method to estimate ventilation rate is based on the EN 16798-7 standard (CEN, 2017), which requires knowledge of the net open surface towards outdoors and climate data.

The ventilation rate could be in principle also recovered from a water vapour (WV) mass balance. The governing mass balance equation is (Lu, 2003):

$$M_{air}\frac{dc_{in}}{dt} = \dot{m}_{wv} + \dot{m} \cdot (c_{out} - c_{in}) + \sum \dot{M}_i \qquad (3)$$

where, besides the quantities seen before, c is the humidity ratio,  $\dot{m}_{wv}$  is the indoor generation mass rate of water vapour and  $\sum \dot{M}_i$  is the sum of moisture transfer rates between room surfaces and indoor air. This can be modeled as an additional storage effect. The moisture storage term can be represented according to different methods, characterized by different complexities (Glass and Tenwolde, 2009), for example, the estimate of the average of the outdoor water vapor pressure to approximate short-term buffering effects (TenWolde and Walkers, 2001), or the admittance model proposed by Jones (1993).

Besides solving the heat and mass transfer model using a finite-difference approach, the most common simplified methods used for considering short-term buffering effects are the Effective Capacitance Model and the Equivalent Penetration Depth Model (Janssen and Roels, 2009). In the Effective Capacitance Model, a multiplier is applied to the left-hand term of Eq. 3 to account for the added moisture capacity due to walls and internal objects. The empirical quantification of the multiplier and the diffculty to give it a physical meaning make this model slightly inaccurate (Woods, 2013). Regarding the Equivalent Penetration Depth (EPD) model, the main underlying hypothesis is that the moisture buffering process is determined by one thin layer of the surface that faces the room, which is subject to a cyclic variation of humidity. When short-term and long-term buffering phenomena have to be accounted for, the use of two layers is envisaged. The water vapour mass balance according to the EPD model is presented in equation 4. In addition to the terms described above,  $m_d$  describes exchange coefficients relative to adjacent airnodes,  $\beta_{surf}$  is the exchange coefficient for airnode-surface buffer and  $c_{surf}$  is the humidity ratio of the surface storage.

$$M_{air} \frac{dc_{in}}{dt} = \dot{m}_{wv} + \dot{m} \cdot (c_{out} - c_{in}) + \sum_{j} \dot{m}_{d} \cdot (c_{in,j} - c_{in}) + \beta_{surf} \cdot (c_{surf} - c_{in})$$
(4)

The dynamics of the water content in the surface buffer layer is presented in Eq. 5, where  $k_{surf}$  is the gradient of the sorptive isotherm and  $M_{surf}$  is the mass of the buffer layer.  $\beta_{surf}$  ( $\beta$  in the following) can be determined based on the equivalent penetration depth, the surface size of the buffer material and the diffusion resistance  $\mu$  of the buffer material. The mass of the surface buffer can be estimated by multiplying the equivalent penetration depth and the density of the buffer material.

$$M_{surf}k_{surf}\frac{dc_{surf}}{dt} = \beta_{surf} \cdot (c_i - c_{surf})$$
(5)

The EPD model is a compromise between the simple, inaccurate, effective capacitance approach and the complex, yet accurate, finite-difference approach.

#### 1.2 Aim of the Research

The aim of this research is to test the accuracy that the water vapour-based model can achieve in estimating the ventilation rate compared to the standard CO<sub>2</sub>-based method. To do this, monitored indoor parameters in a high school were used to implement an CO<sub>2</sub>-based model for the calculation of natural ventilation rates in two classrooms which were then used to calibrate the buffer properties to be used in the water vapour-based method. Finally data collected in two other classrooms were used to compare the results obtained from the two methods. The relevance of the application stems from the consideration that the cost of T/RH sensors is significantly lower than that of CO<sub>2</sub> concentration sensors with comparable accuracy. Moreover, naturally ventilated classrooms offer an interest case study as generation rate is only determined by number of occupants, so as per carbon dioxide generation.

# 2. Method

The case study is a secondary school in Morlupo, Rome, dating back to the 1990s. The building is made of reinforced concrete and non-load bearing brick walls, with no insulation. A two-week measurement campaign was conducted in four classrooms (Figure 1). Air temperature, CO<sub>2</sub> concentration and relative humidity were monitored with a time resolution of 10 min, while temperature and relative humidity were monitored in the adjacent environments and outdoors. Occupancy information was collected by the students with an hourly time resolution.



Fig. 1 – Second floor plan of the IIS Margherita Hack in Morlupo, Rome; classrooms used for training and testing

Data were processed as follows:

 Estimation of ventilation rate. Ventilation rate was estimated by iteration based on CO<sub>2</sub> measurements and occupancy data. Outdoor CO<sub>2</sub> concentration was assumed to be 400 ppm, while CO<sub>2</sub> generation rate G<sub>CO2</sub> was assumed equal to 0.216 l/min, after Johnson et al. (2018). Results from the solution of Eq. 2 were affected by implementation artifacts, partly due to weekly automatic calibration procedure. Therefore, data were smoothed, and outliers were identified as values exceeding the 95<sup>th</sup> percentile and excluded from the dataset. Missing values were replaced by linear interpolation.

- 2. Optimization of Building Energy Simulations. The energy models of classrooms A and B were implemented in TRNSYS (see Figure 1) and they were optimized using meta models (Prada et al., 2018) to determine parameters of moisture storage models. In detail, the target parameters to optimize were the mass of the buffer material (M), the gradient of the sorptive isotherm (k) and the exchange coefficient for airnode-surface buffer (β) for the EPD model. The assumed generation rate of water vapour was 55 g/h, which is the reference value associated to an "active" person according to BS 5250 (BSI, 2011).
- Model validation. The Equivalent Penetration Depth determined from step 3 was used as input value to estimate (β, M) of classrooms C and D (see Figure 1) and validate the model. Ventilation rate is estimated from the water vapour mass balance through an iterative procedure and compared to the results of the CO<sub>2</sub>-based method.

# 3. Results

By specifying the input parameters for the storage model, the assumption was made that the buffer was mostly generated by the plastered surface of the classrooms used to run the optimization (141 m<sup>2</sup> for classroom A, 150 m<sup>2</sup> for classroom B). Other parameters were set as follows: equivalent penetration depth d = 1 mm,  $\rho$  = 900 kg/m<sup>3</sup>,  $\mu$  = 8, k = 0.015 (kgw/kgm/%). These hypotheses translate into  $\beta$ -values of 891 kg/h and 947 kg/h and M-values of 127 kg and 135 kg respectively for classrooms A and B.

Table 1 - Optimized input parameters for the EPD model

Cl.	k (kgw/kgm/%)	β (kg/h)	M (kg)	CVRMSE
А	0.38	371	127	0.086
В	0.43	371	137	0.083

The optimization algorithm returned the values reported in Table 1. While the mass of the buffer layer closely matches the original assumptions, the optimized values of k and  $\beta$  display much larger values, which go beyond physical representativeness of such quantities. This could be related to the buffer effect of other elements, such as the clothing of the students, that has limited impact on the overall mass (around 10 kg considering average fabric density, and an occupancy of 20 students), but whose buffer contribution has different time constants, which might become relevant considering the occupancy patterns of classrooms. The coefficient of variation of the root mean squared error (CVRMSE) displays a good performance of the model.

By equating the original  $\beta$  parameter accounting for plaster only and the effective  $\beta$  parameter derived by the optimization process, it was possible to identify the equivalent penetration depth that better characterized the moisture storage effect. For classroom A, this returned a thickness 0.0038 m, while for classroom B this returned a value of 0.0041 m.

Such input values were used for validation in the two remaining classrooms, C and D. The gradient of the sorptive isotherm was assumed to be 0.405 (kg<sub>w</sub>/kg<sub>m</sub>/%), i.e., the average of the optimized value. Likewise, the equivalent penetration depth was set to 0.004 m. The  $\beta$  and M parameters were calculated from such starting data and energy simulations were run on classrooms C and D for validation. The input parameters and the mean bias error of the models built for validation are displayed in Table 2. The mean bias error expressing the difference between the air changes per hour estimated using the CO<sub>2</sub>-based method and the WV-based method is relatively high – 0.35 1/h (ACH) for classroom C and 0.41 1/h for classroom D.

Table 2 – Input parameters and Mean Bias Error (MBE) of the simulations run on classrooms C and D

C1.	β (kg/h)	M (kg)	MBE (1/h)
С	317	454	0.35
D	321	460	0.41

The difference between the number of ACH calculated from the CO<sub>2</sub> method and the WV method is displayed in Figure 2. The ACH calculated from the CO<sub>2</sub>-based method is in most cases higher than the one retrieved from WV-based method, with an interquartile range of approximately 0.7 1/h.



Fig. 2 – Difference between ACH calculated from  $CO_2\mbox{-based}$  method and WV-based method for classrooms C and D

# 4. Discussion

Estimating ventilation rate from water vapour balance finds an interesting application in naturally ventilated classrooms as the moisture loads due to typical living activities (cooking, having a shower, etc.) can be disregarded and occupancy has specific patterns, potentially easing the modelling of buffer phenomena. Nevertheless, results showed a large discrepancy between ventilation rates estimated from water vapour and CO<sub>2</sub> concentration mass balance.

These differences might be ascribed to several factors. First, the experimental data might bias the results in relation to (i) sensors' position in the classroom, which might have affected the readings of temperature, relative humidity and CO<sub>2</sub> concentration, (ii) sensors' accuracy, propagating calculation uncertainties (iii) data processing noise, as for instance the numerical artifacts introduced by the automatic calibration procedure of CO<sub>2</sub> sensors.

Errors related to the building energy simulation sum up to simplifications introduced by the EPD model; specifically, it should be considered that, in the current study, a single buffer layer was used as the observation period lasted 16 days and it was assumed that seasonal fluctuations were not relevant. The training performed on South-East facing classrooms, facing a closed parking lot, and testing performed on North-West facing classrooms, facing the hills, might have affected results as outdoor conditions might have been slightly different.

Finally, the optimization algorithm which returned effective values of  $\beta$  and M in a comprehensive way accounts also for the buffer storage represented by clothing of subjects in the room and the related temporal variability – contributions that could have been modelled separately.

# 5. Conclusion

This paper aimed at testing the accuracy that can be achieved by estimating ventilation rate from water vapour balance compared to estimates performed using the CO<sub>2</sub>-based method in naturally ventilated classrooms. The environmental conditions in four classrooms, adjacent spaces and outdoors were monitored for 16 days. Two classrooms were used to train a buffer storage model by providing ventilation rates from CO<sub>2</sub>-based models and adjusting the model relevant parameters by minimizing the difference between simulated and measured humidity ratio. This allowed us to tune input parameters for the equivalent penetration depth model, which were then used to model ventilation according to water-vapour based model in the two remaining classrooms, testing the quality of the model against the CO<sub>2</sub>-based model prediction. Water-vapour based ventilation rate was largely underestimated, highlighting the need to provide more accurate estimate of the buffer storage term and its variation over time. Future work will include the analysis of a long-term dataset (7 months) and the implementation of analytical models for specific contributions of the moisture buffer.

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# Assessment and Mapping of the Urban Heat Island Effect: A Preliminary Analysis on the Impact on Urban Morphology for the City of Turin, Italy

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#### Abstract

Urban Heat Island (UHI) effects, intensified by growing urbanization, significantly impact thermal comfort and energy demand in cities. To accurately model these effects in building performance and urban energy simulations, precise weather data and boundary conditions are essential. Although weather stations in city centers are increasingly used to develop typical meteorological years, they often fail to capture the microclimate variations across urban areas. New tools and methods are thus needed to help building professionals and municipalities assess UHI severity, use more representative weather data, and evaluate the impact of buildings on the urban microclimate. Among available tools for UHI impact assessment, Computational Fluid Dynamics (CFD) models offer detailed analysis but are computationally intensive and impractical for largescale, year-round studies. Conversely, equivalent RC networks are more computationally efficient but still require extensive inputs, limiting their widespread use in large cities. This research introduces a new workflow using correlations to estimate UHI effects from rural weather data. The MIT Urban Weather Generator (UWG) was used to simulate UHI in representative districts, with the results employed to develop correlations for mapping local microclimates across urban areas. The proposed methodology is preliminary applied to the Italian city of Turin, focusing primarily on the correlation between urban morphology and the UHI phenomena (i.e., paying attention to those variables with the most significant effects on the local urban microclimate, according to the literature). The UHI impact has been quantified in terms of differential heating and cooling degree-days with respect to the rural environment. Results prove that with a training set of about 5 % of the city, modelled in detail with UWG, developed correlations appear robust enough to describe the phenomenon for residential districts of Turin.

### 1. Introduction

The increasing urbanisation process has led to a notable intensification of the Urban Heat Island (UHI) phenomenon, which is affecting both indoor and outdoor thermal comfort, as well as the energy demand of neighbourhoods and cities (Li et al., 2019). This phenomenon is driven by several factors, including urban morphology, material albedos, anthropogenic heat, and the lack of evapotranspiration due to the absence or limited presence of vegetation. The interaction of these factors, along with their spatial variability within urban contexts, results in a multitude of microclimates within urban areas.

In this context, the use of representative weather data and boundary conditions must be considered to increase the accuracy of the simulation at building and district scale. In the past, weather data were typically obtained from rural areas or external locations such as airports. Nevertheless, data from urban locations have been recently incorporated in building simulations towards a more accurate definition of climatic conditions. However, this solution is not able to entirely capture the microclimate variability within a city. For this reasons, different tools have been developed to assist policymakers in mapping the UHI and formulate mitigation strategies. These tools can be classified in two different categories: Urban Energy Balance (UEB) models and Computational Fluid Dynamics (CFD) models. CFD

models, as ENVI-MET (Bruse & Fleer, 1998), solve the governing equations of fluid motion, allowing for high spatial resolution and precision. However, they necessitate substantial simulation and computational time, as well as advanced expertise and knowledge for model definition. Consequently, CFD applications at the district scale are typically confined to selected case studies over specific periods of the year. In contrast, UEB models use urban metrics to simplify and accelerate the description and calculation of the urban energy balance. The most used and spread tool in this category is the Urban Weather Generator (UWG) (Bueno et al., 2013). The UWG is an RC (resistance-capacitance) model comprising four sub-models: the Rural Station Model (RSM), the Vertical Diffusion Model (VDM), the Urban Boundary-Layer Model (UBL), and the Urban Canopy and Building Energy Model (UC-BEM). This model provides air temperature and humidity data for urban contexts starting from a rural weather data. The advantages of UEB models like the UWG include a faster computational speed compared to CFD models and the ability to generate weather data with UHI effects that can be directly used in urban and building simulation tools. Additionally, these models require less data and expertise for their definition.

However, UHI mapping and weather files still require a significant amount of data to cover both local and entire urban areas. Among the several factors that influence both simulations and real-world scenarios, urban layout has the most significant impact (Salvati et al., 2019). Urban geometry can vary significantly between cities and urban areas, making the definition of representative districts a powerful way to reduce data needs and extend analysis to the entire city. Different methods exist for clustering urban layouts. Among them, the most widely used is the Local Climate Zone (LCZ) classification (Stewart & Oke, 2012). However, other techniques and workflow have been developed to improve the LCZ classification, usually characterized by excessively broad classes. These alternative procedures, such as the one proposed by Joshi et al. (2022) or Boccalatte et al. (2023), integrate additional urban metrics and clustering techniques to obtain more representative districts archetypes that can be used for climate analysis.

Considering this context, a novel workflow is proposed in this study in order to map the UHI and weather data in the cities by the definition of representative district. The proposed methodology is preliminary tested on a case study, considering only urban morphology metrics for the definition of representative districts.

#### 2. Methods

This paper presents a methodology to map the UHI and urban climate. The workflow (Figure 1) is structured in five steps: i) Metrics calculation, ii) Cases selection, iii) Microclimate simulation, iv) Correlation and validation and v) Mapping.



Fig. 1 - Methodology scheme

The main scope of this preliminary analysis is to assess possible correlations between urban parameters and microclimate metrics. To that purpose, different cases are selected according to the urban metrics. The microclimate effect is acknowledged to be significant at neighbourhoods' level. Therefore, the buildings in the city are grouped into urban blocks by clustering all the buildings with adjacent parcels area. The blocks with fewer buildings, irregular shape, or large area (mainly composed by industrial area and factory) are no object of the analysis and so were removed. For each filtered block, 10 urban metrics (Table 1) are defined among the most used metrics in literature (Javanroodi et al., 2023) and among the ones used by Joshi et al. (2022).

Metrics	Formula
Floor Area Ratio (FAR)	$FAR = \frac{\sum A_i * n_i}{A_{block}}$
Volume Area Ratio (VAR)	$VAR = \frac{\sum V_i}{A_{block}}$
Relative Compactness (REC)	$REC = \frac{\sum \frac{6V_l^{\frac{2}{3}}}{A_{i_{frontal}}}}{n}$
Shape Factor (SF)	$SF = rac{A_{block}}{\pi r_{minbounding}^2}$
Surface Coverage (SC)	$SC = \frac{\sum A_i}{A_{block}}$
Green Ratio (GR)	$GR = \frac{A_{veg}}{A_{block}}$
Average Building Height (ABH)	$ABH = \frac{\sum_{i}^{n} h_{i}}{n}$
Sky View Factor (SVF)	Qgis plugin
Average Building Distance (ABD)	$ABD = \frac{\sum_{i}^{n} \sum d_{i}}{n^{2}}$
Vertical to Horizontal (VtH)	$Vth = \frac{\sum A_{vert}}{A_{block}}$

The metrics calculation process requires different software, such as QGIS and Rhinoceros, and python libraries, such as Geopandas. The Sky View Factor (SVF) is calculated using the QGIS plug in Relief Visualization Toolbox (Zakšek et al., 2011) that requires a digital surface model (DSM) as input data and produces the same raster vector with the calculated metrics. From the image raster the SVF for the building block is calculated as the average value on a virtual block positioned at half of the minimum distance to the closest block. This results in assigning to each building block the SVF value that corresponds to the one calculated in the middle of the streets. This approach is used in order to take into account the surrounding street canyon.

To proper select the urban metrics, a Spearman correlation analysis is performed to consider more independent metrics and sample the blocks population. The main statistical values for the selected metrics (e.g.,  $Q_1$ , median,  $Q_3$ ) are combined to define a representative population of districts. The blocks with the closest morphological features to each combination are selected as train subset for the correlation definition. The cases selected are modelled and simulated with the Urban Weather Generator (UWG) to create the urban weather file and data of interest (e.g., Heating Degree Days HDD, Cooling Degree Days CDD, Mean temperature, UHI index). On the selected outcome, different techniques can be adopted and implemented in order to correlate the input variable with the climate metrics and weather data.

The defined correlations are tested and verified on the result of an urban block subset randomly chosen. The outcome of the validation process gives information concerning the possibility to extend the metrics to all the city mapping and extracting information.

# 3. Case Study

The methodology proposed is tested and applied to the city of Turin, which has an estimated population of 848,000. The data used in this study is provided by the Municipality of Turin and includes a GIS model of the city and a digital surface model (DSM) input for the SVF calculation. The city is composed of 128,144 buildings, which are grouped into 4,518 blocks based on their cadastral parcel area. The filtering criteria are selected as follows: each block must have (1) a minimum of four buildings, (2) a SF higher than 0.1, and (3) an area lower than 0.1 km<sup>2</sup>. Those criteria allow for the removal of uncommon blocks geometry, single or few building blocks, as well as removing huge industrial area in outside parts of the city. The final population is composed of 2,804 blocks. All the metrics selected are then calculated. The results of the correlation analysis using the Spearman method are reported in Table 2.

According to the results, the variables selected for the analysis and significant to the representative blocks definition are: i) Green ratio, ii) Surface coverage, iii) Average building height, iv) Vertical to horizontal, which are reported in Figure 2.

SF -	1	-0.095	-0.037	0.059	0.063	0.058	0.064	-0.023	-0.21	0.24
SVF -	-0.095	1	0.2	-0.17	-0.25	-0.26	-0.29	0.32	0.27	-0.34
GR -	-0.037	0.2	1	-0.37	-0.099	-0.27	-0.3	0.13	0.5	-0.34
SC -	0.059	-0.17	-0.37	1	0.08	0.54	0.61	0.013	-0.032	0.19
Abh -	0.063	-0.25	-0.099	0.08	1		0.73	0.71	-0.084	0.61
FAR -	0.058	-0,26	-0.27	0.54	0.6	1	0.85	-0.4	-0.16	0.63
VAR -	0.064	-0.29	-0.3	0.61	0.73	0.85	1	-0.51	-0.13	0.64
REC -	-0.023	0.32	0.13	0.013	-0.71	-0.4	-0.51	1	0.22	-0.53
Abd -	-0.21	0.27	0.5	-0.032	-0.084	-0.16	-0,13	0.22	1	-0.59
Vth -	0.24	-0.34	-0.34	0.19	0.61	0.63	0.64	-0.53	-0.59	1
	SF	SVF	GR	sc	Abh	FAR	VAR	REC	Abd	Vth





Fig. 2 - Distribution of metrics selected

The relevant statistical points, combined for the representative cases, are the minimum, the  $10^{th}$  percentile,  $Q_1$ , median,  $Q_3$ , the 90<sup>th</sup> percentile, and maximum value of the distribution. This approach ensures a complete spatial sample, including the extreme cases. The total train sample, after removing duplicates, is composed of 171 blocks, which represent 6 % of the total sample. The blocks, shown in Figure 3, are uniformly distributed across the city. The test sample is composed of 20 cases chosen randomly (Figure 3).

The geometry property of the selected blocks is employed as input for the UWG, combined with the vegetation information present in GIS data. The other parameters (e.g., the anthropic heat and building archetype) are taken as default values, given the morphological aspect focus of this preliminary analysis. Due to their strong correlation with the building energy demand, the selected metrics are the Heating and the Cooling Degree Days variations between the simulated values and the ones resulting from the rural weather station (TORINO 160590 IWEC), characterized by CDD<sub>18</sub> equal to 381 K d and HHD<sub>18</sub> equal to 2505 K d. As a first trial, a simple linear correlation is performed on both the metrics investigated.



Fig. 3 – Spatial disposition of Train sample (Blue) and Test sample (Green)

# 4. Results

The linear correlation carried out on the datasets provides a positive outcome for both the metrics. The cooling degree days correlation is reported in Figure 4.



Fig. 4 – Cooling degree-days correlation

The trained sample shows a good correlation, as confirmed by a R<sup>2</sup> value of 0.73 and a RMSE value of 2.39 K d. On the test sample, an RMSE value 2.31 K d is considered acceptable for the validation of the correlation, being lower than the RMSE of the training sample. Among the different metrics, the vertical to horizontal (Vth) is the one with the biggest

influence, followed by the surface coverage (SC) and green ratio (GR), which has a counter effect on the CDD variation. The average building height shows a very low impact. Similar results for the heating degree days correlation are reported in Figure 5, with a R<sup>2</sup> of 0.74 a RSME on the train sample of 4.98 K d. The RMSE of 4.63 K d on the test sample is higher than the one found for the Cooling Degree Days analysis but again acceptable for the validation purpose. The trends for the different variables are similar in absolute value and opposite in sign compared to the Cooling Degree Day.



Fig. 5 - Heating degree-days correlation

These correlations allow us to map the metrics variation inside the cities, as shown in Figures 6 and 7. The average variation of the metrics inside the cities are -402 K d for the Heating Degree Days, corresponding to a reduction of 16 %, and a significative increase of 200 K d (+52 %) for Cooling Degree Days. The variation range inside the different blocks configurations is 66 K d for the HDD that correspond to the 3 % of the average urban HDD value. More important is the variation range of the CDD. It corresponds to 30 K d, resulting in 5 % of the average CDD value inside the urban area.


Fig. 6 – Heating degree days spatial distribution



Fig. 7 - Cooling degree days spatial distribution

#### 5. Conclusion

This study introduces a novel methodology for mapping urban microclimates and establishing boundary conditions for urban and building simulations. The approach adopted emphasises the identification of correlations between environmental variables and urban morphological metrics, thereby reducing the computational time and data requirements by a significant extent. By calculating a range of metrics within an urban context, a small, representative subset of districts is identified for the purpose of training the correlation model. Subsequently, the selected districts are modelled using the Urban Weather Generator (UWG) to produce urban microclimate data and extract urban heat island (UHI) metrics based on the established correlations. The methodology is initially evaluated in the case study of Turin, with a primary focus on morphological parameters. By simulating a mere 6 % of the total urban blocks, a clear correlation is identified between urban metrics and variations in Heating Degree Days (HDD) and Cooling Degree Days (CDD) in comparison to a rural climate baseline.

The results demonstrate the considerable impact of urban morphology on climate variations, with vertical-to-horizontal metrics and surface coverage identified as the most influential factors. Furthermore, the study demonstrates that the mean discrepancy in HDD and CDD is considerable, with CDD exhibiting notable disparities across diverse urban zones. The results validate the effectiveness of the proposed methodology in mapping urban heat islands using urban metrics, reducing both the data requirements and the computational time.

The workflow is adaptable and can be readily applied to other contexts and metrics. However, the principal limitation of this approach is its narrow focus on urban morphology, without accounting for other crucial factors such as anthropogenic heat, building archetypes, and wind patterns. Future research should seek to incorporate these additional variables and conduct a real case validation to enhance the precision and applicability of the methodology.

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## Analysis of Control Strategies for Energy Performance Optimization for Educational Buildings: Comparison of Two Kindergartens in the Municipality of Bolzano, Italy

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#### Abstract

In the wake of the worsening of the energy crisis in winter 2022, several public administrations in Italy recommended simple energy systems operation control measures, to be implemented in the local building stock to reduce energy consumption and produce economic savings in the short term. In particular, in the municipality of Bolzano, Italy, these measures ranged from lowering the heating setpoint temperature, implementing systems setbacks or ON/OFF setting and reducing ventilation rates. However, these measures were applied to all buildings, without distinguishing vintage and type, with the risk of worsening the indoor environmental quality (IEQ) in some of them. In this context, this study focuses on the analysis of two kindergartens of dated and recent construction in the city of Bolzano, with the aim of evaluating the applicability of the proposed energy-saving control measures on buildings representative of "old" and recent constructions. Results proved the importance of carefully considering building specific features to design effective HVAC systems operation measures, able to optimize the systems performance and guarantee adequate IEQ conditions.

#### 1. Introduction

In Italy, the worsening of the energy crisis since winter 2022 has increased the urgency to improve the energy performance of the local building stock, which often have dated HVAC systems and operation inefficiencies. Faced with this situation, several public administrations recommended relatively simple, general control measures to be implemented in their own buildings with the aim of limiting energy consumption and producing economic savings in the short term, avoiding soaring energy bills. In the municipality of Bolzano, suggested measures consisted in (i) lowering heating setpoint temperatures of 2 °C, (ii) implementing temperature setbacks or systems ON/OFF setting, and (3) reducing ventilation rates. However, the proposed HVAC systems control measures were implemented regardless of the building type, i.e., function, construction period, envelope and energy systems, with the risk of worsening the thermal comfort conditions for indoor occupants.

Given these premises, several studies can be found in the literature proving the efficacy of energy systems control strategies in optimizing buildings' energy consumption, among which it is worth mentioning the works of De Santoli et al. (2014), Hong et al. (2014), and Wang et al. (2015). Furthermore, great effort has been dedicated to identifying optimal performance enhancement solutions. For instance, Hoyt et al. (2015) found that, if implemented correctly, a widened thermostat setpoint range results in significant energy savings, even though they largely depend on the type of heating or cooling system.

That being said, to the authors' knowledge, limited attention has been given to the actual effectiveness and the impacts of general basic operation control measures when applied to any type of building, regardless of its features and without a proper prior evaluation, which may happen in an "emergency" situation. In this context, the aim of this study is the assessment of the applicability of the proposed HVAC systems operation measures to both recently constructed and dated public buildings, to determine the extent of energy savings and the buildings' ability to maintain acceptable indoor thermal comfort conditions.

#### 2. Methodology

#### 2.1 Case Studies

For the analysis, two public kindergartens in the municipality of Bolzano were selected as case studies. In detail, a recently constructed (A) and a relatively dated kindergarten (B) were chosen.

As for Bolzano, the city is located in a valley at around 250 m above sea level and is characterised by a semi-continental climate, with cold winters and hot summers. Since Bolzano belongs to climate zone E according to the Italian national classification, the heating season starts on October 15<sup>th</sup> and ends on April 15<sup>th</sup>.

Considering in detail the two case-study buildings, building A was built in 2009, it has a rough L-shape with a convex side facing Nort-East, two storeys above ground and an underground floor. The total heated surface per floor is 667.53  $m^2$  and 576.93  $m^2$ for the ground and the first floors respectively, while 339.88 m<sup>2</sup> for the underground floor. The underground level includes a conditioned space, hosting kitchen, inventories and changing rooms for school employees, and an unconditioned garage area. The ground and first floors host classrooms, teachers' rooms and restrooms. A staircase placed at the entrance of the building connects the three storeys and a double-height colonnade shades the mostly glazed west façade. The building is representative of recent constructions with its well-insulated envelope in compliance with local requirements.



Fig. 1 - Building A south-west view



Fig. 2 - Building B south-east view

On the other hand, building B was built in 1971, has an almost square shape, one storey above ground and an underground floor. While the ground floor hosts the kindergarten with a total net heated surface of 1355.47 m<sup>2</sup>, the underground does not belong to it and is not part of the analysis. In detail, kindergarten B is divided into six "sections" blocks, each block is characterised by a classroom, an adjacent "lunchroom" and a restroom area. The six blocks, together with the "service" area (hosting the kitchen, the storage and the personnel's changing rooms), the administration office, and the entrance are developed around a double-high central atrium. The six restroom areas present a double-high part, as well with a gabled roof. The building is provided with external roller shades protecting the glazed surfaces, except for the atrium ones and the restrooms upper windows. The building is representative of partially renovated dated constructions, with uninsulated external walls with retrofitted triple-glazed windows and a recently retrofitted green roof.

Both buildings are provided with a condensing boiler as heating system, serving radiant floor panels as heating terminals in building A and radiators in B. The regular heating setting features a temperature setpoint of 21 °C kept constant for the entire heating season (with no setback or system onoff setting). Furthermore, both kindergartens rely on natural ventilation only, no mechanical ventilation or cooling system are present.

## 2.2 Buildings Energy Models

The buildings' detailed energy models were created via Rhinoceros3D software, with Grasshopper and Honeybee plugins, Window LBNL and EnergyPlus simulation program. While the model for building A was developed in previous research, the one for building B was created on purpose for this analysis. Model A was calibrated and validated against indoor dry-bulb temperature data recorded during monitoring campaigns conducted in 2019. Model B was calibrated and validated against indoor drybulb temperature data recorded during monitoring campaigns conducted in 2019. Model B was calibrated and validated against indoor drybulb temperature data recorded during monitoring campaigns conducted since February 2023. In detail, the months of December 2023 and February 2024 were used for calibration and validation respectively.

In both buildings, the number of occupants and daily occupancy schedules were set based on the school administration's information and technical standards typical values (ASHRAE, 2009). The infiltration rate was defined during the calibration and validation process, while natural ventilation was set with the same rates and schedules in both buildings. Heating system installed capacity limits were set based on the buildings' design data provided by the public administration of Bolzano.

Model A is characterized by 4 thermal zones (*TZs*), corresponding to the heated ground (*P0*), first (*P1*) and underground (*P-1*) floors and the unheated garage area. Model B has 23 TZs, among which the unheated entrance and the underground level (*P-1*), in which constant heating at a setpoint temperature of 20 °C was set.

## 2.3 Control Strategies

Four main control strategies were defined and tested in EnergyPlus on both case-study buildings in a total of eight scenarios (from 1 to 4.2).

## 2.3.1 Baseline scenario

The baseline Scenario (0) is representative of the standard building operation, with (i) a constant heating setpoint temperature (T SP) of 21 °C for the entire heating season and (ii) no setback or system "off" setting.

## 2.3.2 Scenario 1:

#### Lower heating setpoint temperature

This scenario is characterised by (i) a lower constant heating setpoint temperature of 19 °C and (ii) no setback or system "off" setting in all heated TZs.

## 2.3.3 Scenario 2:

#### Heating schedule settings

This strategy consists in an ON/OFF heating schedule setting applied to all heated TZs over the entire heating season, considering daily occupancy, as well as weekends and holidays: ON setting from Monday to Friday during daily occupancy time, OFF setting at weekends and on holidays. A 21 °C temperature setpoint was maintained as in the baseline scenario.

Two alternatives were considered: (i) the first one (Scenario 2.1) characterised by a single daily schedule for all TZs; (ii) the second one (Scenario 2.2) including differentiated daily schedules among the TZs (Table 1).

## 2.3.4 Scenario 3: Combination of lower heating setpoint temperature and heating schedule settings

In Scenario 3.1, Scenarios 1 and 2.2 were combined, applying a temperature setpoint of 19 °C and differentiated heating schedules among the different TZs. In Scenario 3.2, a temperature setback of 16 °C has been introduced during daytime hours: from 8:00 to 11:00 and from 14:00 to 17:00 in P-1 of building A, while from 8:00 to 10:00 and from 14:00 to 17:00 in the service area of building B.

## 2.3.5 Strategy 4: Preheating

Scenario 4.1 consists in preheating every day all TZs two hours before daily activities start. On the other hand, Scenario 4.2 integrates the measures of 4.1 with a preheating of the whole building three hours before the activities start on the first day after holidays "off" setting.

## 2.4 Energy Analysis and Thermal Comfort Evaluation

The energy simulations were carried out via EnergyPlus software and results were analysed in terms of heating energy consumption and indoor air temperature. First, the comparison at building level among results obtained in the different scenarios was carried out, accounting at the same time for thermal comfort levels following the implementation of the considered strategies; then, the comparison between the two buildings in terms of energy savings obtained in the different scenarios was performed. The thermal comfort evaluation was carried out using as reference standard EN 16798-1 (CEN, 2019). In this paper, the thermal environment analysis results, obtained in the main representative scenarios, for P1 TZ of building A and the North-West classroom (W1A TZ) of building B, have been reported, since these spaces are among the main buildings' TZs having the strictest IEQ requirements (as they host children-dedicated spaces) and with the most critical thermal comfort conditions. In detail, the analysed metrics are the following: (i) the specific monthly and annual heating energy needs in kilowatthours per square meter, (ii) the energy savings percentage obtained by applying each control strategy with respect to the baseline scenario, and (iii) the indoor dry bulb temperature in degrees Celsius.

Table 1 - Scenario 2 settings

C	T1	Thermostat	Daily S	chedule	
Scenario	I nermai Zone	ON/OFF	From	То	
		ON	08:00	18:00	Heating
2.1	All Heated TZs	OFF	18:00	08:00	Season Schedule
		ON	07:00	08:00	
	P-1 (Building A) - Service Area (Building B)	OFF	08:00	11:00 (B) / 10:00 (A)	Heating Season Schedule
		ON	11:00 (B) / 10:00 (A)	14:00	
		OFF	14:00	17:00	
		ON	17:00	18:00	
2.2		OFF	18:00	07:00	
	P0 & P1 (Building A) -	ON	08:00	18:00	Heating
	Six "sections" blocks (Building B) Atrium & Office (Building B)	OFF	18:00	08:00	Season Schedule
		ON	08:00	16:00	Heating Season
		OFF	16:00	08:00	Schedule

#### 3. Results and Discussions

Considering building A, as it is possible to observe in Table 2 and Fig. 3, despite the relevant energy savings of about 50 %, strategies from 3.1 to 4.2 are unsuitable as they do not guarantee acceptable indoor thermal comfort levels. Indeed, as shown in Fig. 3, in these scenarios, temperatures fall below 18 °C for more than 10 % of the school-time hours in the month of January.

On the other hand, strategies from 1 to 2.2 allow for relatively acceptable indoor thermal comfort conditions with lower, but still substantial, energy savings reaching 33 % in Scenario 1. As for building B, from Table 3 and Fig. 4 it is possible to observe that strategies 3.1 and 3.2 are unable to guarantee adequate indoor thermal comfort conditions, while strategies 1 and 4.2 allow for relevant energy savings of 33 % and 46 % respectively, and relatively acceptable indoor thermal comfort levels in most of the heated thermal zones. Indeed, in the considered North-West classroom, in both scenarios, temperatures remained equal or above 19 °C most of the time in the coldest months, reaching peaks above 21 °C in the milder months of March, April and October.

Building A - Total Heating Load [kWh/m <sup>2</sup> ]								
Scenario								
	0 Baseline	1	2.1	2.2	3.1	3.2	4.1	4.2
January	5.85	4.57	4.74	4.56	3.72	3.72	3.81	3.81
February	3.42	2.26	2.54	2.51	1.71	1.71	1.70	1.71
March	2.54	1.24	2.44	2.42	1.27	1.27	1.27	1.27
April	0.56	0.17	0.41	0.40	0.13	0.13	0.13	0.13
October	0.52	0.16	0.39	0.35	0.10	0.10	0.10	0.10
November	3.14	1.73	2.45	2.38	1.38	1.38	1.38	1.38
December	5.70	4.41	3.25	3.18	2.48	2.48	2.50	2.50
Total Annual	21.72	14.55	16.21	15.78	10.80	10.80	10.89	10.90
Specific Total Annual Heating Load Ratio with respect to the Baseline	-	67%	75%	73%	50%	50%	50%	50%
Savings Percentage of each Control Strategy with respect to the Baseline		33%	25%	27%	50%	50%	50%	50%

Table 2 – Monthly and annual total heating load and annual energy savings percentage of each control strategy with respect to the baseline scenario for building A

Table 3 – Monthly and annual total heating load and annual energy savings percentage of each control strategy with respect to the baseline scenario for building B

<b>Building B – Total Heating Load [kWh/m²]</b>								
Marth	Scenario							
Month	0 Baseline	1	2.1	2.2	3.1	3.2	4.1	4.2
January	8.05	6.17	6.81	6.45	5.26	5.26	5.24	5.26
February	4.39	2.78	3.89	3.77	2.63	2.63	2.56	2.56
March	1.80	0.52	1.96	1.95	0.61	0.61	0.60	0.60
April	0.28	0.00	0.23	0.24	0.00	0.00	0.00	0.00
October	0.29	0.00	0.27	0.26	0.00	0.00	0.00	0.00
November	4.87	3.04	4.37	4.19	2.76	2.76	2.71	2.71
December	7.35	5.52	4.86	4.65	3.63	3.63	3.52	3.52
Total Annual	27.02	18.03	22.38	21.51	14.89	14.89	14.64	14.65
Specific Total Annual Heating Load Ratio with respect to the Baseline	-	67%	83%	80%	55%	55%	54%	54%
Savings Percentage of each Control Strategy with respect to the Baseline	-	33%	17%	20%	45%	45%	46%	46%



Fig. 3 - Building A - First floor: percentage of monthly school-time hours per temperature interval for the different scenarios (EN 16798-1:2019)



Fig. 4 - Building B – North-West Classroom: percentage of monthly school-time hours per temperature interval for the different scenarios (EN 16798-1:2019)



#### 3.1 Energy Savings Comparison

Fig. 5 - Heating energy savings percentage of each control strategy with respect to the baseline in the two case-study Build-ings

Higher energy savings were registered in building A compared to B in almost all scenarios (see Fig. 5), except Scenario 1 with savings of about 33 % in both buildings. On the other hand, the energy savings trend resulted almost comparable in both buildings:

- The highest savings were obtained by combining the ON/OFF setting strategy with the temperature setpoint lowering in Scenarios from 3.1 to 4.2.
- The lowest savings were registered with the implementation of the ON/OFF strategies in Scenarios 2.1 and 2.2.
- The best compromise between energy savings and relatively acceptable indoor thermal comfort levels was reached in both buildings in Scenario 1, with an energy savings percentage of almost 33 %.

## 4. Conclusions

This study has assessed the applicability of basic energy systems operation measures, which were recommended by several public administrations in Italy, in the wake of the worsening of the energy crisis in 2022, to limit energy consumption and avoid spiking energy bills in the local public building stock. For the assessment, two public kindergartens of dated and recent construction, in the municipality of Bolzano (Italy), were considered as case studies, the energy performance simulations were performed and the energy savings and indoor thermal comfort after the implementation of the proposed measures were analysed.

Results demonstrated that HVAC systems operation control measures should not be implemented regardless of the building type, as buildings of different typology, i.e., function, construction period, envelope and energy systems, show different responses and behaviours.

Thus, the following considerations may be made:

- Relatively simple operation control measures allow us to obtain significant energy savings in both recently constructed and dated building, but, at the same time, they can lead to a worsening of the indoor thermal environment.
- It is difficult to reach and maintain acceptable indoor thermal comfort conditions when lowering the heating system setpoint temperature by 1-2 °C and applying ON/OFF setting or even temperature setbacks at the same time. This occurs especially when relying on natural ventilation only, as it could be observed in scenarios from 3.1 to 4.2 in both case-study buildings.
- When lowering the heating setpoint temperature by 1-2 °C with respect to the recommended design one, continuous heating at constant setpoint is needed to maintain acceptable thermal comfort levels but may not be sufficient to guarantee these conditions in all thermal zones especially in the most dated buildings (Scenario 1).
- With the heating system ON/OFF setting only, it is difficult to reach and maintain adequate indoor thermal comfort conditions over the entire occupancy period, as it resulted in Scenarios 2.1 and 2.2 of both case-study buildings.

Some final design suggestions for the retrofit of both high-performance, recent constructions and more dated, poorly performing buildings are reported below:

- Building envelope typology and HVAC system must be carefully considered for a proper planning of energy systems operation control strategies.
- Mechanical ventilation is needed to provide the required air changes and avoid excessive heat losses during the heating season.

- A differentiation of the heating setpoint setting between the coldest fall-winter months, from December to February, and the months of October, November, March and April may be considered, as a lower setpoint temperature and no temperature setback are required in these milder fall-winter months.

To conclude, well-designed and carefully evaluated energy retrofit measures remain of primary importance to properly optimize the energy performance of both dated and recent constructions and guarantee adequate IEQ levels.

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## Optimization of a Solar Assisted Heat Pump System to Increase Thermal Efficiency Working on the Cold Source

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#### Abstract

This study introduces an innovative high-efficiency air conditioning system that utilizes solar-assisted heat pumps to enhance the coefficient of performance by elevating the thermal level of the lower temperature heat source. Solar energy stored in thermal storage is used to optimize operating conditions by increasing the cold source temperature. A demonstrator of such a system is investigated by referring to the residential building "Chiodo 2" located at the University of Calabria, where an existing plant equipped with heat pumps in master-slave configuration are already operational. The simulation model was developed within the TRNSYS environment. The development process of the virtual system model is presented in detail, encompassing solar collectors, thermal storage, heat pump and a photovoltaic system. Through an analysis of the winter operation of the system, the study identifies key requirements, including the optimal thermal storage volume and the optimal size of solar collectors, to maximize energy efficiency. Specific operating conditions are proposed, such as the synergistic use of solar collectors and heat pump in particular thermal scenarios, to enhance performance.

#### 1. Introduction

On the road toward the reduction of greenhouse gas emissions and increasing sustainability, the building sector plays a pivotal role. The European Union's recent "Fit for 55%" package set ambitious targets and specifically, the Fit for 55% package underlines the pivotal role of HVAC systems in achieving these goals. For such a reason many countries' policies are pushing toward the mandatory adoption of a heat pump system for airconditioning of buildings, dismissing traditional systems based on fossil fuels. The accurate design of such a generator requires a careful consideration of the real operating condition (Bruno et al., 2020). Heat pumps achieve maximum sustainability when combined with solar energy (solar-assisted heat pumps) (Baggio et al., 2018; Bee et al., 2019). In this regard, the most used configuration is the use of a photovoltaic system to supply electric energy to the heat pump (Nicoletti et al., 2022). However, in recent years researchers have focused on integrating heat pumps with solar collectors, photovoltaic panels, and hybrid systems. A study investigated the performance of a ground source heat pump system with free cooling and photovoltaic/thermal collectors at the service of a multi-family building in Stockholm (Pourier et al., 2024). The optimal design features of photovoltaic-thermal collectors for integration with ground source heat pump systems was investigated considering technical and economic factors (Beltrán et al., 2024). The impact of a control logic aimed at maximizing the utilization of excess renewable in a solar-assisted heat pump systems with electrical and thermal storage systems was assessed by Perrella et al. (2024). The thermal performance of a direct expansion solar assisted heat pump was analysed for several refrigerants using two collector configurations (Chata et al., 2005).

The use of appropriate storage system can play an important role in the integration and optimal utilization of renewable energy. In Pinamonti et al. (2021), the integration of a modulating water-towater heat pump in a solar system with a seasonal storage was analysed. In terms of solar fraction, the results showed values reaching 85 %. A solarassisted raw-water source heat pump (Han et al., 2024) was proposed to solve the performance degradation and improve heating performance thanks to solar collectors that can increase the entering water temperature. A multi-source energy system including photovoltaic thermal solar collectors, storage tanks for the heat source and domestic hot water and heat pumps was analysed in reference to a single-family dwelling located in Northeast Italy (Emmi et al., 2017). Results showed that the multienergy source systems increased the energy efficiency by 16-25% compared to an ordinary air-to-water heat pump. A solar hybrid plant consisting of waterbased PV-T collectors integrated with an air-towater heat pump via thermal storage tanks was investigated considering a full-size pilot plant located in Spain and operating under real weather conditions (Herrando et al., 2023). Results showed that thanks to the simultaneous electricity and thermal generation of the PV-T collectors, overall the plant was self-sufficient to satisfy the building energy demand. A solar assisted heat pump solar supplied by thermal-photovoltaic hybrid panels was analysed numerically and experimentally (Del Amo et al., 2019). Results indicated that the system was not properly sized presenting a low solar radiation exploitation. A solar PVT assisted - heat pump system with a cold buffer storage tank on the source side of the heat pump and a hot storage tank for domestic hot water was measured over a nine-month period (Dannemand et al., 2019). The uninsulated PVT collector worked as an energy absorber and was able to extract heat form the ambient air and recharge the buffer storage tank to the ambient air temperature when no solar irradiance was available. In the less sunny and colder periods, the PVT added a significant amount of energy to the cold storage tank.

In this study, an assisted water-to-water heat pump that uses solar thermal collectors to increase the temperature of a water tank employed as cold source for the supply of heating and cooling loads in a university residential complex in Rende (Italy) was investigated. Simulations were performed in the TRNSYS environment to assess the effect of solar thermal collectors and thermal storage size on the fraction of heating demand saved by the integration of the solar source in the generation system

#### 2. Methodology

#### 2.1 Case Study Building

The building considered in the study is part of a student residential complex of the University of Calabria named "Chiodo2". The building's energy demand has been calculated within the TRNSYS environment. The building's 3D model was created using Sketchup, incorporating the TRNSYS 3D plug-in to facilitate a comprehensive representation of its geometry. The geometrical representation of the analysed building is reported in Fig. 1.



Fig. 1 - 3D representation of the building model

The thermal properties and stratigraphy of the main components of the building are reported in Table 1 and Table 2. Table 3 reports the U-values of the main building components.

Table 1 - Thermal properties of the external walls

	Thickness [cm]	Conductivity [W/mK]	Specific hea [J/kgK]	t Density [kg/m³]
Plaster	2	0.9	800	1400
Brick masonry	30	0.157	1000	1250
Plaster	2	0.9	800	1400

	Thickness [cm]	Conductivity [W/mK]	Specific hea [J/kgK]	t Density [kg/m³]
Tiles	2	0.9	800	2000
Screed	14	2	800	900
Insulation	2	0.035	800	55
Plaster	2	0.9	800	1400

#### Table 3 – U-value of the main building components

	U-value [W/m²K]
External wall	0.471
External roof/ground floor	0.236
External window	2.89

Internal gains account for an amount of 440 W of radiative and convective powers. Infiltration was set to 0.5 h<sup>-1</sup>. The heating plant was considered with a set-point temperature of 20 °C.

#### 2.2 The Air-conditioning Plant

The simulated air-conditioning plant of the building is composed of:

- a field of evacuated tube solar collectors designed to ensure maximum efficiency even under suboptimal solar radiation conditions,
- two thermal storage tanks, one supplied by the solar collector to be used as cold source (solar tank), and another supplied by the heat pump for the emitters provision,
- a water-to-water heat pump.

The heat pump was sized according to preliminary results of simulation, as reported in section 3.1. An available commercial model was chosen for simulation, and data of COP and thermal power delivered at the different source temperatures were taken from datasheet and provided to Type 927. In particular the selected model is a water-source reversible water condensed heat pump. The heat pump has a rated power of 12.6 kW and a nominal COP of 3.94. A commercially available vacuum tube solar collector was chosen for simulations and pertinent parameters were provided to Type 71. The data of the solar thermal collector are reported in Table 4.

Table 4 - Parameters of the solar thermal collector

Parameter	Value
Optical efficiency [-]	0.785
First order coefficient [W/m <sup>2</sup> K]	1.847
Second order coefficient [W/m <sup>2</sup> K <sup>2</sup> ]	0.005

The simulation scheme adopted within TRNSYS environment is reported in Fig. 2.



Fig. 2 - Simulation scheme adopted in TRNSYS

The solar collector directly supplies the solar storage tank, according to a control logic that checks the temperature difference between the panel outlet temperature and the tank temperature and decides whether to activate or not the circulation pump by setting a proper dead band. The solar tank supplies the heat pump acting as a cold source. A proper control strategy, monitoring the temperature of both tanks, determines if the solar tank directly supplies the user tank by-passing the heat pump or if it is used as cold source for the generator. In particular, in winter the system operates according to the following conditions:

- If the solar tank temperature is over 60 °C or if there is a temperature difference between the two tanks, space heating is directly satisfied by the solar collectors without the assistance of the heat pump.
- If the solar storage tank is lower than 5 °C, the heat pump does not operate to avoid freezing and heating is carried out by an alternative generation system (gas boiler).

Since this is a solar-assisted air-conditioning plant, the surface capturing solar radiation and the tank for energy store are of great importance. Therefore, a parametric study of the winter performance of the system was carried out varying the storage volume (V= 800 litres and 1600 litres) and the surface area of the collectors (10, 20, 25, 30, 40 m<sup>2</sup>).

#### 3. Results and Discussion

## 3.1 Building Heating Load and Energy Consumption

A preliminary simulation was performed to determine the building heating load and the associated yearly energy consumption. Results of hourly simulation are reported in Fig. 3.



Fig. 3 - Hourly simulation of building thermal need

Accordingly, Fig. 4 reports the monthly energy demand of the building for winter heating. The months of December showed the highest request with a value of 2182 kWh, followed by January and February with an almost equal amount around 2000 kWh. The total amount of energy needs for winter heating amounts to 10771.7 kWh.

Furthermore, a frequency analysis was conducted to quantify the number of hours in which a specific load occurred. Results showed that a load of 12 kW occurred more frequently allowing to identify this value for the heat pump rated power. The set-point temperature of the water tank supplying emitters was set to 60 °C (fan-coils in every room).



Fig. 4 - Monthly heating demand of the building for winter heating

#### 3.2 System Thermal Performance

For each configuration of the parametric analysis, the percentage of the winter thermal energy demand met by the system has been quantified. Furthermore, concerning the addressed thermal demand, a further distinction has been made between the portion directly handled by the solar collectors and that managed through the heat pump. For instance, Fig. 5 depicts results obtained for the heating plant assuming the lowest size (10 m<sup>2</sup>) for collectors and water tank (800 l).



Fig. 5 – Monthly energy demand supplied by the system (left) and percentage of the thermal demand met by heat pump and directly by solar thermal collector (right) A=10 m<sup>2</sup>; V=0.8 m<sup>3</sup>

In particular, Fig. 5 (left) the monthly percentage of energy satisfied by the SAHP system appears, whereas in Fig. 5 (right) the separated share of energy directly supplied from solar collectors to the user and the share provided by the heat pump is shown. As expected, for low active surfaces of solar panels, the amount of energy provided by the system is not sufficient to completely satisfy the demand in the colder winter months, where the lowest percentage is found in January, at 46 %. In spring and autumn, the system is able to provide more than 50 % of the energy demand. Interestingly the solar thermal collector is able to directly provide an adequate amount of heating thermal energy in spring and autumn, reaching the highest value of 58 % in May and the lowest of 9 % in November.

When the solar tank is doubled in its capacity, it is possible to observe better performance in some months. In particular, the system capacity to provide thermal energy increases to 49 % in January and to 57 % in February while in April, May and October the percentages do not vary. As regards the percentage of load directly satisfied by the thermal collector, a substantial increase is observed in May, reaching 73 % while in April and October percentages of 27 % and 39 % are observed respectively.

When the solar collector surface is increased to  $25 \text{ m}^2$  an overall upward trend shift in all percentages can be observed, as shown in Fig. 6.



Fig. 6 – Monthly energy demand supplied by the system (left) and percentage of the thermal demand met by heat pump and directly by solar thermal collector (right) A=25 m<sup>2</sup>; V=0.8 m<sup>3</sup>

From May to November, the ability of the system to provide thermal energy is almost always higher than 90 %, and in the worst condition of January a value of 71 % is reached. The solar collector is in this case, able to directly provide heating to the building in all the months analyzed, with small percentages of 6 % in December and 10 % in January. The best performance is again observed in May where the percentage reaches 54 %. When a solar tank of 1.6 m<sup>3</sup> is used in all the spring and autumn months, the system reaches complete sufficiency (100 %), whereas few increments are observed for the energy directly supplied by the solar collector in winter months, and many more increments are found in May (68 %) and October (57 %). In Fig. 7 the same information is reported for a solar thermal collector surface of 40 m<sup>2</sup> and storage of 800 liters. Clearly the maximum exploitation of solar radiation is achievable in this configuration. In fact, from April to October the system can provide 100 % of energy to the building, and this period extends further to March and November if the solar tank volume is augmented to 1.6 m<sup>3</sup>. In the latter case, the minimum amount of 87 % is reached in January. When looking at the energy from solar collectors directly used for heating, the amount conspicuously augments in May and October, with percentages of 54 % and 52 % respectively, which further increase to 70 % and 65 % with a 1.6 m<sup>3</sup> solar tank.



Fig. 7 – Monthly energy demand supplied by the system (left) and percentage of the thermal demand met by heat pump and directly by solar thermal collector (right) A=40 m<sup>2</sup>; V=0.8 m<sup>3</sup>

Finally, Fig. 8 reports the percentage of energy demand met by the SAHP system at different solar collector areas and for the two different sizes of solar tank volume.



Fig. 8 – Annual energy demand met by heat pump for different solar collector surface areas and solar tank volumes

From Fig. 8 it is clearly evident that increasing the solar collector surface provides notable increments especially for lower capturing areas. In fact, in the case of the bigger solar tank, moving from 10 m<sup>2</sup> to 20 m<sup>2</sup> produces an increment of 32.8 %; moving from 20 m<sup>2</sup> to 30 m<sup>2</sup> produces instead a much more limited increment of 8.2 %.

From the results of simulation, it also emerges that the cost-optimal configuration necessitates a solar panel surface area ranging from 25 to 30 m<sup>2</sup>, because greater areas would not be justified by the relatively small increase in thermal yield. Furthermore, it was observed that a thermal storage volume of 1.6 m<sup>3</sup> can ensure the most efficient system performance. This configuration allows for the maximization of energy efficiency while avoiding unnecessary costs.

Finally, Table 5 reports the average monthly COP of the heat pump along with the yearly average value. The utilization of the solar collector to increase the temperature of the cold source evidently produces benefits in terms of performance of the heat pump.

Table 5 – Average monthly COP of the heat pump for the different collector surfaces considered

	S10	S20	S25	S30	S30
Jan	3.75	3.86	3.84	3.84	3.87
Feb	3.80	3.91	3.96	3.91	3.95
Mar	3.79	3.91	3.95	3.89	3.96
Apr	3.82	3.97	3.90	3.97	3.87
May	4.08	4.03	4.58	4.02	4.39
Oct	4.10	3.92	3.84	3.89	3.99
Nov	3.70	3.92	3.87	3.91	3.94
Dec	3.72	3.80	3.81	3.88	3.86
Ave	3.85	3.92	3.97	3.91	3.98

Interestingly, the average monthly COP surpasses the value of 4 in May for all the collector surfaces. In the other warmer months (October and April), the value is much closer to it. In colder months however, the COP maintains a relatively high value that in January reaches 3.86 for 20 m<sup>3</sup> and in December 3.86 for 40 m<sup>2</sup>. For the same months, the lowest values of 3.75 and 3.72 are observed for a surface of 10 m<sup>2</sup>.

The highest value of 4.58 among all the cases is found in May for a surface of  $25 \text{ m}^2$ .

If the yearly average value of COP is considered it can be observed that a maximum value of 3.98 is found for a surface of 40 m<sup>2</sup>. However, even in the worst case, the COP assumes a value of 3.85 (for 10 m<sup>2</sup>) that can be appreciated to be very close to the nominal value of the heat pump.

#### 4. Conclusion

Heat pumps achieve maximum sustainability when integrated with solar energy (solar-assisted heat pumps). In this study solar thermal collectors are employed to increase the temperature of a water tank used as the cold source of a water-to-water heat pump for the provision of heating loads in a university residential complex in Rende (Italy). The air-conditioning plant of the building is composed of a field of evacuated tube solar collectors and two thermal storage tanks, one at the service of the solar collector, which represents the cold source of the water-to-water heat pump, the other for the emitters' supply.

Simulations were performed with the TRNSYS environment to assess the effect of solar thermal collectors and thermal storage size on the fraction of energy demand covered by the system.

When adopting 40 m<sup>2</sup> of solar collector surface and 1.6 m<sup>3</sup> of volume for the solar tank, the system is able to provide 100 % of energy to the building from March to November. The energy from solar collectors directly used for heating amounted to 70 % and 65 % in May and October, respectively. Results of the simulations showed, however, that increasing the solar collector surface provided notable increments only for lower capturing areas, whereas moving to higher collector surfaces determined lower marginal increments. It emerged how the cost-optimal configuration requires a solar panel surface ranging from 25 to 30 m<sup>2</sup>, and that a thermal storage volume of 1.6 m<sup>3</sup> can ensure the most efficient system performance. Finally, results showed that the utilization of the solar collector to increase the temperature of the cold source of the heat pump produces evident benefits in terms of COP, which can reach a yearly average value of 3.98 and an average monthly value of 4.58 in May, considering that the rated COP is 3.94 assuming the favorable conditions of the cold source at 20 °C to supply hot water at 35°C.

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## Simulative Applications of Novel Indicators for the Characterization and Performance Evaluation of Transparent Facades

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#### Abstract

Modern glazing systems, including triple-glazing with integrated blinds and advanced façade technologies, exhibit complex thermal behaviors that traditional metrics like the Solar Heat Gain Coefficient (SHGC) and the thermal transmittance (U-value) inadequately capture. This paper introduces novel Key Performance Indicators (KPIs) for assessing the solar performance of glazing units under dynamic, realistic conditions. Such new proposed KPIs -Daily Integrated SHGC and Maximum Solar Gain Ratio MSGR - provide a more accurate reflection of a building's energy performance by considering daily variations in solar exposure and the way the radiation is transferred through a complex transparent component. This research aims to validate the new KPIs in a simulated environment before applying them to actual building components, offering a comprehensive evaluation of their variability with changing environmental and configuration variables.

#### 1. Introduction

#### 1.1 Background

One of the most significant challenges in developed countries is upgrading both new and existing buildings to extremely high efficiency standards, aiming for low-consumption structures (Chel & Kaushik, 2018). Specifically, improving the transparent components of building envelopes allows for natural light penetration, leading to substantial energy savings on lighting. However, these elements also significantly contribute to heating and cooling requirements. In recent years, the evolution of glazing systems for windows and facades has resulted in increased technological complexities, enhancing performance (Favoino et al., 2022). While single and double-pane systems were the standard decades ago, contemporary buildings frequently feature triple-glazing systems, often equipped with integrated blinds, internal curtains, fixed and movable shading. Additionally, the market is seeing a rise in façades with ventilated or closed air cavities due to their protective function and appealing aesthetics (de Gracia et al., 2015). Hence, these contemporary façade systems exhibit heightened thermal inertia and complexity compared to traditional glazing units (Demanega et al., 2023).

The conventional metric used for characterizing the solar gain performance of transparent facade components is the Solar Heat Gain Coefficient (SHGC), also known as the g-value, in the presence of solar radiation and the thermal transmittance (U-value). The SHGC quantifies the ratio between primary solar transmission - and secondary - absorbed and emitted toward the inner face - energy fluxes entering indoor spaces and the solar radiation incident on the outdoor layer of the glazing system. This indicator is conventionally calculated or measured in two main ways: numerical methods based on spectrophotometric measurements and solar calorimetric methods under steady-state conditions in a controlled environment. Various established numerical techniques exist for calculating a window's g-value (EN 410:2011, ISO 9050:2003, ISO 15099:2003, UNI EN ISO 52022-1). Despite this, the simplifications, and assumptions inherent in these methods, particularly when dealing with complex window systems,

may lead to underestimated or overestimated outcomes. Conversely, experimental approaches offer researchers a more comprehensive understanding of the underlying heat transfer mechanisms, thus addressing the limitations of numerical methods (Moghaddam et al., 2023).

The conventional measurement of SHGC is performed under steady-state conditions (ISO 19467:2017, NFRC 201-210:2010) and may not accurately reflect the true performance of complex facades. In fact, glazing units are subject to a wide range of solar altitude and azimuth angles, air temperatures, and other weather variables, whereas standard procedures have fixed boundary conditions: i.e., temperatures, wind velocity, irradiance, and orthogonal angle of incidence (ref ISO 19467:2017 and NFRC 201-210:2010), which do not cover the whole environmental conditions that the façades face during their lifetime. Moreover, the complexities of the mentioned facade technologies result in non-uniform and adaptable behaviours to the dynamic outdoor conditions. Nevertheless, during the design phase the conventional SHGC is adopted to estimate the solar heat loads to design the cooling system. Goia & Serra (2018) proposed a methodology for calculating the solar factor and Uvalue for glazing units under real conditions, developing a set of sensors that can be installed on windows or facade transparent elements. This method accounts for the variability of results according to solar altitude.

This research aims to address the limitations of traditional steady-state calculations for assessing the solar performance of glazing systems. Specifically, it seeks to develop and validate novel Key Performance Indicators (KPIs) that accurately reflect the dynamic environmental conditions affecting glazing units. By introducing the Daily Integrated SHGC and the Maximum Solar Gain Ratio, the study attempts to provide a more comprehensive and realistic evaluation of solar heat gains, considering the variability in solar altitude, azimuth angles, and other climatic factors.

#### 2. Methods

#### 2.1 New KPIs Definition

To overcome the limitation of the current calculation approach of the solar gain, this paper introduces and discusses novel KPIs to characterize the solar performance of glazing units under real and dynamic conditions, along with a comprehensive methodology for their calculation. Specifically, the first proposed indicator is the Daily Integrated SHGC (INT SHGC), representing the integrated value of the SHGC over an entire clear sky day. The second is the Maximum Solar Gain Ratio (MSGR), quantifying the ratio between the daily maximum solar heat gain flux and the daily maximum solar irradiance incident on the outer side of the facade. The first KPI, considered for clear sky days, is calculated as follows:

$$INT \ SHGC = \frac{\int_{i=1}^{N} q_{int_{i}} + \int_{i=1}^{N} I_{sol, int_{i}}}{\int_{i=1}^{N} I_{sol, ext_{i}}} \quad [-]$$
(1)

Here, q<sub>int</sub> represents the secondary flux, I<sub>sol,int</sub> is the solar shortwave irradiance entering the indoor environment, and I<sub>sol,ext</sub> is the solar irradiance hitting the outer face of the window. Within this approach, the dynamics of the façade systems and of the solar movement are crucial for the overall results, differently from a steady-state calculation as the one standard SHGC. With this approach, the daily overall performance is considered, without focusing on just one setting.

Additionally, MSGR, is defined as:

$$MSGR = \frac{(q_{int} + I_{sol,int})_{max}}{I_{sol,ext}_{max}} \quad [-]$$
(2)

The MSGR quantifies the ratio between the maximum amount of power entering the indoor environment through the glazing throughout the day and the maximum solar irradiance hitting the external side of the glazing. Knowing the peak irradiance hitting on the outer surface on a certain day, this metric aids in estimating the peak solar gain that the cooling system must compensate. The offset of these two peaks can be calculated, to determine time delay from one to the other.

## 2.2 Numerical Evaluation

To perform the analysis, a TRNSYS model was built integrating different components. TRNSYS solves equations for dynamic simulations using a modular approach, integrating numerical solvers for differential and algebraic equations, and iterating between modules to ensure convergence of solutions. An existing model simulating the behavior and performance of a window with a ventilated cavity (Demanega et al., 2022) was adopted. Such a model is composed of a Type56 for the building (with its window) and a Type169 to simulate the airflow in the cavity according to ISO 15099. In this model, the window is installed in a shoebox building without any other windows. All the simulations were performed using timesteps of 10 minutes.

The glazing configuration was represented, in terms of the optical and thermal model, using a BSDF (Bidirectional Scattering Distribution Function) data file generated with WINDOW software v. 7.8 (Software Tools | Windows & Daylighting (lbl.gov)). The window (1 m x 1.34 m in dimension) consists of a low emissivity double-glazed internal unit with two panes separated by a layer of Argon (95 %) and air (5%), along with a ventilated cavity where Venetian blinds are installed. The cavity is enclosed by an external single glass pane. In this simulation campaign, the Venetian blinds are constantly kept deployed at 0°. WINDOW not only produced a BSDF data file, but also calculated the SHGC and other KPIs according to the numerical standard approaches. The most important KPIs are reported in Table 1.

Table 1 – Significant KPIs of the window calculated according to ISO 15099 in WINDOW 7.8

SHGC	61.2 %
U factor	2.159 W/(m <sup>2</sup> K)
T <sub>sol</sub>	45.8 %
Tvis	56.2 %

#### 2.3 Parametric Simulations

To investigate the variability of the proposed KPIs according to the external conditions, simulations and KPIs calculations have been performed for a set of variables. These variables included the location, the season, and the façade orientation. The locations chosen for this study are Athens (Greece), Bolzano (Italy) and Oslo (Norway). These are located at different latitudes and climatic zones. The weather files for the locations under study were obtained using METEONORM software (Meteonorm Version 8 - Meteonorm (en)), which provided the respective Typical Meteorological Years. The orientations of the facade have been defined exactly as the four cardinal points (Azimuth: 0°, -90°, 90°, 180°). The analysis covered all four seasons, each evaluated within a specific timeframe centered around the solstice or equinox day marking the beginning of the season. The evaluation period extended from 7 days before to 7 days after this reference day. For each of these periods, only the two days with the highest solar radiation levels, considered as clear sky days, have been taken into consideration, and the results of these two days have been averaged.

The variables involved in the series of simulations are reported in Table 2.

0		
Location	Season	Orientation

Table 2 - Variables involved in the simulation campaign

Location	Season	Orientation
Bolzano	Spring	South
Oslo	Summer	East
Athens	Autumn	West
	Winter	North

## 3. Results and Discussion

Table 3 presents the "INT SHGC" and "MSGR" values for the four cardinal directions (South, North, East, West) in three different locations (Bolzano, Oslo, and Athens) across the four seasons (Spring, Summer, Autumn, Winter).

The results highlight that, in general, the KPIs are lower than the standard SHCG (61.2 %). This indicates the calculated performance based on ideal steady-state conditions tends to overestimate the SHGC compared to real-world dynamic conditions.

		Spring		Summ	er	Autun	n	Winter		
		INT SHGC	MSGR	INT SHGC	MSGR	INT SHGC	MSGR	INT SHGC	MSGR	
South	Bolzano	33.2%	33.9%	30.2%	30.0%	32.4%	33.7%	49.2%	48.5%	
	Oslo	40.6%	42.0%	30.3%	31.6%	37.7%	39.9%	55.5%	56.5%	
	Athens	30.8%	32.3%	35.3%	33.1%	29.6%	31.2%	41.6%	39.2%	
North	Bolzano	39.4% 39.4%		36.3%	34.3%	39.5%	39.5%	39.2%	39.2%	
	Oslo	39.0%	38.9%	37.6%	40.4%	39.3%	39.4%	39.3%	39.3%	
	Athens	39.6%	39.6%	36.6%	35.5%	39.7%	39.7%	39.4%	39.3%	
East	Bolzano	39.6%	50.7%	38.6%	46.4%	39.5%	47.2%	40.1%	49.2%	
	Oslo	41.6%	52.9%	40.2%	51.8%	42.4%	53.5%	34.8%	35.2%	
	Athens	39.6%	51.8%	38.1%	41.6%	39.0%	50.2%	38.8%	49.7%	
West	Bolzano	40.0%	48.1%	39.2%	43.2%	40.8%	50.1%	39.1%	50.3%	
	Oslo	42.1%	49.9%	40.3%	44.9%	43.0%	53.8%	32.8%	34.2%	
	Athens	38.7%	51.4%	38.9%	43.0%	39.5%	53.8%	38.9%	52.1%	

Table 3 – Results for the novel KPIs calculation

Table 4 – Difference between calculated novel KPIs and SHGC calculated with WINDOW (61.2 %)

		Spring		Summ	er	Autun	ın	Winter		
		INT SHGC	MSGR							
South	Bolzano	-28.1%	-27.4%	-31.1%	-31.2%	-28.9%	-27.5%	-12.1%	-12.7%	
	Oslo	-20.6%	-19.2%	-31.0%	-29.7%	-23.6%	-21.4%	-5.8%	-4.7%	
	Athens	-30.5%	-28.9%	-25.9%	-28.1%	-31.6%	-30.1%	-19.6%	-22.0%	
North	Bolzano	-21.9%	-21.8%	-25.0%	-26.9%	-21.8%	-21.7%	-22.0%	-22.0%	
	Oslo	-22.3%	-22.4%	-23.6%	-20.8%	-21.9%	-21.9%	-21.9%	-21.9%	
	Athens	-21.6%	-21.6%	-24.6%	-25.8%	-21.6%	-21.5%	-21.9%	-21.9%	
East	Bolzano	-21.7%	-10.6%	-22.6%	-14.9%	-21.7%	-14.1%	-21.1%	-12.1%	
	Oslo	-19.6%	-8.4%	-21.0%	-9.4%	-18.9%	-7.7%	-26.4%	-26.0%	
	Athenes	-21.6%	-9.4%	-23.2%	-19.7%	-22.3%	-11.1%	-22.5%	-11.6%	
West	Bolzano	-21.2%	-13.2%	-22.0%	-18.0%	-20.5%	-11.2%	-22.1%	-11.0%	
	Oslo	-19.1%	-11.4%	-20.9%	-16.3%	-18.3%	-7.4%	-28.5%	-27.0%	
	Athens	-22.5%	-9.8%	-22.3%	-18.3%	-21.8%	-7.4%	-22.4%	-9.1%	

The calculated KPIs exhibit significant variability based on the location, orientation, and season, underscoring the importance of considering these factors in the design and evaluation of building envelopes. This discrepancy is particularly pronounced during the summer months in Bolzano and Athens, where the Daily Integrated SHGC drops by approximately 31.1 % and 25.9 %, respectively. This significant difference is due to the high solar elevation in this season, which cause higher angles of incidence on the façade throughout the days. This reduction highlights the impact of dynamic environmental conditions, which are not accounted for in standard steady-state calculations.

#### 3.1 Location Analysis

In Table 3, it is possible to observe how the calculated KPIs vary according to the location, keeping the same orientation and same season. Generally speaking, the variability of the KPIs based on location is higher for the southern orientation, due to the significant range of solar elevation across different latitudes. For instance, the differences in KPIs during spring for the south orientation are illustrated in Figure 1. In this case, Oslo, with a higher latitude, exhibits the highest values, while Athens, with a lower latitude, shows the lowest values. The range of values is close to 10 %.



Fig. 1 - KPIs values for South facade - Spring

In Figure 2, the trends of the energy fluxes through the window are illustrated for two days in spring in Oslo and Athens, for south-oriented façade. While the contribution of the secondary flux is similar (around 20 % compared to external incident radiation), in Oslo there is a higher contribution of the directly transmitted radiation, because of a lower solar elevation. This causes the increase in the KPIs values.

For other combinations of season and orientation, such as Winter-South façade, the range of results is even higher than the previously illustrated combination, while in many other cases the range is significantly lower, indicating a smaller impact of the location.

#### 3.2 Seasonal Analysis

From another point of view, it is possible to appreciate the differences in results according to the season in which the simulations are run. Also in this case, the solar elevation and the incidence angle on the façade are subject to high variability throughout the year. One interesting situation to analyse is the combination Oslo-South orientation. In Figure 3, the overall KPIs results are represented. In this chart, the large difference between summer and winter is quite noticeable. Also in this case, the influence of the sun path is crucial.

The trend of energy fluxes for one day of winter and one day of summer are illustrated in Figure 4. Because of a lower solar angle, the transmitted solar radiation amount, with respect to the incident solar radiation, is significantly higher in winter, causing high values of the KPIs.



Fig. 2 - Energy fluxes trends for the locations of Athens and Oslo



Fig. 3 – KPIs values for Oslo – South



Fig. 4 – Energy fluxes trends for Winter and Summer in Oslo

#### 3.3 Orientation Analysis

Furthermore, the orientation of the façade has an influence on KPIs simulated results. From Table 3 and Table 4 it is possible to clearly see how South orientation presents lower values of the KPIs. On the other hand, West and East orientations show higher values. As an example, in Figure 5, there is a representation of the results for the location of Bolzano in the summer season.

To understand the reasons behind these results, also in this case the trends of the energy fluxes can be analyzed. In the morning (or in the afternoon for the west orientation), the sun is low and frontal to the façade, increasing the amount of transmitted solar radiation. The performance is different for the south orientation, as the sun hits the façade at different angles of incidence throughout the day. Within this comparison, it is evident that, in the east configuration, the peak of energy flux passing through the window is happening much earlier than the peak of solar radiation hitting the external side. In fact, while for this configuration the offset between the peaks is of approximately 90 minutes, for south configuration the two peaks are simultaneous.



Fig. 5 - KPIs values for Bolzano - Summer



Fig. 6 – Energy fluxes trends for South and East orientation in Bolzano

#### 3.4 Overall Discussion

The variability observed in the calculated KPIs underscores the complex interplay between environmental conditions and the performance of glazing systems. This variability highlights the necessity of considering dynamic factors such as location, season, and facade orientation when evaluating and designing energy-efficient building envelopes. It becomes evident that traditional steady-state calculations are insufficient for capturing the true performance of these systems, tending to overestimate the solar gain, which can lead to incorrect choice in the design of the building envelope and HVAC system. The significant differences (up to 31 %) between the KPIs and the standard SHGC values emphasize the need for a more nuanced approach that accounts for real-world conditions. By doing so, we can achieve a more accurate prediction of solar heat gains, leading to better-informed and conscious design and ultimately contributing to more sustainable and energy-efficient buildings.

## 4. Conclusions

The evolution of glazing systems for windows and facades has significantly contributed to the energy efficiency of buildings. This paper introduces novel Key Performance Indicators (KPIs) to better characterize the solar performance of glazing units under real and dynamic conditions, offering a more comprehensive understanding of their actual performance compared to traditional steady-state metrics. The research utilized a TRNSYS model to simulate the behaviour of a window with integrated Venetian blinds in fixed horizontal position, calculating the proposed KPIs. Results across different locations, orientations, and seasons were analysed. The findings highlight several key points. Firstly, the Daily Integrated Solar Heat Gain Coefficient and Maximum Solar Gain Ratio show considerable variability based on location, season, and orientation. This underscores the importance of considering these dynamic factors in the design and evaluation of building envelopes. The actual performance of façade systems cannot be accurately captured by steady-state calculations alone.

Secondly, the results demonstrate that the performance of glazing systems calculated in dynamic and more realistic conditions is often different than what is predicted by standard steady-state SHGC values. This discrepancy is especially pronounced during the summer months and in locations with high solar elevation, where the dynamic conditions lead to lower actual solar heat gain compared to steadystate predictions. Lastly, the proposed KPIs, Daily Integrated SHGC and Maximum Solar Gain Ratio, provide a more realistic measure of glazing performance under dynamic conditions. They account for the variability of solar altitude, azimuth angles, and other environmental factors, offering a better prediction of solar heat gains and thus aiding in the accurate design and evaluation of cooling systems.

Current limitations of the model are related to the possibility to consider thermal inertia of the window, which is currently not included in the calculation method. Influencing mainly the MSGR indicator calculation, which also considers the time-delay of the solar energy peak respect to the incident radiation. In this sense, further developments may involve the improvement of the TRNSYS model to better represent the real performance of the glazing system.

Future research should also focus on experimenting and validating these KPIs with experimental data and extending the analysis to other types of glazing systems and façade configurations. Additionally, the development and integration of advanced sensors and data collection methods in real buildings will further enhance the accuracy and applicability of these KPIs in practical settings. By incorporating real environmental conditions into the evaluation process, architects, engineers, and designers can make more informed decisions, ultimately leading to buildings that are better adapted to their specific climatic and operational contexts.

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## Predicting Daylight Preferences Using HDRI and Deep Learning

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#### Abstract

This paper utilizes High Dynamic Range Imaging and deep learning that utilize pixelwise information from the entire luminance distribution in the field of view to classify daylighting preferences of office workers. Generated luminance and contrast similarity maps were used for training convolutional neural network (CNN) models to classify the occupant's visual preferences. Preference datasets for 11 individuals, collected in real offices, were used to evaluate the preference classification performance. The results showed the superiority of the luminance similarity map as a visual preference indicator compared to common static lighting parameters.

#### 1. Introduction

The spatial luminance distribution within the field of View (FOV) has a high correlation with the human perception of brightness and comfort (Wymelenberg et al., 2010) and is therefore valuable for assessing visual comfort and visual preferences in general. Realtime FOV luminance monitoring is achieved by acquiring per-pixel luminance using High Dynamic Range Imaging (HDRI) sensors (Inanici et al., 2006) combined with wide-angle fisheye lens, now a wellestablished methodology in lighting research (Pierson et al., 2021).

HDRI measurements have been used to correlate scene luminance characteristics to subjective visual comfort responses (Konstantzos & Tzempelikos, 2017; Konis, 2014; Suk et al., 2017), as well as for realtime daylighting and glare control in buildings (Newsham, 2009; Motamed et al., 2017; Kim et al., 2020). Despite these obvious advantages, the full potential towards human-centered daylighting operations has not been explored. Building systems that learn human preferences and integrate them into building operations can achieve occupant satisfaction as well as energy savings (Xiong et al., 2019; Villa et al., 2013). Detecting visual discomfort scenarios does not necessarily translate to learning or providing preferred conditions for occupants. Instead, learning lighting preferences without considering discomfort scenarios (Xiong et al., 2018) is preferred for optimized visual environment and control in buildings. But learning and modeling human visual preferences can be extremely complex (Lindelof & Morel, 2008; Xiong et al., 2020). True visual preferences dynamically depend on different environmental, contextual, or (unmeasurable) subjective factors, outside view and aspects such as perceived control (Bakker et al., 2014) or multi-domain interactions, and have rarely been used in building control and optimization applications.

The selection of meaningful variables remains a challenge even when considering only environmental factors. Using simple variables such as horizontal or vertical illuminance, average luminance or simple contrast ratios from captured luminance maps is maybe sufficient for specific glare assessment cases, but not for inferring preferred conditions, partly due to averaging pixel information and neglecting information in different parts of the luminance field. Although HDRI sensors present information through pixelwise luminance maps, there is no agreement on which features can better represent visual preferences of occupants in typical daylighting settings.

This paper presents a novel method for inferring personal daylight preferences using image pixelwise similarity analysis applied in a deep learning framework. Instead of studying how occupants' preferences are affected by instant physical and contextual parameters using numeric scaled responses, we utilize information from the entire luminance distribution in the FOV and extract pair-wise similarity features between HDRI-based luminance maps (different conditions). We also compare models using common lighting variables with the CNN-based models using the new metrics.

## 2. Pixelwise Similarity Index and Luminance Similarity Maps

A pixelwise similarity index is introduced to quantify the degree of similarity between two luminance distributions. The index is used to generate a new variable named the luminance similarity map, which is an important part of inferring preference between two visual scenes with daylight. It compares pixels at the same location inside two luminance maps, one by one directly (pixel-wise comparison), and it considers both the direction and magnitude of relative luminance change. In contrast to grayscale images containing color data from 0 to 255, luminance maps have much greater variation in pixel intensity. The pixelwise luminance similarity index is:

$$LSim(x_1, x_2) = [sign(x_1 - x_2)] \cdot \left(1 - \frac{|x_1 - x_2|}{\max(x) - \min(x)}\right)$$
(1)

where x1 and x2 are pixelwise luminance values in luminance maps 1 and 2 respectively (comparative luminance map data) and max(x) and min(x) compute the maximum and minimum luminance values from the entire two luminance maps for normalization. The two luminance maps represent two different scenes (two different visual conditions). To consider the directional relative luminance change in each pixel between two conditions, the sign of luminance difference is also applied to the similarity index equation. An absolute similarity of 1 means that the luminance of those pixels in the two luminance maps is the same. Lower absolute pixel similarity values indicate a difference in luminance; a zero-similarity index between two pixels means that the luminance difference at the same pixel location is the maximum possible (= max-min between the two maps). The -1 similarity value is excluded from further analysis to avoid repetition.

The luminance similarity map is generated by directly comparing two luminance maps and calculating the luminance similarity index pixel-by-pixel. A representative example of generating luminance similarity index maps is shown in Fig. 1. After RGB color data of two HDR images (two different conditions) is converted to luminance maps (Inanici, 2006), the luminance intensity of each pixel is used to calculate *LSim* values according to Eq. (1). Then all the *LSim* values are mapped on the camera FOV to produce the entire luminance similarity map in a graphical way that includes the relative luminance change (magnitude and direction).



Fig. 1 – Generating a luminance similarity index map (c) from two luminance maps (a and b) corresponding to different conditions

## 3. A Comparative Luminance Map Dataset for Evaluating Daylight Preferences

To evaluate the ability of different models (and variables) to infer daylighting preferences, comparative luminance map datasets were created with simultaneous occupant feedback. HDR images were captured at the eye level of 11 office occupants in identical, side-by-side private offices with large windows (Xiong et al., 2019) and controllable shades, under various daylight and interior luminance conditions without glare. Calibrated Canon Rebel T2i cameras equipped with fisheye lens were used to generate reliable luminance maps. The highest DGP observed in the data set was 0.35. Additionally, conditions with vertical illuminance exceeding 2760 lux were also excluded. The daylight conditions were changed every 10 minutes by adjusting the position of window shades, and shortly after the 11 occupants were asked about their visual preference between current and previous conditions. Electric lights were automatically controlled to maintain the required work plane illuminance (300 lux).

The collected HDR images were converted to luminance maps and directly compared pixel-by-pixel to generate luminance similarity index maps. Since the HDR images were acquired under comfort conditions, a resolution of  $330 \times 330$  was selected for this study considering the computation load required to produce the similarity maps. The luminance maps were converted to 11 comparative luminance map datasets (one for each occupant) by grouping successive luminance maps into pairwise comparative data (corresponding to current vs previous condition) and linking corresponding occupant binary visual preference data (preferring current or previous visual condition) to each pair.

Since the occupants responded with their preference between successive conditions every 10 minutes, part of the collected pairwise comparative data was considered to be the test data for assessing the classification performance of the trained models. As shown in Fig. 2, 40 % of pairwise HDR images with preference responses were used as a test dataset and used only once for evaluating the trained visual preference classification models. For the training data, the remaining 60 % of original HDR pairwise images were used and augmented by the automatically captured HDR images with 2 min-intervals, since the users have maintained their visual preference response during this time -except if they override the system in the meantime. Then, to avoid overfitting, the training dataset was randomly divided into 5 to 1 ratio to generate the validation dataset. The training dataset consists of around 500 luminance map pairs and the test dataset is about 40 pairs.



Fig. 2 – Schematic procedure for generating comparative preference test and training data

## Performance Evaluation of Daylighting Preference Learning Models Using Common Variables

In this section we evaluate the ability of different methods and variables to infer preferred visual scenes with daylight. Using the comparative luminance map dataset, simple and advanced methods using commonly used lighting variables are compared with a deep learning model that uses the luminance similarity index maps.

## 4.1 Common Lighting Variables Used to Predict Daylight Preferences

To evaluate the efficiency of luminance similarity index-based metrics, a comparison is first made with common lighting parameters. The 7 "reference" parameters listed in Table 1 are selected since they have been extensively used to predict lighting preferences and comfort in daylighting settings. DGP, average luminance of entire scene, and average luminance of 40° horizontal band are computed directly by Evalglare, while the rest of the parameters can be computed by masking the window part.

Table 1 - Selected reference variables

Lig	Lighting metrics used as model variables							
1.	Percentage of pixels exceeding 2000 cd/m <sup>2</sup> ( $p_{2000}$ )							
2.	Average luminance of entire scene (avlum)							
3.	Daylight glare probability (DGP)							
4.	Standard deviation of window luminance $(std_{win})$							
5.	Average luminance of 40 ° horizontal band							
	$(avlum_{B40})$							
6.	Maximum luminance in window divided by 200							
	cd/m <sup>2</sup> ( <i>wmax</i> 200)							
7.	Average luminance in window divided by 200							
	cd/m <sup>2</sup> ( <i>wav</i> 200)							

## 4.2 Logistic Regression Model Trained with Reference Variables

To estimate the need for using more complex variables or advanced models to infer personal daylight preference, a logistic regression model is first trained using Eq. (2) with each of the reference parameters:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2)}}$$
(2)

where  $\beta_i$  are model parameters and  $x_i$  is the selected reference variable from Table 1. Each logistic regression model was trained using each reference parameter computed from each pair of HDR images in the dataset. The classification accuracy for each person was tested by computing the ratio of correctly classified test data over the entire test data.

The classification results with each variable are shown in Fig. 3 for each of the 11 subjects (noted in the x-axis). In some cases, for example for subjects 1 and 4, the logistic regression model could classify visual preferences quite well for most variables. In other cases, the selection of variables significantly affected the prediction accuracy. Most importantly, the classification performance varies significantly between subjects. Although this is somewhat expected because of the natural preference inconsistency between individuals, sometimes this model fails to predict any preference at all (although the subject reported specific preference trends). Considering that the classification problem in this study is a binary classification problem, the trained model with about 60 % accuracy means that it is not possible to train the model with the selected reference parameter.



Fig. 3 – Preference classification results for each subject: logistic regression model trained with selected reference parameters

The limited and variable classification performance can be attributed to the simplicity of the logistic regression model or the insufficiency of the selected variables. To eliminate the first possibility, the performance of more advanced (deep learning-based) models is evaluated with the same reference variables.

#### 4.3 ANN Model Trained with Reference Variables

An Artificial Neural Network (ANN) model that uses the reference variables to estimate personal visual preference was evaluated next. As shown in Fig. 4, two constant values, representing one reference parameter, were computed from current and previous luminance maps and used as input to the model. This ANN model contains three hidden layers, and each hidden layer consists of 100 neurons. After all the neurons in the hidden layers extract relationships between two input values, two output values were computed. The model classifies the person's visual preference by selecting the greatest between these two values. In addition, a second ANN model (Fig. 4) was trained using all 7 reference parameters to check if the classification accuracy could be increased. The only difference is the number of input values ( $2 \times 7 = 14$  values were input to the hidden layers in this case). The training was monitored using the cross entropy loss function:

$$Loss = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(p_i) + (1 - y_i) \cdot \log(1 - p_i)]$$
(3)

where  $y_i$  is the binary preference label (e.g., current vs previous condition),  $p_i$  is the probability that the person prefers the current condition, and N is the data size. A stochastic gradient decent algorithm with 0.9 momentum was used as optimizer with batch size = 16. In addition, 10<sup>-3</sup> was used both for learning rate and for L2 regularization strength. Then, 100 epochs were predefined for training the ANN models, monitoring validation loss to avoid overfitting. Following one of the recommended early stopping criteria (Prechelt, 2012), the training procedure was terminated when the validation loss at a specific epoch (t) was greater than the loss at previous epoch (t-5) twice.

The ANN model classification results (Fig. 4) showed better overall classification performance compared to logistic regression while the performance variation among variables was reduced. In addition, the ANN model trained with all the reference variables (marked with red markers) performed similar or better than models trained with single variables for every subject. However, the classification accuracy is still low for several subjects even with this complex model. This indicates that the static lighting variables cannot really estimate daylight preferences; they cannot include important visual information located in different areas of the visual scene and they cannot express the change in perceived luminance distribution (similar values of input parameters have different preference labels and vice versa). As discussed next, the pixelwise luminance similarity-based metrics present a clearer characterization of personal daylight preferences.



Fig. 4 – Preference classification results for each subject: ANN model trained with selected reference parameters and with all parameters together

## Using The New Luminance Similarity Index Maps to Infer Daylighting Preferences

#### 5.1 CNN Model Architecture Trained with Luminance Similarity Index Maps

In contrast to the reference variables, similarity index maps extracted from luminance similarity maps are in 2D array data format. A Convolutional Neural Network (CNN) model structure is therefore developed to preserve pixelwise information and patterns as much as possible. Luminance similarity index maps are both used solely and together to study their ability to classify personal visual preference. As shown in Fig. 5, the CNN model consists of 4 convolutional layers and 2 fully connected layers. Unlike typical CNN model architectures, which consist of convolutional and maxpool layers, only convolutional layers were used. This is because computing maximum values in the maxpool layers might result in erasing important similarity index patterns, which can be the combination of positive and negative similarity index values. Instead, convolutional layers with stride 2 were selected, which not only preserve necessary information but also reduce CNN model parameters considering computational efficiency. Stride 1 is only used in the first convolutional layer to capture pixelwise information in detail as much as possible. All the layers used 32 kernels with size of 3 x 3 to extract helpful features for preference classification. After the input luminance similarity index maps move through the 4 convolutional layers, the initial 330 x 330 size is reduced to 42 x 42 and input to the fully connected layers to link all the parameters with each other. By selecting the greatest between the two output values, the CNN model will classify the occupant's preference.

Similar to ANN model training, loss function was evaluated using cross entropy, a stochastic gradient decent algorithm with 0.9 momentum was used as optimizer with batch size = 16, and 10<sup>-3</sup> was used both for learning rate and for L2 regularization strength. 50 epochs were set for training in this case and the same early stopping criteria were applied to prevent overfitting.



Fig. 5 - CNN model architecture, trained with luminance similarity index maps

## 5.2 Classification Performance of CNN Model with Luminance Similarity Index Maps

The CNN models using luminance similarity index maps show excellent classification performance compared to other models (Fig. 6). More importantly, the CNN models performed much better than the ANN especially for Subjects 5-11, where the previous models performed poorly. This proves that the luminance similarity map, which contains a great amount of pixel-wise information from each pair of daylighting conditions, is a superior preference indicator when used in powerful deep learning models, in contrast to constant variables used in previous studies.



Fig. 6 – Preference classification results for each subject: CNN model trained with luminance similarity index maps. The results of ANN model trained with all reference variables are shown for comparison

The training results of Fig. 7 show that the CNN model with the similarity index maps presents stable training, fast convergence and excellent test accuracy. That is the case for all 11 occupants in the dataset. Therefore, the similarity index is a superior metric when inferring personal visual preference in daylight scenes; in fact, the luminance similarity map concept is valuable even when compared with other powerful CNN models considering raw luminance maps.



Fig. 7 - Representative CNN training results for subject #6

## 5.3 Impact of Similarity Index Sign on Preference Classification Performance

The sign function in the new similarity index indicates the relative change in luminance (e.g., from higher to lower and vice versa) for every pixel in the map. To examine if this information is useful (and necessary), we compared the CNN model classification performance using similarity indices without the sign. The results of Table 2 show that the model performance was drastically reduced -in some cases worse than the models trained with reference parameters. Therefore, preserving the direction of change in luminance distribution is necessary when inferring personal daylight preference, and the luminance similarity index is the appropriate metric to capture that information. Excluding this information would eventually confuse the classification model during all stages of training.

Table 2 – Preference classification accuracy for each subject without the sign function (indicating relative change in luminance) and relative reduction compared to CNN models using luminance similarity index maps.

Classification accuracy	Sub1	Sub2	Sub3	Sub4	Sub5	Sub6	Sub7	Sub8	Sub9	Sub10	Sub
Without sign	0.59	0.61	0.63	0.51	0.68	0.54	0.53	0.56	0.60	0.56	0.5
Relative reduction	60.7%	64.6%	65.2%	53.8%	75.9%	59.5%	57.9%	62.3%	66.5%	66.3%	69.5

#### 6. Discussion

Satisfaction with visual conditions dynamically depends on different environmental, contextual and subjective factors. Especially for daylighting conditions, the dynamic nature of daylight, related to outside views, requires a continuously updated evaluation of comparative preferences. The developed luminance similarity index that captures dynamic changes in luminance patterns, utilized in a powerful CNN model, showed an impressive preference classification performance under fixed contextual settings. Outside view preferences are outside the scope of this study; however, there is strong evidence that outside view quality, perception and preference affect satisfaction with the overall visual environment (Giraldo Vasquez et al., 2022; Chinazzo et al., 2019). This study did not consider interaction effects in the preference learning framework. The predictive framework can be used to study if personal daylighting preferences can change with different views and other environmental (Te Kulve et al., 2018; Belia et al., 2021; Pittana et al., 2023) or contextual factors.

Our study is focused on personal daylighting preferences using CNN-based preference classification, which is more challenging than predicting comfort limits under constant luminance distributions. However, our results cannot be generalized like visual comfort metrics. In addition, our training data set was rather limited. It was used to develop the proof of concept and test the ability of luminance similarity maps as personal preference input variables. More daylight scenes with larger variation of luminance patterns are needed for a more complete demonstration of the luminance similarity index concept in real settings.

Finally, in our experimental setting we had the camera next to the person, in order to capture the human FOV and extract lighting metrics (used as reference parameters). The results of this study showed that there is no need to extract these static parameters since they cannot really predict daylighting preferences. The sensor does not necessarily need to match the occupant FOV for the purpose of this work, although estimating or re-projecting the camera-captured luminance distribution to the occupant FOV is possible (Kim & Tzempelikos, 2021, 2022).

## 7. Conclusion

This study presents a new approach for inferring personal daylight preferences using a new composite luminance similarity index and deep learning techniques. Information from the entire luminance distribution in the FOV was used to extract pair-wise similarity features between HDRI-based luminance maps (different conditions). The luminance similarity index considers both the direction and magnitude of relative luminance change instead of instantaneous metrics.

Comparative visual preference datasets for 11 individuals were generated using collected pairwise HDR images. The generated luminance similarity maps were directly used for training convolutional neural network (CNN) models to classify the occupant's visual preferences. The results showed the superiority of the luminance similarity index map as a preference indicator variable. CNN models trained with luminance similarity index maps showed impressive classification accuracy for all tested subjects in the dataset. Static lighting variables cannot really estimate daylight preferences. Preserving the direction of change in luminance distribution pixel-wisely, is necessary when inferring personal daylight preference.

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# An Investigation Into Thermal Bridging Effects in an Envelope Integrated With End-Of-Life Photovoltaic Panels

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#### Abstract

Upcycling End-of-Life Solar Photovoltaic panels in buildings is a novel approach to manage the imminent growing problem of PV waste. The EoL-PV panels have been characterized to have a high U-value and low thermal mass. To address this issue, interventions involving tandem plywood (preferably EoL packaging plywood) have been proposed and tested through whole building simulations in our preceding studies. A typical PV panel is encased in an aluminium frame whose thermal conductivity is of two orders of magnitude higher than a PV panel. This causes thermal bridging, which must be accounted for in the Uvalue calculation of PV panels. In this study, the thermal bridging effect due to the aluminium frame is analysed using two-dimensional finite-element method-based tool, THERM. A rise in the U-value of around 13% has been estimated due to the presence of a frame in PV panel. To demonstrate the impact of U-value of PV panel on the building's thermal performance, simulations have been performed with lumped-capacitance simple single zone model in TRNSYS. One of the interventions, having the highest plywood thickness in tandem to the EoL-PV panel, was the least sensitive to the thermal bridging effect on annual heating/cooling load and fared best in terms of thermal mass.

#### 1. Introduction

The issue of the alarming rise in the End-of-Life Photovoltaic (EoL-PV) panels is surfacing worldwide. By 2050, 60 ~ 78 million tonnes of PV waste (EoL-PV Panels) are expected globally (Weckend et al., 2016). Recycling and recovery technologies are not currently economically viable (Mathur et al., 2020). Given the inherent durability of the materials comprising PV panels, a hitherto untried upcycling solution has been proposed in using EoL-PV panels

as a building material. The rising need for building materials in developing countries is imminent. Most conventional building materials are industrially sourced and inherently carry a high embodied energy (Typical brick: 1.26 ~ 3 MJ/kg; Cement: 3.6 ~ 20 MJ/kg (Praseeda & Venkatarama Reddy, 2017)). EoL-PV could be a low-cost, low-embodied energy building material. While PV has been integrated as a building envelope, the challenge of integrating EoL-PV lies in examining the impact of degradation on its solar and thermal transmittance properties and assessing its climatic-response as a building envelope. Experimentally, thermal transmittance measurements for building materials are conducted in a HotBox facility, wherein the real-life specimen is subject to a steady-state temperature difference on either side. In the context of EoL-PV, thermal transmittance (U-value) measurements for the thin nonopaque specimen have been examined in our recent study (Rao et al., 2023). A full-scale PV panel (glassbacksheet crystalline silicon PV) has been tested in a state-of-the-art HotBox facility. The U-values of the PV panels are estimated based on the heat flux and temperature difference in the controlled (environment) chamber. The dynamic thermal performance of the EoL-PV envelope, integrated as a façade, has been studied for a prototype structure (Fig. 1). The prototype structure was monitored real-time for its indoor air temperatures, EoL-PV surface temperatures (outdoors and indoors), and indoor globe temperature. The whole building simulations of the same building (calibrated) has been performed for different climatic zones in India. The decrement factor and time lag were found to be 1.13  $\pm$  0.12(sd) and 1.6 min  $\pm$  11 min (sd) respectively. These values indicate that the building envelope is unable to adequately regulate indoor temperatures, due to the high thermal transmittance and low ther-
mal mass of the EoL-PV. This calls for suitable interventions in the building envelope integrating EoL-PV panel, for improved thermal performance.



Fig. 1 – End-of-Life Photovoltaic panel integrated building with noticeable source of thermal bridging at the edges

The interventions involve adding another EoL-PV panel in tandem or plywood. (Fig. 2) describes the construction of the interventions.



		(kJ/m²K)
No intervention	EoL-PV (5mm) Panel	7
Intervention 1	EoLPV (5mm) – 100mm air – EoLPV panel (5mm)	14.1
Intervention 2	EoLPV (5mm) – 50mm air – plywood (5mm)	7.03
Intervention 3	EoLPV (5mm) – 50mm air – plywood (15mm)	21.02
Intervention 4	EoLPV (5mm) – 50mm air – plywood (30mm)	42.01

Fig. 2 – Interventions explored to improve the thermal performance of the EoL-PV envelope in a building

The scope of these studies until now was limited to the heat transfer through the EoL-PV panel without

considering the effects of the aluminium frame encasing the panel. The thermal conductivity of the PV panels measured is 0.55 ~ 0.7 W/mK (Rao et al., 2023) and the aluminium is nearly two orders of magnitude higher than PV panels. When the PV panels are used as the envelope of a building in a repetitive manner, the aluminium frame can be categorized as the linear (repeating) thermal bridge (Fig. 1). As such a high thermal conductivity of the aluminium frame certainly dissipates heat faster than the PV panel, the estimation of magnitude of thermal bridging and its impact on thermal performance is important. The U-value of the EoL-PV should involve the effects of the aluminium frame. The cross section of the aluminium frame is shown in the (Fig. 3). The objective of this study is to estimate the Uvalues considering the thermal bridging at the aluminium frame and its impact on the overall U-value of the building. The changes in the sensible heat load of a building considering the thermal bridging are estimated.



Fig. 3 – A typical commercial c-Si photovoltaic panel construction detail of the edges

The U-value of the PV panel with an aluminium frame is calculated by THERM tool (LBNL, 2023), which allows two-dimensional heat transfer using finite-element method. Previous studies (Siviour et al., 1988; Schwab et al., 2005; Boafo et al., 2015) have adopted two-dimensional heat flow analysis tools to estimate the thermal bridging effect on the envelopes. The percentage change in the U-value between ignoring and accounting for thermal bridging has been reported to parameterize the effect of thermal bridging. Further, to estimate the effect of an increased U-value on the indoor air temperature, a lumped-capacitance model is simulated in TRNSYS.

## 2. Methodology

# 2.1 Finite-Element Method for Heat Transfer Analysis (THERM)

THERM is a computer program developed at Lawrence Berkeley National Laboratory (LBNL). Using THERM, two-dimensional heat-transfer effects in building components such as windows, walls, foundations, roofs, and doors can be modelled as well as in other products where thermal bridges are of concern. THERM's heat transfer analysis is based on finite-element method, which can model complex geometries of building products. Here, the PV panels with and without a frame have been modelled for heat transfer analysis. The boundary conditions for the PV panel envelope are shown in (Fig. 4). The dimensions of the cases considered here are mentioned in (Fig. 2).



Fig. 4 – Boundary conditions applied to the heat transfer analysis in the THERM tool

Only one of the frames is analysed here as the heat flow pattern would be symmetrical along x- and yaxis. The length of the PV from frame is truncated to ~ 200 mm (total length of a typical panel is ~ 1600 mm) for analysis.



Fig. 5 – Different cases considered for heat transfer analysis without aluminum frame. (a) No intervention, (b) Intervention 1, (c) Intervention 2, (d) Intervention 3, (e) Intervention 4



Fig. 6 – Different cases considered for heat transfer analysis with aluminum frame. (f) No intervention, (g) Intervention 1, (h) Intervention 2, (i) Intervention 3, (j) Intervention 4

The considered length is based on the development of a consistent temperature gradient beyond a critical length from the frame. The PV panels without an aluminium frame (Fig. 5) have been modelled to verify the U-values calculated by THERM with our estimations based on Hotbox measurements (Rao et al., 2023). U-values of cases (a) to (e) (Fig. 5) agree with our previous estimations. Further, to estimate the U-value accounting for thermal bridging, cases (f) to (j) (Fig. 6) have been modelled and analysed.

## 2.2 Lumped-Capacitance Single Zone Model (TRNSYS)

Table 1 – Cases considered for simulations using lumpedcapacitance model in TRNSYS

Case	WWR	Scenario	Thermal bridging
1	10	No intervention	no bridging
2	25	No intervention	no bridging
3	40	No intervention	no bridging
4	10	Intervention 1	no bridging
5	25	Intervention 1	no bridging
6	40	Intervention 1	no bridging
7	10	Intervention 2	no bridging
8	25	Intervention 2	no bridging
9	40	Intervention 2	no bridging
10	10	Intervention 3	no bridging
11	25	Intervention 3	no bridging
12	40	Intervention 3	no bridging
13	10	Intervention 4	no bridging
14	25	Intervention 4	no bridging
15	40	Intervention 4	no bridging
16	10	No intervention	with bridging
17	25	No intervention	with bridging
18	40	No intervention	with bridging
19	10	Intervention 1	with bridging
20	25	Intervention 1	with bridging
21	40	Intervention 1	with bridging
22	10	Intervention 2	with bridging
23	25	Intervention 2	with bridging
24	40	Intervention 2	with bridging
25	10	Intervention 3	with bridging
26	25	Intervention 3	with bridging
27	40	Intervention 3	with bridging
28	10	Intervention 4	with bridging
29	25	Intervention 4	with bridging
30	40	Intervention 4	with bridging

The simple lumped-capacitance single zone model in TRNSYS has been chosen here to allow modelling an overall U value for the entire structure. It is useful to gain a comparative estimate of the heating and/or cooling load with and without accounting for heat transfer through aluminium frame. Here, the building considered is the BESTEST case 600 FF (a block of 6 m X 8 m and height of 2.7 m). The roof

and walls are considered to be integrated with EoL-PV. A maximum window-wall ratio (wwr) of 40% is considered (Bureau of Energy Efficiency, 2017). Double-glazing properties (U-value of 5.1 W/m<sup>2</sup>K) are set to the floor (Bureau of Energy Efficiency, 2017). Simulations are performed for three wwr of 10%, 25% and 40%. Clay tile floor properties (Uvalue of 0.25 W/m<sup>2</sup>K) are set to the floor (Bureau of Energy Efficiency, 2017). The overall U value for the entire structure is calculated based on the U-values for the PV (calculated from THERM), floor, and glazing with their corresponding areas for all the 30 cases tabulated in (Table 1). The building loss coefficient (overall U-value (W/m<sup>2</sup>K)) and the building capacitance (thermal capacitance (kJ/K)) are input in TRNSYS. Other parameters like building volume, surface area and the specific heat capacity of the building air are 129 m<sup>3</sup>, 171.6 m<sup>2</sup> and 1.007 kJ/kgK respectively. The weather data of New Delhi (composite climate zone or Cwa) is used which represents a climate zone with annual maximum temperature of ~ 45 °C and an annual minimum of ~ 5 °C. The indoor air temperature from the TRNSYS simulations is further analysed to estimate the sensible heating/cooling load. The simulations are run with 15 min interval for one year (8760 hours). A set temperature of 23 °C ~ 27 °C indoor are considered to estimate the sensible loads. The following expression is used to estimate the annual sensible load.

$$q = \sum_{t=0}^{t=8760 \text{ hours}} \rho V c_p \Delta T_t. \ (kJ)$$

 $\rho$  is the density of the air (1.2 kg.m<sup>3</sup>), V is the volume of the indoor air (129 m<sup>3</sup>),  $c_p$  is indoor air specific heat (1.007 kJ/kgK),  $\Delta T_t$  is the difference in the set and indoor air temperature at each point.

## 3. Results and Discussion

The heat transfer through a PV panel without a frame is ideally one-dimensional, from the outdoor to indoor (in this study). Once accounting for the aluminum frame, a sharp drop in the temperature is seen at the frame due to higher thermal conductivity of the frame (Fig. 7). A zone of lower temperature is developed around the frame and heat transfer in the

lateral direction is also seen in (Fig. 7). A uniform temperature gradient is set after a critical distance from the frame perpendicular to the gradient. The presence of another PV panel (case (b)) or plywood in (case (c-e)) creates a higher temperature gradient due to lower thermal conductivity of PV panel and plywood.



Fig. 7 – Temperature profile of the PV cross-section for different cases

Heat flux along the aluminum frame is of several orders of magnitude higher than that of the PV panels (Fig. 8). The heat flux magnitude reduced with an increase in the resistance to flow of heat by the presence of low thermal conductivity material (case b-e) (Fig. 9). The rise in the net heat transfer through the system results in higher thermal transmittance (Uvalue). The U-value rise on accounting for thermal bridging is tabulated in (Table 2). Ideally, to understand the impact of more frames on the sides of the panel, the percentage change needs to be multiplied by the number of frames under consideration.



Fig. 8 - Heat flux through PV panel and the frame

The overall building U-values are calculated and are tabulated for all the cases in the (Table 3). The lumped-capacitance model was run for 30 cases (Table 1), the resulting indoor minimum and maximum air temperatures were analyzed. The effect of accounting for thermal bridging is analyzed. Thermal bridging causes the minimum temperature reached in the whole year to drop further (Fig. 10) and the maximum temperature reached in the whole year to rise further (Fig. 11). This phenomenon is consistently observed in all the cases (interventions and window-wall ratios). Amongst the cases, intervention 1, consisting of the EoL-PV panels in tandem back-to-back with a 100 mm air cavity induces maximum change in the indoor temperatures.



Fig. 9 – Heat flux through PV panel and the frame for the four interventions

Table 2 – The U	values of EoL-PV	envelopes	with and without
thermal bridging	effect		

Case	U value (W/m²K)		Change
	No	With	
	thermal	thermal	(%)
	bridge	bridge	
No intervention	5.6	6.35	+ 13.4
Intervention 1	0.23	0.89	+ 286.9
Intervention 2	0.45	1.07	+ 137.7
Intervention 3	0.43	0.95	+ 120.9
Intervention 4	0.42	0.83	+ 97.6

This widening in the maximum and minimum indoor temperature ranges leads to an increase in the sensible heating/cooling load as the temperature difference between the set temperature and the indoor air temperature rises. The percentage change in the annual sensible heating/cooling load for three set temperatures are analyzed.

Table 3 –The Overall U values of	the EoL-PV integrated	building
with and without thermal bridging	effect	

WWR	Case	Overall U (W/m	U value <sup>12</sup> K) With	Change
		No thermal bridging	thermal bridging	(%)
10	No intervention	4.11	4.59	+ 11.58
25	No intervention	4.08	4.51	+ 10.55
40	No intervention	4.04	4.43	+ 9.49
10	Intervention 1	0.46	0.90	+ 97.48
25	Intervention 1	0.78	1.18	+ 51.61
40	Intervention 1	1.10	1.46	+ 32.57
10	Intervention 2	0.60	1.02	+ 70.04
25	Intervention 2	0.91	1.29	+ 41.81
40	Intervention 2	1.21	1.55	+ 27.86
10	Intervention 3	0.59	0.94	+ 59.05
25	Intervention 3	0.90	1.21	+ 35.04
40	Intervention 3	1.21	1.49	+ 23.27
10	Intervention 4	0.58	0.86	+ 48.23
25	Intervention 4	0.89	1.14	+ 28.37
40	Intervention 4	1.20	1.42	+ 18.76



Fig. 10 – Annual minimum indoor air temperature with and without thermal bridging effects



Fig. 11 – Annual maximum indoor air temperature with and without thermal bridging effects

A maximum of ~1.2% increase in the sensible heating/cooling load is seen for the considered building (Fig. 12, Fig. 13, Fig. 14). Higher window-wall ratio implies lesser area of PV panels and results in lesser contribution of thermal bridging as well. A low percentage change in the heating/cooling load is observed in intervention 4 consistently. This translates to lesser thermal bridging effects in intervention 4. This is due to a 30 mm thick layer of plywood in tandem with PV panel, which dilutes the thermal bridging effect.



Fig. 12 – Increase in the annual sensible heating/cooling load for set temperature 23  $^{\circ}\mathrm{C}$ 



Location - New Delhi (Composite / Cwa) Building - 600FF BESTEST

Fig. 13 – Increase in the annual sensible heating/cooling load for set temperature 25  $^{\circ}$ C



Fig. 14 – Increase in the annual sensible heating/cooling load for set temperature 27  $^\circ\text{C}$ 



Fig. 15 – Desirable intervention considering thermal mass and thermal bridging effects

On comparing the interventions in terms of desired thermal mass and thermal bridging effect, it is seen that intervention 4 fares best in both criteria. The

Location - New Delhi (Composite / Cwa) Building - 600FF BESTEST

desirable region in the (Fig. 15) is higher thermal mass and lower percentage increase in sensible heating/cooling load. This optimum region is achieved by intervention 4. One of the strategies to avoid thermal bridging is to add an insulation layer to the envelope which is naturally designed in intervention 4 to address the low thermal mass issue. The 30 mm thick plywood serves as a common solution to improve thermal mass and reduce thermal bridg-ing effects.

## 4. Conclusion

Thermal bridging effects in the envelope integrated with EoL-PV panels are studied through two-dimensional heat transfer modelling in THERM tool. The thermal bridging effects on the U-values of different intervention cases are calculated. In the case of an EoL-PV panel, around a 13% increase in the Uvalue is expected. The effect on the building's heating/cooling loads is dependent on various factors including thermal bridges. Here, a simple demonstration of the thermal bridging effects on a simple block is considered. Out of all the cases, intervention 4 seems to be a promising choice having a higher thermal mass and lower effect of thermal bridging due to high plywood thickness. The analysis considering the effects of all the frame around the PV panel is the scope of further studies. The role of climate zone, building type, humidity, corrosion or degradation in aluminium over time and heat capacity of the aluminium frame have not been considered here and adds to the scope of studies ahead.

## Nomenclature

## Symbols

- q Annual sensible heating/cooling loadρ Density of air
- *V* Volume of the indoor air
- *c*<sub>p</sub> Specific heat capacity of air
- $\Delta T_t$  Difference between set and air temperature

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# Modelling Actions at the Building Stock Level for Decision-Making Towards Carbon-Neutral Cities

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#### Abstract

The building sector plays a major role in terms of energy consumption and consequently carbon emissions in a city. In a typical European city, the share of CO<sub>2</sub> related to this sector is around 40-50%, being the most impacting one. In this context, characterised by high complexity, it is necessary to develop manageable, science-based models that policymakers can use to design and simulate the impact of feasible decarbonisation actions over space and time.

This paper presents a simulation platform capable of modelling actions for city decarbonization, particularly focusing on the building sector. Each action is modelled in terms of primary energy exploitation (type and quantity) and its impacts on energy consumption and emissions using a tailored set of metrics. This involves considering the unique characteristics and challenges of the city, such as its existing infrastructure, building stock, energy sources, and policy context.

The proposed approach is applied to a real European city to demonstrate its feasibility and assess its effectiveness in achieving emissions reduction targets. The results provide effective support to the municipality in setting up the city action plan towards climate neutrality.

## 1. Introduction

Climate change is a global problem, but attention should be focused on the city context. Despite occupying only 2% of the Earth's surface, cities are responsible for more than 70% of global emissions and consume 2/3 of global energy (Zapata Arango et al., 2024; Hoornweg et al., 2020). Additionally, they offer a favourable context for implementing targeted actions, leading to significant results, not only in emission reductions, but also in air pollution, biodiversity loss, and energy poverty reduction. Scaling down further, the building sector alone is responsible for 37% of global CO<sub>2</sub> emissions and 34% of energy demand. This creates an urgent need to decarbonize and improve the energy performance of the urban built environment (Hoornweg et al., 2020) searching for cost-optimized solutions (Ferrara et al., 2018). This paper proposes a science-based approach to achieving these goals, focusing on the macro-actions needed to make existing buildings near-zero energy buildings (NZEBs) (Ferrara et al., 2015; Jaysawal et al., 2022), considering climate change and creating useful tools for policymakers facing these challenges.

#### 1.1 Scope of the Work

This paper aims to present a simulation platform capable of modelling actions for city decarbonization towards carbon neutrality (Anselmo et al., 2023), particularly focusing on actions related to the building sector. This was created in the context of the EU Mission "100 carbon-neutral cities by 2030" (The 100 Climate-Neutral and Smart Cities by 2030, 2024) aiming to support cities in defining their path towards carbon neutrality.

## 2. Materials and Methods

## 2.1 Conception of the Simulation Platform

The primary goal of a city should be to reduce GHG emissions from anthropogenic activities within a

well-defined city boundary. To achieve this crucial goal, it is essential to have a complete understanding of the starting point, i.e., the emissions produced by the city in a specific year considered as a baseline, and then to define a timeframe to achieve the set targets.

This process implies a thorough analysis of the key sectors within the urban environment that contribute significantly to emissions, enabling the definition of a list of effective "macro-actions" that can guide decision-makers who will then select more specific actions to be implemented, moving from a general to a particular view.

Understanding the impact of these macro-actions is crucial as it helps create emission reduction scenarios that are both reasonable and effective.

To provide real support to policymakers, it is planned to formalise these actions and link them to the "city's ontology" (Fig. 1). The ontology maps the logical relationships between various entities and forms the basis for defining individual actions and all 'what if' analyses. The goals are to:

- Formalise the correlations and interactions between entities in the City;
- Understand how actions generate a change in the state of the city.



Fig. 1 - Conceptual scheme of the City Ontology, EST Lab

By creating a Python code, accompanied by a formal document specifying all the data, primary and secondary, used and the mathematical approach behind the functions, it will be possible to quantitatively evaluate the impacts of the considered actions. By defining then an "Action Type" and characteristic parameters linked to it through a Json file, it will be possible to establish new, more sectorial and specific actions, linked to the city context (Fig. 2).



Fig. 2 - Functional scheme of the function libraries

This concept is the foundation of a new interactive simulation platform named CLICC, where various actors in a city can enter the actions that have been conceived, implemented or are underway, leading to a reduction in CO 2 emissions and defining a path towards carbon neutrality.

City system data are automatically and systematically organised into an ad hoc data room, based on a data lakehouse architecture, with web crawlers and automatic validation systems.

Furthermore, the platform is particularly useful for monitoring the current situation thanks to an interactive dashboard, which allows users to:

- track the evolution of the city systems with respect to climate neutrality goals;
- monitor the trend of GHG emissions (CO2, N2O, F-gases, SF6, NF3, CH4), in terms of current value, current target and final target;
- monitor the overall investments, in terms of current value, current target and final target;
- graphically see the evolution of normalised emissions and investment over the whole-time horizon.

Therefore, policy decision-makers can easily understand the evolutionary trajectory of the systems and the potential need for corrective actions to accomplish the final goals.

In addition, an interactive tool supports this by allowing users to explore the city, understand its main peculiarities, and access several georeferenced data. In particular, it permits:

- Exploring each building on a 2D/3D map, obtaining information on the building type, surface area, heating system, solar PV producibility and Energy Performance Certificate (EPC).
- Geolocating all the generation plants (PV, hydro, and traditional non-res) and the city's feeders, primary and secondary substations.

- Exploring the main energy infrastructures of the city (e.g., electricity distribution lines).
- Graphically selecting areas or groups of buildings on the map for simulating specific policy actions.
- Monitoring public and private transport through parameters such as kilometres travelled and fuels used.

The platform also manages financial aspects (time horizon, funder, amount of investment), details ("what" and "where"), co-benefits, and barriers of each action.

All necessary methodologies are included in the platform (Fig. 3), from identifying the baseline inventory of the city's GHG emissions (by type of gas and by sector) to combining actions, identifying relevant time horizons and impacts in terms of GHG reductions compared to the baseline inventory, and including investment details over the time horizon for each action included in the pathway (both in absolute value and as a percentage of the total) and the relevant financiers.

With these tools, the decision-maker can combine the actions inserted in the platform into different scenarios and evaluate the most appropriate one for the city. This decision-making process is complemented by a cost/benefit analysis of these scenarios, considering all possible barriers but also the co-benefits.

Another crucial aspect is the opportunity for citizens to be an integral part of the city's reality, thanks to access to general evolutionary tracking information. In this way, citizens become active participants in the community's growth and development, encouraging a sense of shared responsibility.



Fig. 3 – Platform scheme

## 2.2 Function Modelling

A function is the formalization and implementation of a model that allows the computation of its outputs for given inputs and parameters (in terms of  $CO_{2eq}$  avoided, in general whichever outcome of the action). The functions reported in this paper focus on reducing emissions in the built environment sector.

The first step towards this goal was to select and analyse all implementable actions in the built environment sector, starting with a study based on data provided by the International Energy Agency (IEA), which examined the main sources of CO<sub>2</sub> emissions in the life cycle of buildings (Italy 2023, 2023).



Cooking Lighting Space cooling Water heating Appliances Space heating

Fig.4 – Emissions of GHG from Building's activities in 2021 (Italy 2023, 2023)

The analysis showed that most CO<sub>2</sub> emissions came from the operational use of energy in buildings, including daily activities such as heating, cooling, lighting and using household appliances. In particular, space heating and household appliances are the main emitters.

The first general step, common to all actions, is to create a detailed GHG inventory. This inventory must report all emissions broken down by sector, according to the Global Protocol for Community-Scale GHG Emission Inventories (GPC), complying with the 2006 Intergovernmental Panel on Climate Change (IPCC) guidelines (GHG Protocol for Cities, 2024).

In some situations, cities may use direct measurements of GHG emissions (e.g. through the use of continuous emission monitoring systems in power plants), resulting in a highly accurate inventory. However, for most emission sources, cities will have to rely on estimates. In general, a quantity referring to human activity, responsible for the emissions to be estimated, is combined with a coefficient to quantify emissions per unit of activity. The first quantity is called Activity data (AD) while the coefficient is identified as Emission factor (EF), as follows:

$$Emissions = AD \cdot EF[tCO_{2eq}] \tag{1}$$

Therefore, the generic Eq. 1 provides cities with a systematic method for evaluating greenhouse gas emissions. This procedure requires the accurate acquisition and analysis of data on the activity in focus and the detailed implementation of appropriate emission factors.

Based on this, models for the different macro-actions identified for a specific context can be developed, as described below.

## 2.2.1 Increasing The Number Of Connected Users And Optimising The DH Network

This action evaluates the GHG emissions that can be avoided by replacing traditional, fossil-fuelled domestic heating systems with a connection to the district heating network. The environmental benefit comes from switching from multiple heat generation units distributed throughout the municipality to a few centralised combined heat and power generation sites.

$$Vol_{DH_{new}} = Vo\frac{l_{DH_1}*k_{new}}{k_1}$$
<sup>(2)</sup>

Where  $k_{new}$  is the percentage of the total volume of buildings connected to district heating and  $k_1$  is the percentage of buildings connected in the reference year.

Accordingly, a proportion is also implemented for the calculation of new MWh installed:

$$E_{DH_{new}} = \frac{E_{DH_1} * Vol_{DH_{new}}}{Vol_{DH_1}}$$
(3)

If  $\Delta E_{DH,s} < E_{DIESEL,s}$  the district heating will be used to connect buildings with an existing diesel heating system, where

$$\Delta E_{DH_S} = E_{DH_{new_S}} - E_{D1_S} \tag{4}$$

So, the reduction of emissions will be:

$$\Delta CO_{2_{DIESEL}} = \Delta E_{dh_s} * (f_{DIESEL})$$
<sup>(5)</sup>

$$\Delta CO_{2_{Tot}} = \Delta E_{dh_s} * (f_{DIESEL} - f_{DH_{new}})$$
<sup>(6)</sup>

If  $\Delta E_{DH,S}$ >EDIESEL,s the district heating will be also used to connect buildings with an existing natural gas heating system, starting from those in class G and F (the energy provided by district heating will be equally distributed to class G and F - this will be used for following actions).

$$\Delta CO_{2_{GN}} = (\Delta E_{dh_x} - E_{DIESEL}) * (f_{GN_1})$$

$$\Delta CO_{2_{ToT}} = E_{DIESELS} * (f_{DIESEL} - f_{DH_{new}}) + (\Delta E_{dh_x} - E_{DIESELS}) * (f_{GN_1} - f_{DH_{new}})$$
(8)

#### 2.2.2 Improvement Of Thermal Insulation

The model function evaluates avoidable GHG emissions as a result of improved thermal insulation of buildings. In particular, the function evaluates the difference in emissions that would occur if no improvements were made, and the emissions related to buildings after increasing their energy performance. When a building carries out this intervention, it

makes a jump in energy class. Consumption, and consequently also emissions, are calculated according to the change from a lower to a higher energy class and thus the reduction in average thermal energy as defined by the EPA. First of all, the new area is calculated for each energy class in the final year: the example represents the transition of buildings from class E to class D and the respective reduction in consumption of the next class.

The following equations must be applied separately for the industrial, residential and tertiary sectors.

HFA<sub>CLD,new</sub>=HFA<sub>CLD,1</sub>+HFA<sub>CLE</sub>-HFA<sub>CLD,eff,new</sub> (9)

Where HFACLD,1 is the heated floor area of the current class D, HFACLE is the area of the class E buildings that with the thermal insulation action move to class D, and HFACLD is the area of the class D buildings that move to class C. These values can be calculated considering a percentage of building for the class that has to be renovated with thermal insulation:

 $HFA_{cl,eff,new} = k_{Cl} \cdot HFA_{CL,1}$ (10)

With kci the percentage of buildings for a class that we want to renovate (from 0 to 100%);(the default values are listed in the tab7: Renovated surfaces by energy class and sector) this calculation has to be done using the same renovation rate for both for buildings with natural gas heating system and for buildings connected to district heating because the specific thermal energy per class is different.

The consumption for each class is obtained as follows (this is an example for class D).

$E_{th,Cl,D_{,,1}}=Q_{h,D}\cdot HFA_{CL,D,1}$	(11)
$E_{th,Cl,D,new} = Q_{h,D} \cdot HFA_{CL,D,new}$	(12)

where  $Q_{h,D}$  is the average thermal energy, obtained from APE data. The total amount of energy per class is calculated as follow:

$$\begin{aligned} E_{th_G N_{new}} &= \sum E_{th_{Gl_{GN_{new}}}} * x & (13) \\ E_{th_D H_{new}} &= \sum E_{th_{Gl_{GN_1}}} & (14) \\ E_{th_G N_1} &= \sum E_{th_{Gl_{GN_1}}} * x & (15) \\ E_{th_D H_1} &= \sum E_{th_{Gl_{DH_1}}} & (16) \end{aligned}$$

With  $\sum E_{th_{Cl_{DH}}}$  and  $\sum E_{th_{Cl_{DH}}}$  respectively the amount of energy consumption for all the classes for the gassupply buildings and the district heating and  $\chi$  the scaling factor due to an overestimation of the natural gas emission with the APE compared to the baseline.

For calculating the emissions reduction directly affected due to the action of thermal insulation we calculate the reduction of energy consumption.

$$\Delta E_{th_{GN}} = E_{th_{GN_{new}}} - E_{th_{GN_1}}$$
(17)  
$$\Delta E_{th_{DH}} = E_{th_{DH_{new}}} - E_{th_{DH_1}}$$
(18)

And the reduction of emissions is:

$$\Delta C O_{2_{GN}} = \Delta E_{th_{GN}} * f_{GN_1}$$
(19)  
$$\Delta C O_{2_{DH}} = \Delta E_{th_{DH}} * f_{DH_1}$$
(20)

With  $f_{GN}$  and  $f_{DH}$  respectively the emission factor of natural gas and district heating.

#### 2.2.3 Heat Pumps And PV Installation

The model function estimates the avoidable greenhouse gas emissions as a result of installing heat pumps in buildings. The heated floor area of buildings for an energy class in which we want to install a heat pump is equal to:

$$HFA_{HP_{Cl}} = k_{CLHP} * HFA_{GN_{Cl}}$$
(21)

(01)

With k<sub>CLHP</sub> is the percentage of buildings with natural gas heating systems that we want to replace and HFA<sub>GN\_CI</sub> is the floor area for the class of buildings that have a gas heating system. The energy to be supplied by heat pumps is equal to the annual thermal energy demand of the building to which is added that for the production of domestic hot water, and is equal to:

$$E_{nd_{HP_{CID}}} = HFA_{HP_{CID}} * EPH_{nd_{CID}} + HFA_{HP_{CID}} *$$

$$EPW_{nd_{CID}}$$
(22)

Where HFAHP,CID is the floor area of buildings that are installing a heat pump and are upgrading to another class,  $EPH_{nd\_CID}$  is the useful thermal performance index for heating, and  $EPW_{nd\_CID}$  is the useful heat performance index for domestic hot water production.

The new gas consumption will be:

$$Et_{h,GN,ClD,new} = E_{th,GN,Cl,D} - E_{th,HP,Cl,D}$$
(23)

Where  $E_{th,GN,CID}$  is the thermal consumption of the class equal to:

$$E_{th_{GN_{GD}}} = Q_{H_{GN_{GD}}} * HFA_{GN_{CD}}$$
(24)

Where  $Q_{H,GN,CID}$  is the average thermal energy supplied to the heating system for class D, taken as a general example and HFA<sub>GN,CID</sub> is the natural gasheated floor area of the class before the installation of heat pumps.

$$E_{th_{HP_{CID}}} = \frac{E_{nd_{HP_{CID}}}}{\eta_{imp}}$$
(25)

With  $\eta_{imp}$  the seasonal average efficiency of a gas heating system. However, the installation of the heat pump implies an increase in electricity consumption, which must be evaluated according to the change in class of the building.  $E_{el,HP_{Cl_{A1}}} = \frac{E_{nd_{HP_{CL}}}}{COP}$ (26)

With E<sub>el,HP,CIA1</sub> the new electrical consumption of Class A1 due to heat pumps, COP, coefficient of per-

formance, which represents the efficiency of a heat pump, that is the ratio of heat delivered to the room to be heated to the electrical energy consumed, taken equal to 3.

To calculate the new gas consumption, the total increase in electricity consumption and the total heat energy supplied by the heat pumps, we will sum the gas consumption, the increase in electricity consumption and the heat energy supplied by the heat pumps for all classes.

$$E_{th_{GN_{2030}}} = \sum E_{th_{GN_{Cl_{2030}}}}$$
(27)

$$E_{el_{HP_{new}}} = \sum E_{el_{,HPCl}}$$
(28)

$$E_{th_{HP_{\text{new}}}} = \sum E_{th_{HP_{Cl_{new}}}}$$
(29)

If the energy would be taken by the national grid there will be to consider a new emission factor of the electricity f<sub>el,new</sub>, so the equation would be:

$$\Delta CO_2 = E_{th_{HP_{new}}} * f_{GN_1} - E_{el_{HP_{new}}} * f_{EL_{new}}$$
(30)

A scenario is also proposed in which a photovoltaic system is also installed at the same time, so that the energy supplied to the heat pumps is generated directly by the photovoltaic panels, with no emissions generated.

$$\Delta CO_2 = E_{th_{HP_{now}}} * f_{GN_1} - E_{el_{HP_{now}}} * f_{ElpV}$$
(31)

Where  $E_{th,HP,new}$  is the thermal energy supplied by heat pumps in the year in which it is wanted to evaluate the emission reduction for all energy classes and  $f_{GN,1}$  is the natural gas emission factor in the reference year and  $f_{EL,PV}$  the emission factor of PVs, assumed equal to 0.

PV panels are dimensioned depending on how much energy should be consumed by heat pumps; considering that these panels are discontinuous in that production, which is greatest in the middle of the day, when solar irradiation is at its highest and lower in the morning, evening and cloudy days, the installation of a storage system was also assumed. Considering a self-consumption of less than 100 per cent, the photovoltaic panels are sized to generate more energy than is needed to run the heat pumps. This energy will be recovered with a storage system. Thus, the electricity per class produced by the photovoltaic panels is equal to:

$$E_{el_{PV}} = \frac{(EPH_{nd} + EPW_{nd}) * HFA_{eff_{Cl}}}{k_a * COP}$$
(32)

Where  $E_{eLPV}$  is the energy generated by PVs, EPH\_nd and EPW\_nd are the useful thermal performance index for heating and the useful thermal performance index for domestic hot water production respectively, COP is the average efficiency of the heat pump, and HFA<sub>eff\_CI</sub> is the heated surface area of a class in which is installed a heat pump,  $k_a$ is the auto consumption.

## 2.2.4 Electricity Storage

The purpose of storage systems connected to photovoltaic systems is to store the electricity produced by photovoltaic panels during periods of overproduction and to release it when solar production is lower than demand; this system improves the efficiency of the system and allows a more stable energy supply.

This scenario assumes the installation of a storage system in buildings that already have a heat pump and consequently a photovoltaic system installed. The storage system makes it possible to use the energy generated by the photovoltaic panels even at times when production is lower and thus to increase self-consumption, to achieve 100 per cent self-consumption.

It is assumed that the energy to be supplied by the E\_st storage system is equal to the electricity generated by the photovoltaic panels that is not self-consumed.

(22)

$$E_{st} = (1 - k_a) * E_{el_{PV}} \tag{33}$$

The storage action will have an impact on the reduction of emissions because the energy that is autoconsumed during the hours when PVs cannot supply the energy needed, would be lost. So, the reduction is equal to:

$$\Delta CO_2 = E_{st} * f_{el} \tag{34}$$

Where  $f_{el,1}$  is the electricity emission factor in the baseline year.

We can also consider buildings, which have installed photovoltaic panels and a storage system, as a result of the action of thermal insulation and the installation of heat pumps, can be considered to be in class A4 as the non-renewable primary energy index will be close to 0.

#### 2.2.5 Energy Class of Appliances

The model function calculates the reduction in emissions resulting from the use of more efficient appliances and electronic devices in buildings, evaluated considering the new energy labels defined for the most frequently used appliances.

The consumption for electrical devices in an household would be equal to

$$E_{el_x} = E_{el_{sector_1}} * \beta_x \tag{35}$$

Where  $E_{el,sector}$  is the electrical consumption of each sector in the baseline year, and  $\beta_x$  is the percentage of electrical consumption per use referring to the total.

The action will reduce the electrical consumption as follows:

$$E_{el_{dev-improved_{pew}}} = \alpha * E_{el_{dev_{pew}}}$$
(36)

With  $\alpha$  the percentage of buildings that we want to improve.

So, for each sector we have a reduction equal to:

$$\Delta E_{sl} = E_{sl_{dev-improved_1}} - E_{sl_{dev-improved_{new}}}$$
(37)

The emission reduction due to the reduction of electrical consumption is equal to:

 $\langle \mathbf{n} \mathbf{n} \rangle$ 

$$\Delta CO_2 = \Delta E_{el} * f_{el} \tag{38}$$

## 2.3 The Case Study and the Decarbonisation Scenario

The proposed methodology was applied to the practical case of the city of Turin, one of the 100 cities selected by the European Commission in the context of the mission '100 climate neutral and smart cities by 2030'. A decarbonization scenario was simulated, considering 100% of buildings in classes G, F and E retrofitted (45% of buildings), extending the goal included in the proposal for the recast of EPBD (Energy Performance of Buildings Directive), which mandates that all residential buildings reach at least class D by 2033. The percentage of renovated floor surfaces would be 65.1% of residential, 46.3% of tertiary and 81.1% of industrial buildings. Additionally, heat pumps will be installed in 45% of buildings that are not connected to the district heating network, with electricity demand entirely covered by PV with storage systems. Then the proposed plan involves converting all buildings with oil systems to district heating, with the remaining volume comprising buildings with natural gas systems, covering 70% of the total built environment volume. The recovery of waste heat from data centres is also considered, providing a new source of clean energy for district heating.

## 3. Results

## 3.1 The CLICC Platform

The CLICC platform allows the results of the proposed decarbonisation scenario to be tracked. It monitors the trends of GHG emissions and investments, showing their current value, current target and final target (Fig. 5).



Fig. 5 - CLICC Interactive dashboard

The platform can automatically calculate the emission reduction in [t/y] referring to each action that the policy maker selected during the creation of the pathway, and evaluate their combined effect on the value of the emission factors (Fig. 6). The proposed actions reduce the emission factors of the different commodities used and this leads to a significant reduction in emissions.

Newworkspace Modify workspace	Ny workspaces				
PATHWAYS INVESTMENT PLAN B	ASELINE TARGET BARRIERS	OTHERS SAVE			
Period workspace	Building -			1.	Delete + Add
01-01-2019		Date			602
Kost these	Actions	55275	and	s/y	
31-12-2030	N FS1057 Heating 8 FS2 Thermal Insulation	2019-01-01 2019-01-01	2030-12-31 2030-12-31	52,023.9 544,092,75	5.99% No.64%
Action details	8 KS Data Control Heat	2019-01-01 2019-01-01	2030-12-31 2030-12-31 2030-12-39	224,872,58 29192,55	25.895
FS2 Therenal Insulation	× VS6 Knergy Class of agaigment	2019-01-01	2030-12-31	54,693,65	4.46%
F53 Data Center Heat	Tetal	1014-01-01	2010-02-04	868,437.3	300%
FS4 Heat Pumps IPV	>				
FSS Electricity storage					
FSR Energy Class of equipment	0.077369 0.17978	OCOM (keptozielen) *			Compute CO

Fig. 6 - CLICC Workspace - Built environment action results

Moreover, thanks to its data management and visualisation system, it is possible to keep the entire built environment of Turin under control, through a digital twin of the city (Fig. 7).



Fig. 7 - CLICC City explorer- Built environment in Turin

## 3.2 Decarbonisation of the Building Sector

Another important result of this modelling is the decarbonisation of the city's built environment (Fig.8). In fact, the proposed actions, in a first analysis, succeeded in reducing emissions by approximately 37% in 2019, the baseline year chosen by the city.



Fig. 8 - CO2 avoided due to actions related to the building sector

## 4. Conclusions

This research demonstrates the feasibility of decarbonising cities through a scientific approach, providing models and a simulation tool to assess the impact of proposed decarbonisation actions. The construction of an automated simulation platform facilitates the complex process of city energy transition, allowing real-time monitoring and modification of actions to align with set targets. The study also emphasises the importance of the building sector and how interventions in this area can significantly contribute to urban decarbonisation and serves as a starting point for further future developments based on data with greater granularity and, therefore, a lower degree of uncertainty. Specific actions implemented in Turin demonstrate the effectiveness of such interventions, but these are only indicative results aimed at demonstrating the effectiveness of the model, and require further steps to obtain actual decarbonisation results. However, this shows that the application of the method is adaptable to the data available as well as to different levels and in different cities and contexts, extending to other sectors such as transport and industry, in support of a comprehensive approach to urban transition.

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## Nomenclature

#### Symbols

AD	Activity Data		
f	Emission Factor		
k	Share of buildings' volume		
	connected to DH network		
E	Energy consumption		
HFA	Heated Floor Area		

k <sub>Cl</sub>	Share of building renovation		
$E_{th}$	Thermal energy		
χ	APE scaling factor		
$EPH_{nd}$	Heating performance index		
$EPW_{nd}$	DHW performance index		
QH,GN,Cl	Average thermal energy supplied		
	to the heating system		
η_imp	Gas heating system seasonal		
	average efficiency		
COP	Coeffient of Performance		
ka	Share of autoconsumption		
Eel	Electrical consumption		
βx	Share of electricity per use		
α	Percentage of buildings with		
	renovated electrical appliances		

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# A New Evaluation Framework to Assess the Prosumer Efficiency in Thermal Source District Heating Networks

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#### Abstract

Thermal Source Network (TSN) district heating systems are a sustainable solution for integrating renewable energy and waste heat sources in the urban heating sector. These networks typically employ heat pump-based prosumers on the supply side. On the demand side, a heat pump substation at each consumer upgrades the heat received from the district heating network to the suitable temperature for a given building. However, there is a gap in the literature for an evaluation metric for assessing the efficiency of the prosumers in TSN networks. This paper proposes a new evaluation framework, the Prosumer Performance Index (PPI), to evaluate low-grade heat prosumers' efficiency in a TSN system from the aspects of energy, economics, and environment. This framework facilitates district heating owners' decisionmaking using low-grade waste heat in TSN networks. The simulation results demonstrate the variation of PPI over a year for four different scenarios of the central heat pump plant's supply temperature setpoints. Overall, by promoting energy efficiency, economic viability, and environmental sustainability, the PPI contributes to advancing sustainable urban heating solutions in alignment with global climate objectives.

#### 1. Introduction

The heating and cooling sector transition is an important step in Europe's proposed energy transition goal (Zhang et al., 2022). In this context, developing sustainable district heating technologies can be pivotal in achieving the EU's ambitious climate goals (Revesz et al., 2020).

For a district heating system, a lower temperature allows the integration of renewable energy into the network and the use of low-grade waste heat sources, increasing the efficiency of the heat network (Guelpa et al., 2023).

District heating systems consist of a central heat-generating plant that supplies heat to a group of buildings or a district by circulating a heat-carrying fluid through a system of interconnected pipes. Over the past few decades, district heating systems have evolved, leading to a trend of decreasing temperature and increasing sustainability. This trend can be observed by looking at the shift from the first generation (pressurised steam of 150 °C) to the fourth generation (hot water of less than 80 °C) (Dang et al., 2024).

A subclass of the 4th generation district heating systems is the "Thermal Source Network (TSN)". In these systems, the water temperature ranges from 5 °C to 35 °C (Wirtz et al., 2020). Therefore, each building connected to the network must be fitted with a "substation" that is equipped with watersource heat pumps to raise the supply water temperature to the necessary levels for space heating and domestic hot water. In the literature, these TSN systems are often referred to as "fifth-generation district heating". However, in 2024, the IEA DHC Executive Committee (IEA DHC, 2024) recommended that the term "5th generation district heating" should not be used as it could be mistakenly perceived as an upgrade over 4th generation district heating. Instead, the executive committee suggested that pipe networks that are primarily used as a source for heating and cooling through decentralised heat pumps should be labelled as "thermal source networks" (TSN). These TSNs should be considered as a subclass of 4th generation district heating.

The term 'prosumer' is frequently used in the literature as a critical component of TSNs. It can be referred to any component of the system that plays both roles of energy consumer and energy producer. In the context of this research, "prosumers" are the central heat pump plants in a TSN that "consume" energy from the electricity grid and "produce" heat for the thermal grid.

Due to their low temperature, TSNs offer a key potential for harvesting Low-Grade Waste Heat (LGWH) such as data centres, metro stations, and sewage systems (Volkova et al., 2022). One of the key opportunities TSN technology provides is the shift from a monopolistic energy market to a market with multiple active prosumers (Angelidis et al., 2023). However, the lack of a clear evaluation metric for prosumers can threaten the future operation of decentralised TSNs.

A few studies have analysed the performance of TSNs based on various KPIs. For example, (Li et al., 2023) compared the techno-economic performance of TSN, individual air-source heat pump heating, and individual gas-fired heating. This analysis was conducted with five KPIs: levelised cost, upfront cost, peak load, exergy, and carbon emissions. This study provided a tool for policymakers to decide between technology options. However, they did not analyse the performance of different prosumers that propose to supply heat using the same technology within a TSN.

It is observed from the literature that there is a significant research gap for a comprehensive evaluation framework that considers the performance of prosumers from the three aspects of energy, economics, and environmental impacts.

The aim of this paper is to fill this gap by defining and formulating proper evaluation metrics and implementing them in a dynamic model of a TSN system. This multi-criteria metric is called the Prosumer Performance Index (PPI). Simulations are carried out for a hypothetical case study located in Dublin. The PPI metrics are calculated for different network supply temperature scenarios.

The novelty of this work lies in introducing a new set of metrics, specifically designed to evaluate the energy, economic, and environmental performance of prosumers in a TSN. Unlike traditional metrics such as the Coefficient of Performance (COP) and Levelized Cost of Heat (LCOH), the PPI metrics incorporate specific TSN parameters like pumping energy consumption and the income generated from selling heat by the prosumer. This comprehensive approach provides a more accurate and detailed assessment of prosumer efficiency within TSN systems, addressing gaps in the existing literature.

The structure of this paper is as follows:

Section 2 introduces the formulation of the PPI framework and a dynamic simulation of a TSN by applying the PPI metrics. The analysis results of the prosumers' energy, economic, and environmental performance in the case-study TSN model within the PPI framework are provided and discussed in Section 3. The discussion also provides limitations and challenges of applying the PPI framework in actual TSN networks. Finally, conclusions and future work are outlined in Section 4.

## 2. Materials and Methods

The methodology presented in this paper focuses on developing and applying the Prosumer Performance Index (PPI) framework. This framework offers a novel, generalisable approach to evaluate prosumers in TSN systems. By formulating the PPI framework, the research addresses the gap in the literature by providing a comprehensive approach to assess prosumer efficiency considering energy, economic, and environmental aspects. This dynamic simulation model enables the analysis of PPI metrics under varying conditions and different scenarios for the prosumer plant's setpoint temperature. An overarching diagram of this methodology is illustrated in Fig. 1. The methodology showcases an innovative and generalisable approach to evaluating prosumer performance in the TSN system. This method applies to any TSN system.



Fig. 1 – Overarching methodology diagram of developing and applying the PPI framework

## 2.1 Prosumer Performance Index

The Prosumer Performance Index (PPI) is a multicriteria evaluation framework that aims to assess the performance of a heat prosumer in a TSN system based on their energy efficiency, economic efficiency, and environmental efficiency. The PPI metric for each of these three domains is formulated in the next sections.

The TSN system contains a prosumer that consumes power from the grid to produce the heat from a lowgrade heat source through a heat pump. The network consumes power from the grid to distribute the heat carrying water in the district. Finally, at each building, a heat pump substation consumes power from the grid to upgrades this heat to the desirable temperature and deliver it to the building. This trade-off is illustrated in Fig. 2.



Fig. 2 – Diagram of the TSN system with central prosumer and heat pump substations

#### 2.1.1 Energy Analysis Model

The PPI metric for the energy efficiency of prosumers is formulated as:

$$PPI_{Energy} = \frac{\sum_{n=1}^{n=N} Q_{Bui}}{W_{HP} + W_{Pu} + \sum_{n=1}^{n=N} W_{Bui}}$$
(1)

Where N is the number of buildings,  $\sum_{n=1}^{n=N} Q_{Bui}$  is the total heat demand of all buildings connected to the TSN,  $W_{HP}$  is the central heat pump's compressor power consumption,  $W_{Pu}$  is the circulating pump's power consumption, and  $\sum_{n=1}^{n=N} W_{Bui}$  is the total sum of all substations' heat pump power consumptions.

#### 2.1.2 Economic Analysis Model

The PPI metric for economic efficiency is calculated as:

**PPI**<sub>Economic</sub>

$$= \frac{\dot{c}_{heat} \times (\sum_{n=1}^{n=N} Q_{Del})}{\frac{\text{TIC} \times r}{1 - (1 + r)^{\text{T}}} + C_{O\&M} + \dot{c}_{elec} \times (W_{HP} + W_{pu})}$$
(2)

Where TIC is the total investment costs paid in a lump sum (€),T is the number of years,  $C_{0\&M}$  is the fixed Operation & Maintenance Cost (excluding power bills),  $\dot{c}_{heat}$  is the heat price for TSN consumers,  $\dot{c}_{elec}$  is the electricity price for the central heat pump, and  $\sum_{n=1}^{n=N} Q_{Del}$  is the total sum of delivered heat to the evaporator side of all substations.

It should be noted that since the stakeholder for economic PPI analysis is the district heating owner and it is assumed that the substations are installed and maintained by the consumers, the boundaries for the definition of PPI<sub>Economic</sub> does not include the capital and operational costs related to the substation.

## 2.1.3 Environmental Analysis Model

The equivalent carbon emissions for the TSN's electricity are quantified using the emission factors:

$$EM = EF \times \left( W_{HP} + W_{pu} + \sum_{n=1}^{n=N} W_{bui} \right)$$
(3)

Where EF is the emission factor for electricity (gCO<sub>2</sub>/kWh), which is obtained from the (Sustainable Energy Authority of Ireland (SEAI), 2022). The PPI metric for environmental efficiency is calculated as follows:

$$PPI_{Environmental} = \frac{\sum_{n=1}^{n=N} Q_{Bui}}{EM}$$
(4)

It can be observed from the equation that higher heat production for lower emissions leads to higher ratio of PPI<sub>Environmental</sub> which is desirable.

## 2.2 TSN System and Supply-Side Model

## 2.2.1 Modelica-based Network Model

Modelica language offers high flexibility in reusing and extending component models. This makes it a suitable modelling tool for modelling the various configurations in the TSN systems that also include various components from thermodynamics, fluid mechanics, and control domains (Abugabbara et al., 2020). Being a flexible object-oriented, equationbased modelling language for physical systems, Modelica has already been successfully used in the dynamic thermal modelling of TSNs (Bünning et al., 2018). Compared to other tools such as EnergyPlus (Crawley et al., 2001), Modelica offers advantages for dynamic performance evaluation and control testing in district heating simulations. Modelica libraries facilitate capturing dynamic changes during system startup and realistic controller behaviors. (Chen et al., 2022).

In this research, the TSN system was simulated on a desktop computer with an Intel(R) Core (TM) i7-1255U processor and 32 GB of RAM running under Windows 11 Pro 64-bit. Dymola version 2024 (Dassault Systèmes, 2024) was used as the Modelica simulation environment since it offers a user-friendly interface for model development and post-processing. To develop the TSN system, validated component models from the free open-source Modelica Buildings Library (Wetter et al., 2014) were used.

Simulations were performed for one year with onehour intervals. Fig. 3 shows the diagram view of the developed model in the Dymola environment, which includes the building models, heat pump substations, pipe models, central heat pump plant and the low-grade waste heat source.



Fig. 3 - Diagram view of the TSN model in Dymola

#### 2.2.2 Heat Pump Models

The Carnot refrigerant cycle was used to model both central and substation heat pumps. The Coefficient of Performance (COP) was scaled according to the Carnot efficiency, which is a basic approximation that is not influenced by the performance curves of any specific commercial heat pump product (Zarin Pass et al., 2018). This method eliminates the possibility of errors arising when extrapolating manufacturer performance data to low-lift operating conditions. The COP for a Carnot heat pump is calculated as:

$$COP_{HP} = \eta_{Carnot} \frac{T_{HP,Cond}}{T_{HP,Cond} - T_{HP,Evap}}$$
(5)

Where  $\eta_{Carnot}$  is a prescribed Carnot efficiency (assumed 0.3 here),  $T_{HP,Cond}$  is the heat pump's condenser temperature and  $T_{HP,Evap}$  is the evaporator temperature.  $P_{Comp}$  is the compressor's power consumption and is calculated using equation:

$$COP_{HP} = \frac{\dot{Q}_{h}}{P_{Comp}}$$
(6)

Where  $\dot{Q}_h$  is the supplied heat at the condenser side. The mass flow rate at the condenser and evaporator of the heat pumps are calculated by:

$$\dot{m}_{\text{Cond}} = \frac{Q_{\text{h}}}{c_{\text{p}}\Delta T_{\text{Cond}}}$$
(7)

$$\dot{m}_{\rm Evap} = \frac{\dot{Q}_{\rm h}}{c_{\rm p}\Delta T_{\rm Evap}} \tag{8}$$

Where  $c_p$  is the specific heat capacity of water in J/kg·K,  $\Delta T_{Cond}$  and  $\Delta T_{Evap}$  are the temperature difference between the inlet and outlet of the condenser and evaporator respectively.

#### 2.2.3 Pump Models

The circulation pump carries and circulates the water between the central heat pump's condenser and the substation heat pumps' evaporator sides. The power consumption of this circulating pump is calculated as:

$$W_{Pu} = \frac{\dot{V}_{Cond} \times \Delta P}{\eta_h \times \eta_m}$$
(9)

Where  $V_{Cond}$  is the volume flow rate in m<sup>3</sup>/s,  $\Delta P$  is the pump pressure rise in Pa,  $\eta_h$  and  $\eta_m$  are the hydraulic and motor efficiencies of the pump.

## 2.2.4 Demand Side Models

The demand side of the TSN model includes a heat pump substation and a building heat demand model. The heat pump substation includes a heat pump, a circulating pump, and a heat exchanger. This heat pump receives the TSN's heat in the evaporator side, upgrades it to the desired temperature level of the building, and delivers it to the circulating hot water through the condenser side. This hot water exchanges heat with a heat exchanger (which represents the building's terminal heating equipment) and provides the required heat demanded by the building.

## 3. Case Study

This research analyses a hypothetical TSN system proposed in a paper by for a cluster of 100 buildings located in Dublin, Ireland.

The simulation is carried out for Dublin (lat: 53.4°, long: 6.2°, altitude: 74 m), a Humid Continental climate in Ireland (The American Society of Heating, Refrigeration and Air-Conditioning Engineers, 2020). The weather data file for Dublin was downloaded from the EnergyPlus<sup>™</sup> website. The input design parameters for the district heating network are summarised in Table 1.

A simplified grey-box building model is used to calculate the TSN model's heat demand for this network's demand side. This model is based on the ISO 13790 Standard (International Organization for Standardization, 2008) and written in the Modelica language and validated by (Maccarini et al., 2021). The behaviour of buildings' thermal properties is described by a model resembling an electric network consisting of five resistances and one capacitance. They used four cases of the (ANSI/ASHRAE Standard 140, 2007) validate the model. The model demonstrated good accuracy in general, and the validation results were within the acceptable ranges. This research uses case 600 from those four cases as a case-study. Fig. 4 shows the geometry of this model.

Table 1 - Case study design input parameters

Parameter	Value	Unit
Building indoor setpoints	20	°C
Substation supply temperature	70	°C
Ground temperature	6	°C
Carnot efficiency	30	%
Pump hydraulic and motor efficiencies	70	%
Evaporator temperature difference of the heat pump	-10	К
Condenser temperature difference of the heat pump	10	К



Fig. 4 – Dimensions of the test model based on ANSI/ASHRAE Standard 140 Case 600

## 4. Results and Discussion

In this section, the PPI values for the energy, economic, and environmental domains are calculated based on four scenarios for the central heat plant's setpoint temperature. This temperature is considered 15 °C, 20 °C, 25 °C, and 30 °C for the scenarios 1 to 4 respectively. These values are selected from the temperature range of TSN systems as reviewed by (Buffa et al., 2019). The model is simulated for each scenario to compare the scenarios, and the resultant PPI values for each domain are plotted in Fig. 5 to compare prosumers' efficiency in each scenario.



Fig. 5 – Annual PPI values for the modelled case study with four scenarios for the network setpoint temperatures

#### 4.1 Energy Analysis Results

It can be observed in Fig. 5 that lower setpoint temperatures lead to higher prosumer efficiency because reducing this setpoint leads to lower temperature difference between the heat source and heat sink in the central heat pump, which results in less energy consumption by the compressor ( $W_{HP}$ ). Over the whole year, scenario 1 (best case) has an annual PPI<sub>Energy</sub> of 0.85, and for scenarios 2 to 4, it equals 0.78, 0.70 and 0.62, respectively.

#### 4.2 Economic Analysis Results

The economic analysis was done by assuming a discount of 8% (Saffari et al., 2023), an electricity price of  $\in$  0.21/kWh (Saffari et al., 2023), and a hypothetical heat price of  $\in$  0.15/kWh. The capital and operation costs were obtained from SEAI's 2023 cost database. The system's lifetime for economic analysis was assumed to be 25 years.

Fig. 5 shows the PPI<sub>Economic</sub> for each scenario for a full year. The results demonstrate that a lower set point temperature leads to a better economic efficiency of the prosumer. The arithmetic mean values of PPI<sub>Economic</sub> for scenarios 1 to 4 are 3.3, 1.55, 0.94 and 0.66, respectively.

#### 4.3 Environmental Analysis Results

An emission factor of 332 gCO2/kWh was used to calculate the environmental impacts based on SEAI's database. As illustrated in Fig. 5 for the four scenarios, the PPI<sub>Environmental</sub> ranges from 2.47 in the best case (scenario 1) to 1.43 in scenario 4.

#### 4.4 Discussion

This paper formulated and calculated a theoretical evaluation framework metric for a hypothetical case study of a TSN located in Dublin using detailed dynamic models in Modelica. The motivation for proposing this metric was to develop an evaluation framework that fits the structure of TSN energy systems more specifically compared to other evaluation metrics, such as Coefficient of Performance (COP) and Levelized Cost of Heat (LCOH).

From an energy perspective, traditionally, the COP has been a commonly used metric to measure energy efficiency in heat pump-based DH supply systems (Tomc et al., 2024). The main limitation of using COP for evaluating prosumers in a TSN is that it only considers the heat pump's thermal performance and not the pumping energy consumption of the network. From an economic perspective, the LCOH is a widely used metric for estimating the lifetime heat production costs of a DH system (Saini et al., 2023). However, the LCOH accounts for production costs and does not consider the financial profit from selling the heat based on each prosumer's proposed heat price. As a result, the insights gained from the LCOH might be limited.

The goal of developing the PPI framework is to evaluate prosumers from various aspects. An interesting subject for future research is applying this evaluation framework in TSN networks with multiple prosumers. Each prosumer has a different share of heat supply in the same network, and the prosumers can be compared with each other in the PPI framework.

The formulation proposed in this research can be applied to any TSN system with heat-pump-based prosumers in any location. However, there are important limitations in the application of the PPI framework that should be considered. First, the PPI framework is a new metric and has never been used in other studies, making the validation of this metric challenging. Second, for the same reason, the calibration of the values calculated in the PPI framework is also problematic due to the lack of previous works and real-world implementation. Finally, being a newly proposed metric, it is difficult to communicate with various stakeholders using this metric, because stakeholders are typically familiar with traditional metrics such as LCOH, COP, and equivalent CO2 emissions, so they may not readily understand the values of PPI evaluation. These limitations pose key challenges for the application of PPI compared to other metrics.

Despite these challenges, the development of the PPI framework provides a novel approach to the multidimensional evaluation of prosumers within TSN systems. This work contributes to the theoretical foundation necessary for comprehensive performance evaluation in district heating networks and will be a useful reference for future studies in this area.

# 5. Conclusion

This paper has introduced a novel evaluation framework, the Prosumer Performance Index (PPI), designed to address the gap in assessing the efficiency of prosumers in Thermal Source Network (TSN) district heating systems. Through the development of the PPI, this research provides a valuable tool for district heating owners to assess prosumers' energy, economic, and environmental efficiency within TSN networks. By considering these multiple criteria, decision-makers can make informed choices regarding the utilization of low-grade waste heat and the optimization of TSN operations.

The simulation results presented in this paper demonstrate the variability of the PPI across different scenarios, highlighting the impact of network supply temperature setpoints on prosumer efficiency. The PPI framework aids TSN stakeholders in evaluating prosumer efficiency from various perspectives (energy, economic, and environmental), thereby facilitating better decision-making from the initial contracting with prosumers to the operational management phase.

However, there are important limitations to the PPI framework that should be considered. The validation of this new metric is challenging due to its novel nature and the lack of previous studies. Calibration of the PPI values is also problematic because of the absence of real-world implementation. Additionally, communicating the significance of PPI values to stakeholders, who are more familiar with traditional metrics like LCOH, COP, and equivalent CO2 emissions, poses a challenge.

Further research and validation of the PPI framework across diverse TSN networks with different heat generation technologies will be essential. The PPI framework can also serve as a foundation for implementing innovative control mechanisms and designing scenarios for developing TSN systems. In conclusion, while the PPI framework represents

a significant theoretical advancement in evaluating prosumer efficiency, its practical application requires further investigation and validation. Nonetheless, the PPI framework contributes to the theoretical groundwork necessary for advancing sustainable urban heating solutions in alignment with global climate objectives.

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## Nomenclature

## Symbols

TSN	Thermal Source Network
DH	District Heating
PPI	Prosumer Performance Index
COP	Coefficient of Performance
LCOH	Levelized Cost of Heat
KPI	Key Performance Indicators
TIC	Total Investment Costs
SEAI	Sustainable Energy Authority of Ireland
EM	Equivalent Carbon Emissions
EF	Emission Factor (gCO2/kWh)
Р	Power (W)
W	Electricity Consumption (kWh)
$\Delta T$	Temperature difference (K)
ΔP	Pressure drops (Pa)
V	Volume flow rate (m <sup>3</sup> /s)
ṁ	Mass flow rate (kg/s)
Q	Heat flow rate (W)
η	Efficiency

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# The Influence of Acoustic Stressors in Educational Environments for Autistic Individuals: Preliminary Investigations

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#### Abstract

Today, the increasing need for inclusive school environments is driven by the growing population of neurodivergent individuals, particularly those sensitive to sudden and loud noises. Addressing their specific needs enhances their educational and social performance and improves conditions for all students. Inclusive design can lead to more effective learning environments, fostering a sense of belonging and reducing stress for all occupants. This study investigates the influence of acoustic stressors in school environments that accommodate neurodivergent individuals who are sensitive to sudden and loud noises. The research focuses on identifying noise sources such as objects falling, doors shutting, school bells and chairs scraping. A range of classroom settings will be simulated to determine whether the produced noise could be configured as a potential stressor for autistic individuals.

## 1. Introduction

In recent years, the need for inclusive spaces for living and learning has become increasingly urgent. Research by numerous scholars (Alison et al., 2020; Sherilyn, 2018; Kanakri et al., 2017) on indoor comfort has revealed that parameters such as acoustics, and more specifically noise levels within living environments, can significantly impact the well-being of individuals in these spaces. This importance is amplified in environments where individual performance needs appropriate conditions, such as schools. For instance, (Huang et al., 2012) demonstrated that performance on specific tasks decreased when background noise exceeded 50 dB(A). When considering neurodivergent individuals, particularly those with autism, these thresholds have yet to be determined. Testing on vulnerable populations presents challenges, making it difficult to obtain consistent responses from such tests.

The significance of acoustics within educational buildings has been well-documented (Bistafa & Bradley, 2000; Minelli et al., 2022). Research indicates that parameters like reverberation time, clarity, and speech intelligibility play crucial roles in creating environments where students and teachers can listen and speak effortlessly. However, despite their scientific importance, these studies do not provide guidelines regarding sound pressure levels caused by common internal noise sources, such as falling books or pens, scraping chairs, slamming doors, and school bells. Many of these auditory events are neither standardized nor intentional but contribute to the overall acoustic climate of a classroom, potentially causing stress for students.

It is well-known (Chang et al, 2014; Belek, 2019) that neurodivergent individuals are often more sensitive to auditory events than neurotypical individuals. Therefore, this study aims to begin examining certain auditory events within classrooms as potential stressors for neurodivergent individuals. Typical sources considered include a falling book, a slamming door, a school bell, falling pens, and a chair scraping the floor. These sources are virtually placed within various real environments to understand their impact on the typical acoustic climate of a classroom (Megan et al., 2012; Noble et al., 2018; Caren, 2016).

# 2. Materials and Method

## 2.1 Environment

Three distinct environments were considered:

- Elementary school classroom
- Elementary school cafeteria
- University classroom

These environments were paired with their respective atriums or corridors, where school bells were located. The classroom configurations were as follows:

- Reverberant classroom as found during site inspections (Scenario 1)
- The same environment as the previous point, but with the addition of sound-absorbing materials to meet the UNI 11532-2 standard (UNI 11532-2:2020, 2020) (Scenario 2).

#### 2.2 Sound Sources

The following sound sources were considered as acoustic stressors:

- Mechanical school bell (A)
- Dragging chair (B)
- Falling book (C)
- Falling markers (D)
- Slamming door (E)

## 3. Sound Level Measurement Methods

The noise sources were measured using a sound level meter positioned one meter away in a semireverberant field. The reverberation time of the rooms was measured using the impulse response technique with a logarithmic sine sweep source, following the guidelines of UNI EN ISO 3382 (ISO Standard, 2009).

## 3.1 Model Calibration

The three-dimensional model of the environments was created through virtual reconstruction using geometric surveys of the spaces. A *3D* acoustic software utilizing pyramid tracing algorithm was employed for acoustic simulations. The soundabsorbing properties were assigned using the software's database. The sound-absorbing material used for the "absorptive" configuration included polyester fiber covered with an acoustically transparent membrane, placed in square panels of 1.2 m x 1.2 m dimensions. The certified laboratory sound absorption coefficient is as follows (Fig. 1):



Fig. 1 - Sound absorption coefficient of polyester fiber

## 4. Results and Discussions

The results of the experimental and numerical investigations are depicted below.

#### 4.1 Sources Sound Pressure Levels

The measured levels of the considered sound sources are reported in Fig. 2.



Fig. 2 - Sound pressure levels of different sound sources

It is clear that the ringing bell is the only noise source with a different frequency trend. All the other sources present similar frequency trends, yielding low frequencies.

#### 4.2 2D-Sound Pressure Level Mapping

In the following pictures (Fig. 3–14), the 2D sound pressure levels are reported for the condition "open door" (for brevity) for the two above-depicted scenarios (1= reverberant room, 2= room with sound absorbing materials).

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Fig. 3 – Canteen with open door. Sound source: school bell. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 5 – University classroom with open door. Sound source: school bell. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 4 – Elementary school classroom with open door. Sound source: school bell. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 6 – Canteen. Sound source: dragging chair. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 7 – Elementary school classroom. Sound source: dragging chair. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 8 – University classroom. Sound source: dragging chair. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 9 – Canteen. Sound source: falling book. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 10 – Elementary school classroom. Sound source: falling book. Scenario 1 (UP), Scenario 2 (DOWN)

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classroom

1



hall classroom hall hall

Fig. 13 – Elementary school classroom. Sound source: falling markers. Scenario 1 (UP), Scenario 2 (DOWN)

hall canteen hall hall canteen

Fig. 12 – Canteen. Sound source: falling markers. Scenario 1 (UP), Scenario 2 (DOWN)



Fig. 14 – University classroom – Sound source: falling markers. Scenario 1 (UP), Scenario 2 (DOWN)

Fig. 11 – University classroom. Sound source: falling book. Scenario 1 (UP), Scenario 2 (DOWN)

## 4.3 Frequency Trends Analysis

In Figs. 15–20 the frequency trends are depicted, for each noise source, in all environments and scenarios.





#### 4.4 Discussion

It can be observed that in the different environments, the behavior of impulsive sources and those with low frequencies (see Fig. 2) does not significantly depend on the placement or scenario. However, the maps (Figs. 3–14) show a notable reduction in peak emission when the source is placed in an absorptive environment. This reduction clearly implies less stress for the occupants, particularly for neurodivergent individuals.

Another noteworthy consideration is the levels obtained. None of these sources fall below the 50 dB(A) threshold, where literature (Huang et al., 2012) indicates the onset of stress. Nevertheless, it is important to distinguish between voluntary and involuntary sources. The "falling book" and "falling markers" are almost always involuntary and unavoidable, typically resulting from distractions or unintentional actions.

Conversely, the "slamming door" and "dragging chair," though often unintentional in causing noise, can be easily avoided with simple measures to prevent acoustic stress for the occupants.

A special discussion is warranted for the school bell. This source is intentional and serves the purpose of signaling to students and teachers when it is time to change classes, take breaks, or end the school day. In some cases, it also functions as a fire alarm. Because the bell is a deliberate source, its position can be adjusted, or its volume can be modified based on actual needs. For example, the bell can be relocated if there is a class with neurodivergent individuals nearby (or the students can be moved further away), ensuring that the corridor or atrium is not excessively reverberant, which would negate the distance effect. Another consideration is its volume. As shown in Figs. 3–5, the maximum perceived level is always above 75 dB(A). This level is quite high, considering that a teacher should not exceed 60 dB(A) at one meter (Zannin & Zwirtes, 2009). Reducing the bell's volume could mitigate the stress caused by this repeated, intentional source. Alternative signaling strategies, such as flashing lights or directional sound sources, can also be employed to reduce the induced stress.

# 5. Conclusion

This paper has presented the preliminary investigation on possible acoustic stressors for neurodivergent hyperacusis individuals in school environments. Diverse noise sources were considered, included in virtual environments featuring several conditions like open or close door, sound absorbing or semireverberant sound field. Preliminary considerations were made about the chance to mitigate the induced stress on neurodivergent individuals. Future works should include more scenarios, noise sources and the compliance of the indoor sound field with the national and European standards.

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# Machine Learning and Data Augmentation Techniques to Cope With Solar Data Scarcity to Simulate PV Generation in Mountain Environments

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#### Abstract

Accurate prediction of Global Horizontal Irradiance (GHI) is crucial for optimizing solar power generation systems, especially in mountainous regions characterized by complex topography and specific microclimates. These areas face significant challenges due to limited availability of reliable data and accuracy issues stemming from the dynamic nature of the atmosphere and local weather conditions. This scarcity of precise GHI measurements impedes the development of accurate solar energy prediction models, affecting both economic and environmental aspects. In this framework, this paper proposes a novel methodology to address data scarcity challenges in solar energy prediction, particularly focusing on Alpine regions. We employ machine learning techniques such as Random Forest (RF) and Extreme Gradient Boosting (XGBoost) regressors, in conjunction with synthetic data generation, to predict GHI. To assess our approach's accuracy, we selected Bolzano as a case study and modelled the PV AC power outputs before and after optimizing GHI data.

## 1. Introduction

Solar energy stands as a pivotal pillar of sustainable development, as underscored by the International Energy Agency (IEA, 2020). Consequently, accurate solar irradiance prediction plays a central role in harnessing this renewable resource efficiently, in particular when it comes to the Global Horizontal Irradiance (GHI). However, obtaining accurate GHI measurements presents formidable challenges, rooted in the dynamic nature of the atmosphere and the variability of weather conditions (Qazi et al., 2019). Furthermore, assembling a comprehensive and precise dataset of GHI measurements is often a resource-intensive endeavour, demanding expensive equipment and periodic maintenance (Kalogirou, 2009). Indeed, inaccuracies in GHI measurements can reverberate through the entire solar energy prediction process, carrying ramifications that ripple through economic and environmental aspects (Kosmopoulos et al., 2015).

Machine learning (ML) techniques have gained traction in the field of solar energy prediction, holding significant promise for technological advancements (Javed et al., 2019). However, a major concern arises: the effectiveness of these ML algorithms relies heavily on the quantity and quality of the training dataset (Javed et al., 2019). Frequently, the scarcity of accessible data becomes a bottleneck, hindering the creation of accurate solar energy prediction models. Therefore, there is a pressing demand for cost-effective approaches capable of efficiently obtaining and utilizing GHI data to enhance the accuracy of solar energy prediction models.

In response to this pressing challenge, our study introduces a new approach designed to enhance the accuracy of GHI predictions, even when confronted with limited datasets. Our method capitalizes on the power of machine learning, specifically the Random Forest (RF) regressor (Breiman, 2001), to identify the optimal distribution of training data based on cloud opacity values — a pivotal factor in GHI measurements. Subsequently, we harness the same RF regressor to construct a new RF model, which generates synthetic data points. These synthetic data points undergo augmentation via techniques such as flipping, rotating, scaling, and the introduction of random noise (Maharana et al., 2022). This augmentation strategy enriches dataset variability, enhanc-
ing model robustness. In the last step of the proposed approach, we trained and tested the Extreme Gradient Boosting (XGBoost) regressor (Chen & Guestrin, 2016) on the combined structured dataset, which integrates the original and synthetic data via data augmentation techniques.

## 2. Methodology

### 2.1 Data Collection

In our study, we started by collecting hourly values of various meteorological and atmospheric quantities and Global Horizontal Irradiance (GHI) during the years 2019 and 2021. We selected four distinct Alpine locations (Fig. 1), with intricate topography and unique microclimates (Ohler et al., 2020): Bolzano (46.50° N, 11.35° E), Aosta Valley (45.75° N, 7.34° E), Locarno (46.16° N, 8.88° E), and Esine (45.92° N, 10.25° E).

Our data collection process relied on two primary sources: local weather stations for GHI data and satellite imagery for other predictor variables. Specifically, for Bolzano, we obtained GHI data from the weather station situated at the Free University of Bozen-Bolzano campus. For the remaining locations, we collected GHI data from weather stations located in close proximity to each respective site. Additionally, we acquired the Actual Meteorological Year (AMY) dataset from Solcast.com (Solcast, n.d.). This dataset encompasses seven crucial meteorological and atmospheric parameters, including air temperature, cloud opacity, precipitable water, relative humidity, surface pressure, wind direction, and wind speed. We also incorporated solar geometry variables, as well as time-related information such as azimuth and zenith angles, year, month, day, and hour, to serve as predictors in our analysis.

### 2.2 Data Preprocessing

Before analyzing the dataset, data preprocessing was conducted according to (Nugroho et al., 2021). This preprocessing phase included essential data cleansing steps, with a primary focus on the removal of missing values and a thorough identification and treatment of outliers.



Fig. 1 – Map of selected alpine locations (source: https://en-gb.topographic-map.com/)

## 2.3 Data Splitting and Optimization

To ensure robust model training and evaluation, we partitioned the dataset into training (1 %) and testing (99 %) subsets, simulating a scenario with limited data available for training, using data from the years 2019 and 2021 for the training and testing subsets, respectively. Subsequently, we embarked on the task of optimizing the training dataset. This optimization process was fueled by the pursuit of the most effective distribution of training data, with the primary goal of maximizing the model's performance in terms of metrics such as the coefficient of determination (R<sup>2</sup>) score, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Bias Error (MBE). In essence, we sought to find the ideal arrangement of training data that would yield the best predictive accuracy. To accomplish this, we leveraged the Random Forest (RF) regression model, which allowed us to discern the distribution that corresponded to specific cloud opacity values, a fundamental factor influencing GHI measurements

## 2.4 Synthetic Data Generation and Augmentation

The process of generating synthetic data revolved around a Python-based algorithm designed to harness the capabilities of the Random Forest (RF) regressor. The objective was to create synthetic variables of predictors known as input features and generate new predicted GHI data points that closely mimicked real-world conditions while significantly expanding the size of our training dataset.

We created a grid of input feature values that covered the full range of possible values for each feature, utilizing the same feature ranges and resolutions as the original, limited training dataset. This enabled us to construct a more diverse and expansive dataset than the original one. Subsequently, we passed the input features through the trained Random Forest (RF) model to predict the corresponding GHI values. This approach enabled us to create supplementary data points, thus improving the precision of our ML algorithm for GHI prediction. This strategy significantly enriched our training dataset, effectively expanding its size by a factor of up to 200 times its original magnitude.

To further improve the diversity of the dataset, we implemented a range of established data augmentation techniques (Maharana et al., 2022):

- Flipping: mirroring existing data points to introduce variations that capture inverted scenarios, such as changes in solar angles.
- Rotating: applying rotations to data points to simulate different solar angles and azimuths, thereby expanding the dataset's coverage of potential conditions.
- Scaling: introducing scaling factors to data points to represent varying magnitudes of meteorological and atmospheric parameters, effectively diversifying the dataset.
- Introducing Random Noise: injecting controlled random noise into the synthetic data to mimic the inherent variability in real-world atmospheric conditions.

# 2.5 Model Testing and Evaluation

In the next stages of our methodology, we employed the Extreme Gradient Boosting (XGBoost) regressor (Chen & Guestrin, 2016) as our primary machine learning model. This model was trained using a structured dataset from 2019, which we created by combining the original dataset with the synthetic and augmented data. To evaluate the model's performance thoroughly, we used a testing dataset from 2021, ensuring the robustness of our approach by testing the model with data from a different year.

# 2.6 PV System Modelling

To understand the impact of our methodology in increasing the accuracy of predicted GHI, we utilized the PVLib library (PVLIB, 2020) to model the AC power output of a photovoltaic (PV) system, focusing on Bolzano as a case study. PVLib is an open-source library that provides a set of tools for simulating the performance of PV energy systems. We modeled the AC power output using three different sets of GHI data: measured GHI, GHI predicted from augmented data, and GHI predicted from scarce data. The GHI data served as the primary input, the impact of which we analyzed before decomposing it into Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI) components for our PV system simulation. The analysis of the impact of decomposition on the PV system performance was not implemented as it is outside the scope of this research. This approach assumes the common scenario where only GHI data is known. For the estimation of the diffuse horizontal irradi-

ance (DHI) from the predicted GHI, the model by Erbs (1982) was adopted. Furthermore, the Perez model, described in (Perez et al., 1987; Ineichen & Perez, 2002), was implemented to estimate beam and diffuse components on tilted surfaces.

## **PV** System Configuration

The PV system was configured using the following parameters from the PVLib library (PVLIB, 2020):

- *Temperature Parameters*: the open-rack glass-glass temperature model parameters.
- *Module*: the Trina Solar TSM-300DEG5C-07 II module, with efficiency of 18.19 %.
- *Inverter Specifications*: the ABB MICRO-0.25-I-OUTD-US-208 inverter.

To evaluate the accuracy of the modeled AC power output, we employed four statistical metrics: Mean Absolute Deviation (MAD), Root Mean Squared Deviation (RMSD), Coefficient of Variation (CV), and Autocorrelation Function (ACF). These metrics were chosen to assess how well each model captured the smooth transitions in AC power output typically observed in real-world PV systems.

Mean Absolute Deviation (MAD):

$$MAD = \frac{1}{n} \sum_{i=1}^{n} |y_i - \bar{y}|$$
(1)

Root Mean Squared Deviation (RMSD):

$$\text{RMSD} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \overline{y})^2}$$
(2)

Coefficient of Variation (CV):

$$CV = \frac{\sigma}{\bar{y}}$$
(3)

Autocorrelation Function (ACF):

$$ACF(k) = \frac{\sum_{i=1}^{n-k} (y_i - \bar{y})(y_{i+k} - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$
(4)

Where  $y_i$  is the hourly AC power output,  $\bar{y}$  is the mean AC power output,  $\sigma$  is the standard deviation and k is the lag.

The primary purpose of using these statistical metrics is to identify which model best captures the gradual changes in AC power output over consecutive hours, thereby minimizing outliers. A model with lower MAD, RMSD, and CV values, combined with a higher ACF, suggests fewer unrealistic fluctuations and smoother transitions in the predicted AC power output.

To gain deeper insight into the accuracy of modeled AC power output under varying GHI conditions, we conducted an analysis of how cloud opacity influences PV AC output.

## 3. Results and Discussion

### 3.1 Data Splitting and Optimization

Fig. 2 reports the minimum number of hours with favorable sky conditions necessary to train our machine learning model, enhancing its accuracy in predicting GHI (Sarmas et al., 2022). As can be seen in the figure, various locations across the Alps exhibit notable similarities in terms of hours with corresponding cloud opacity values. This insight provides valuable guidance on pinpointing specific days of the year that require attention for instrument inspection, maintenance, and the collection of training data for ML models to make precise predictions. Furthermore, this knowledge aids in the more accurate calibration of instruments, obviating the need for year-round inspections (Lester & Myers, 2006; Santiago, 2023).

In addition, our approach offers several advantages in terms of data collection. It streamlines data gathering by concentrating resources on days with specific sky conditions crucial for precise predictions (Zellweger et al., 2023). This approach hints at potential optimizations in the allocation of time and resources, which could result in a more cost-effective process. This is especially relevant in remote or hard-to-access locations where data collection can be resource-intensive (Ohler et al., 2020). Moreover, improved data quality arises from the reduced influence of confounding variables like cloud cover or extreme weather conditions, which can introduce inaccuracies into the dataset (Krishnan et al., 2023). Data collected under favorable sky conditions is assumed to yield more consistent and reliable measurements.



Fig. 2 – Cloud opacity range and corresponding hours of measured GHI

### 3.2 Models Accuracy and Reliability

Our model has achieved a R<sup>2</sup> score ranging from 0.91 to 0.97 when evaluated against the 2021 testing dataset. This outstanding performance signifies a robust correlation between the predicted and actual GHI values. Importantly, this high level of accuracy has been consistently observed across multiple Alpine locations, as evidenced in Table 1.

Furthermore, the low RMSE, MAE, and MBE values provide strong evidence of the quality of prediction accuracy. Particularly noteworthy is the substantial decrease in RMSE and MAE values when synthetic data augmentation techniques were applied, indicating that our model's predictions closely align with actual GHI values. To provide a more tangible demonstration of our approach's impact, we included Scatter Plots in Fig. 3, that illustrate the model's performance before and after the application of synthetic data generation and augmentation techniques. The inclusion of synthetic data generation and augmentation techniques has not only improved the model's accuracy but also strengthened its overall reliability. By significantly enlarging our initially limited training dataset, our model now exhibits enhanced abilities to make precise predictions that can generalize effectively. The synthetic data generation process, covering a wide range of meteorological and atmospheric conditions, has equipped the model to adapt to various scenarios and comprehended the intricate patterns of GHI in mountainous regions.

Table 1– Performance metrics for GHI prediction with and without synthetic data generation and augmentation techniques

Aosta Valley								
Method	<b>R</b> <sup>2</sup>	RMSE [W m <sup>-2</sup> ]	MAE [W m <sup>-2</sup> ]	MBE [W m <sup>-2</sup> ]				
Data Scarcity	0.84	99.75	71.36	39.03				
Augmented data	0.97	42.64	20.33	3.13				
Bolzano								
Data Scarcity	0.79	114.93	78.61	38.58				
Augmented data	0.91	74.61	41.82	3.06				
Esine								
Data Scarcity	0.80	110.58	73.93	38.80				
Augmented data	0.93	66.40	38.62	3.12				
Locarno								
Data Scarcity	0.80	111.75	77.77	38.73				
Augmented data	0.92	69.97	38.42	3.06				

# 3.3 AC Power Output Result Analysis

The study aims also to evaluate the smoothness of transitions in AC power output from one hour to the next, which serves as an indicator of the model's accuracy in capturing gradual changes in solar irradiance. This evaluation spans four seasons and considers three scenarios: using measured GHI, predicted GHI from augmented data, and predicted GHI from limited data, as depicted in Fig. 4.



Fig. 3 – Performance comparison scatterplots

Across all seasons, the AC power output modeled with measured GHI consistently exhibits the smoothest transitions with minimal fluctuations. In contrast, using predicted GHI from augmented data shows moderate fluctuations, while using predicted GHI from scarce data exhibits more pronounced irregularities, suggesting lower accuracy.

Table 2 provides a quantitative assessment of each model's performance using statistical metrics (MAD, RMSD, CV, and ACF). We can observe that:

AC power output modelled with measured GHI consistently shows the lowest MAD and RMSD values. It also has the lowest CV values, reflecting stable power output predictions, and the highest ACF values, suggesting smoother transitions.

- AC power output modelled with augmented GHI shows slightly higher MAD and RMSD values than measured GHI, suggesting moderate accuracy. CV values are slightly higher but remain relatively stable. ACF values are lower than measured GHI but still indicate relatively smooth transitions.
- AC power output modelled with scarce GHI exhibits the highest MAD and RMSD values, indicating higher deviations and less accuracy. CV values are the highest, particularly in winter, indicating the most variability. Low ACF values suggest more abrupt changes.



Fig. 4 - Modeled AC Power Output by seasons and GHI models

Table 2– Performance metrics for modeled AC power output with GHI data inputs

GHI data	Season	MAD	RMSD	CV	ACF
		[W]	[W]	[•]	[·]
Measured	Summer	16.53	30.17	0.30	0.94
Augmented	Summer	18.83	34.35	0.33	0.93
Scarced	Summer	22.07	37	0.36	0.92
Measured	Fall	15.12	28.06	0.46	0.92
Augmented	Fall	16.76	30.46	0.51	0.9
Scarced	Fall	21.36	37.29	0.58	0.86
Measured	Winter	10.12	20.74	0.71	0.89
Augmented	Winter	12.46	25.93	0.79	0.86
Scarced	Winter	14.97	30.93	0.97	0.77
Measured	Spring	18.67	38.71	0.40	0.92
Augmented	Spring	20.16	42.02	0.46	0.91
Scarced	Spring	23.48	47.06	0.49	0.90

Fig. 5 illustrates the relationship between cloud opacity and PV AC output, highlighting the impact of cloud optical properties on power generation. The correlation plot shows a clear inverse relationship between cloud opacity and AC power output. Higher cloud opacity results in lower power output, reflecting reduced solar irradiance.

The model with measured GHI exhibits a more linear and consistent correlation, indicating its effectiveness in capturing the impact of cloud opacity on power output. This consistency further supports its superior performance in modeling smooth transitions. The models with GHI predicted from augmented and scarce data show greater variability in correlation, especially pronounced in the model with GHI predicted from scarce data. This suggests a less accurate representation of cloud effects on power generation. This scatter indicates potential inaccuracies and greater fluctuations in predicted power output.

Analysis of Figs. 4 and 5, along with the statistical metrics in Table 2, highlights that, when using measured GHI, the model consistently produces smoother transitions in AC power output between consecutive hours. This is reflected in its lower MAD, RMSD, and CV values, and higher ACF values, indicating more accurate and stable power output predictions. The model with augmented GHI shows moderate fluctuations and variability, indicating acceptable accuracy, though it is slightly less

accurate than the model with measured one. In contrast, the model with scarce GHI exhibits the highest fluctuations and variability, particularly in less predictable seasons like winter, suggesting significant inaccuracies that may lead to over-/underestimation of power output.

Accurate representation of cloud opacity is therefore crucial for reliable PV power output modeling. Inadequate representation of solar irradiance variability can lead to unrealistic jumps in power output, which are unlikely in real-world scenarios. The augmented model offers a reasonable alternative, while the scarce model's high variability and error rates make it less realistic.



Fig. 5 – Correlation between Cloud Opacity and PV AC output

# 4. Conclusion

This study addresses the critical challenge of data scarcity in solar energy prediction, particularly in Alpine regions characterized by complex topography and microclimates. Accurate predictions of Global Horizontal Irradiance (GHI) are paramount for optimizing solar power generation. However, limited data availability in such regions poses a significant hurdle to achieving precise predictions. To overcome this challenge, our approach combines machine learning techniques, training data distribution, synthetic data generation, and augmentation. Integration of synthetic data generation and augmentation techniques to expand the training dataset enhanced the model's ability to generalize and make accurate predictions. Machine learning models achieved high accuracies, with an R<sup>2</sup> score ranging from 0.91 to 0.97 and substantial reductions in RMSE, MAE, and MBE values across various Alpine locations. Findings also suggest that optimizing the distribution of training data based on cloud opacity values can identify specific days with favourable sky conditions for accurate GHI measurements.

The results of PV AC power output modelling suggest that when using GHI data, decomposed into DNI and DHI, predicted with the use of synthetic and augmentation techniques, the model shows moderate fluctuations and acceptable accuracy. In contrast, the use of GHI predicted from scarce data exhibited the highest fluctuations and variability, indicating significant inaccuracies. This highlights the importance of using our approach to increase the accuracy of PV system modelling in alpine and mountainous regions.

However, potential applications of this approach extend beyond traditional design and performance assessment of solar systems. The methodology could improve data collection efficiency, reduce costs, enhance data quality, and aid in instrument calibration. It may also optimize maintenance schedules, reduce downtime, lower maintenance costs, and extend equipment lifespan.

Future research will be dedicated to refining synthetic data generation processes, optimizing the integration of additional meteorological and environmental parameters, and extending the methodology to other regions.

# **Reproducibility Statement**

The authors are committed to ensuring reproducibility and facilitating research by readily sharing source codes upon reasonable request.

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# Building Performance Simulation From Research to Professional Practice

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### Abstract

This paper explores the challenges and opportunities in integrating Building Performance Simulation (BPS) in the the design of the built environment. While the complexity of building performance and the challenging sustainability target would benefit from a more systematic adoption of BPS, some limitations are still evident. Processbased changes and new business approaches should complement BPS tools technical innovation to better equip practitioners to contribute to addressing future challenges. The paper addresses the barriers to integrating BPS into professional practice, such as the complexity of simulation tools, the need for specialist knowledge and education, and the lack of a shared participative approach to design and building. The potential of BPS to support integrated performance analysis and its role in transforming design practices to meet national and international carbon reduction targets are examined. Recommendations are suggested for overcoming these barriers and promoting a wider adoption of BPS in professional practice.

### 1. Introduction

It is well recognised that in order to address the environmental, social and economic goals of sustainable development, efficient energy utilisation and the mitigation of environmental impact are important factors. The role of the built environment in both contributing to the environmental impacts and providing huge opportunity to reduce emissions is also recognized, to the point that many government initiatives worldwide over the last 40 years have focused on this sector (Gao *et al.*, 2017). However, building energy systems are complex, their performance depending on the interaction of multiple factors and on the occupants' activities and behavior. In the absence of a means by which the performance benefit of proposed measures can be predicted reliably, such initiatives will fail.

Studies in the UK by the Building Research Establishment (BRE) as long ago as the late 1980s indicated that energy consumption in buildings could be reduced by 30 % with low and no-cost interventions that have negligible impact on users in terms of the way in which they perceive and use buildings (Building, 2024). However, in order to improve the likelihood that governments achieve internationally agreed emission reduction targets related to the built environment by their target date (Scottish Government, 2023), a raft of new building regulations and associated legislation has been introduced (EU, 2023). Building designers have a key role to play in delivery, and while the systems required to deliver such targets exist in large measure, there is no universally available decision support mechanism.

It is generally accepted that human activity is a key contributor to climate change and that our profligacy in the use of finite resources, from building materials to fossil fuels, necessitates behavioural change. If nothing else, in order to achieve national and international Carbon reduction targets, design professionals will be required to transform their existing design practices.

# 2. Overcoming Barriers to Integrated Working

Although dynamic simulation tools have existed since the 1970s, and despite their ability to accurately simulate buildings and their systems, their use has been restricted to specialist modellers who apply the tools on users' behalf. The principal reason for this is that in order to use such tools in earnest, users require in-depth knowledge of a range of thermodynamic processes, environmental systems and controls issues.

Further, for over 30 years there has been talk of integrated design team working but little evidence of buildings that exemplify this process has emerged. In order to bring the professions together, each discipline needs to be aware of the unilateral effects of any design decision on the performance of the building as a whole, and not just the aesthetics, the cost or the thermal behaviour for example. Bioclimatic issues and a more holistic approach to sustainability mean that buildings can no longer be seen in isolation whereby myriad building components, interactions with users and overall performance are intrinsically linked both internally and with the external surroundings.

In order to accommodate such thinking, the professions need to recognise the need for an overhaul of current work practices and to make significant improvements in design team interaction, in order to equip the professions with better insights and the right tools for the job. Attempts have been made to tackle this at a number of levels in the past: research, educational and professional, and although in-roads have been made, some design practice and process-based barriers are more difficult to tackle than others. However, fortunately, alleviation methods for some issues exist already.

# BPS: Integrated Performance Analysis

In the context of the development of tools to support integrated working, building simulation tools have long been the preserve of a few specialist consultancies rather than being used where they can have the greatest impact – within construction design practices. This has resulted in additional costs for designers (time and financial) in terms of buying-in specialist services. In addition, the designer is not able to fully explore the design potential: being restricted by what the specialist reports back. There are well-documented reasons for this situation: most notably the perceived difficulty of using simulation tools; the associated cost (hardware, software licenses, staff training); and liability issues. Also, the construction industry is traditionally a poor investor in research and development, preferring to operate core business activities on proven ground.

However, for design practice to gain maximum benefit from the potential of simulation, simulation must be embedded within the design process (McElroy *et al.*, 2007). The most problematic issues are that members of the design team will require access to models at different stages as the design progresses and that the problems surrounding the exporting and retrieval of models by multiple users are non-trivial.

This is further complicated by the fact that over the last two decades the construction industry, in attempting to become more streamlined, has moved increasingly away from the notion of integrated working towards a risk averse culture – despite the best of intentions. Instead of traditional design teams with architect and client overseeing the process, we are now faced with disruptive factors such as: value engineering, nominated subcontractors, diminishing direct labour resources and skills shortages, thus the delivery mechanism is now one step away from design team control. All of this makes it more difficult to know exactly what is going to be delivered at the end of the day - so, is there any real point in undertaking simulations to predict performance when for many all that matters is 'on time, on budget'?

The problem for BPS in terms of taking the next steps may have at one time related to lack of information, but this is no longer the case. There is no shortage of knowledge and a plethora of design guidelines exist for both designers and clients, but the problem is a lack of a procedure for integration of the emerging sustainability issues into the design process. And in the absence of a framework within which to work, those designers who wish to pursue a low carbon philosophy face significant barriers within a process that tends to be piecemeal and ridden with gaps. To tackle the problems, and to make the required degree of progress, a paradigm shift is required, involving a complete change of mind-set in terms of the design process.

While the shift to a more participative design process should have been fostered by the fast uptake of BIM, this has not yet led to a widespread adoption of paradigms such as the Integrated Design Process. Even when those are applied, it seems the role of simulation specialists is more that of providing off-line estimation of the requested performance metrics.

# 4. BPS: Design Tools

BPS has rapidly gained a wide popularity within the scientific community, particularly among the researchers responsible for its introduction and development. Not only has it been recognised as a valuable method of virtualizing the in-depth analysis of the multifaceted aspects of building performance, but it has become established as one of the most significant contributions of science to professional practice.

Integrated performance simulation offers building designers a spectrum of new analysis possibilities. Prior to the advent of simulation, computer-based design tools traditionally relied on simplifying reality in order that calculations could be undertaken manually. Dynamic, integrated simulation on the other hand uses complex mathematical models to represent energy flow paths and their interactions as they vary over time, thus allowing an in-depth analysis of the factors that influence the energy and environmental performance of buildings. This provides users with:

- the ability to handle a level of complexity hitherto not possible;
- the ability to address all relevant environmental issues; and
- the ability to explore all energy flow paths simultaneously.

By employing detailed building input data and using realistic weather data, dynamic simulation allows designers to understand the relationships between thermodynamic interchanges as they actually occur in buildings. This allows designers to explore the complex relationships between form, fabric and systems (conventional and renewable) in terms of the underlying dynamic transfers of heat, mass and momentum. In this way simulation allows the exploration of design issues in a holistic manner and in a way that respects the integrity of the actual physical system.

However, while the potential of BPS in supporting the investigation of the complex behaviour of buildings cannot be disputed, the actual impact (should this exist), on everyday practice, and the subsequent diffusion into professional practice does not match up to the potential or the expectations of the experts. At the same time, more and more BPS tools and players have emerged and/or entered the market, indicating that there should be a real interest. A deep analysis and constant monitoring of market trends and the diffusion of BPS tools would allow a better understanding of the direction of travel, highlighting opportunities as well as constraints and limitations, which would enable IBPSA to be more effective in promoting and supporting the use of BPS in practice.

The challenges to using BPS in practice have been documented by over time by various users and researchers: ranging from the need for specialist computing equipment, through a steep learning curve, to fear of unrecognised data input errors and lack of credibility of predictions Howrie (1995). Despite progress, (Clarke & Hensen, 2015), there also remains a perception that simulation is costly and slow, that users lack trust in outputs and in their ability to interpret results, and progress is also hampered by a lack of recognised quality assurance procedures, poor interoperability between tools and an ongoing problem in relation to the jargon associated with the technology (Hand, 1999; Donn, 1997).

How fast the existing tools are moving towards the exploitation of the full potential of BPS, and how this can be connected to the integration with other design or project management tools, including BIM, remains to be understood, and possibly promoted.

### BPS: Constraints and Drivers

In the interim, the following outlines the main constraints and drivers that have had an impact on the development and use of BPS (in chronological order). Many of these are well known and have been covered in previous IBPSA papers, notably Clarke (2015) and PhD research (McElroy, 2009) Despite the passage of time and the overcoming of some of these limitations there has been no measurable corresponding boost for the diffusion of simulation. The reasons for this are varied and in order to resolve these we need to better understand the drivers and challenges.

## 5.1 Calculation Power

If the complexity of the simulation algorithms has been a key factor in preventing the spread of simulation, it could be argued that the increasing availability and calculation capacity of personal computers should have supported the resolution of this as an obstacle to the diffusion of simulation in professional practice. From a research perspective, the increased capacity has indeed permitted the development of more and more complex and accurate algorithms and models: extending the areas (thermal, visual, acoustic, air quality, moisture migration and fire safety, etc.); moving the boundaries (e.g. from the envelope to the climatic surrounding); increasing the detail (envelope/ system/ control components, users, and so on) and time discretization (control), enabling the integration and comprehensiveness (co-simulation), and upscaling the size and scale of the analysis (multizone, urban and regional areas). On the other hand, increased complexity and capability of models does not always lead to better models or improved output with the margins for error increasing with additional functionality. Perhaps as a direct result of this, the diffusion and successful implementation of simulation in practice from a professional perspective does not appear to feature a corresponding trend and yet, the potential benefits are well documented (Clark & Hensen, 2015).

# 5.2 User Interfaces

Simulation programs allow users to explore in detail the multi-variate performance (temperature, energy, comfort, environmental impact, etc.) that arises when occupants interact with buildings as they respond, in turn, to weather and control system influences. Compared with simplified tools,

which derive from many in-built assumptions, simulation requires users to input large amounts of data, much of which is unfamiliar and expressed in an unfamiliar language. This results in a steep learning curve for new users and can create confusion and a lack of trust in the programs, causing novice users to doubt themselves and so reverting to simplified alternatives due to a perception that simulation tools are difficult to use in routine design work.

As the power of integrated BPS has increased, the need to develop interfaces that support a structured approach to design hypothesis specification and evolution has emerged as a non-trivial issue. Increasing the user-friendliness of a program is often done in a manner that belies the true complexity of the issues to be analysed, there thus a balance to be struck between protecting the user from the vagaries of the program and allowing access to the complete functionality of a powerful, multi-domain simulation environment. The problem is compounded by the fact that users' needs continue to evolve with experience, suggesting a need for an evolving interface - i.e. one that would support the transition from novice to experienced user, providing early stage support and offering insights as to more novel approaches as the users' understanding evolved.

As integrated BPS tools emerged, there existed a perception that as soon as users had access to better interfaces, the barriers to using integrated simulation in practice would evaporate. The reality is often the opposite, with the user-interface giving rise to as many problems as it solves. There is no easy answer to this dilemma and attempts to develop user interfaces over the years have been fraught with problems despite the substantial increase in the available computer power. A lack of support for program use in practice and the absence of quality assurance procedures relating to model evolution and performance appraisal procedures was seen by designers as a major barrier to the routine use of simulation modelling in practice.

# 5.3 Problem Definition

Because simulation specialists are not building designers, and building designers are not profi-

cient in use of BPS, the mapping of design questions to simulation intent is a particularly challenging activity. Furthermore, an appreciation of the level of detail required to answer the design questions to be addressed is a skill that comes with experience. This gives rise to an additional barrier imposed by the fear of user error in inputting data and an associated concern of a potential discontinuity between program capabilities and the scale and complexity of real buildings.

The creation of appropriate models that are suited to exploring the key issues is an art. It is equally as possible to create an overly complex model, as it is to over-simplify the model to the detriment of addressing the critical aspects of the design. Thus, the use of simulation can be seen as costly and slow, with no guarantee of useful results.

### 5.4 Performance Assessment

Underlying model construction is the question of appropriateness: the model may be accurately constructed but is it the right model to answer the questions? What analysis does the profession need to undertake and at what level of detail? Is one model enough to explore all pertinent aspects? Can the same model be used to explore contaminant dispersal, lighting distribution, summertime overheating risk and annual energy consumption? If not, what level of detail is required in each separate model? The answer to this is not straightforward. The time required to extract and understand simulation outputs and results in terms of design performance predictions should not be underestimated. Insufficient time invested in analysis can contribute to misinterpretation of results and a failure to spot significant issues.

### 5.5 Expertise and Training

Kaplan (1992) suggested that, "models are to error as sponges are to water". In the past, users were easily frustrated by systems that did not support model creation, documentation, archiving and retrieval systems, designed to trap errors, but the degree of training required to access BPS tools has been progressively reducing thanks to the development of user more user-friendly graphical interfaces, simulation suites and environments, optimization tools, reporting tools, etc. These have reduced the informatics skills requested to access simulation and have simplified the use of simulation tools for professionals with no specific training in building science. But there are risks: while it is easier to use tools, it is also easier to make mistakes due to input errors, misinterpretation of results, etc. (McElroy, 2009; Clarke, 2015; Beausoleil-Morrison, 2021). Thus, increasing the number of possible users, has also contributed to raised concerns about the reliability and trust users can place in simulation results. This has fuelled scepticism, with some presumable impact on the actual diffusion of simulation.

### 5.6 Results Analysis

Even when a user is confident with a program's inputs, can the user trust the outputs? And if so, results interpretation can present significant problems. In the absence in fully integrated models, how can a designer transform simulated predictions into design action? How can a designer be sure which design parameter is driving the results? Ultimately, the only way to assess the accuracy of a simulation program is to construct the building, monitor its performance and compare the actual and predicted data. While tool developers may have reason to be confident in program outputs, there existed at the outset of the research no mechanism whereby this confidence could be passed to users. The main reasons for this are twofold:

- the multi-variate nature of the problem makes it difficult to identify the design parameters that give rise to performance outputs; and
- each design has unique characteristics that make it difficult to compare outputs across designs or with benchmarks.

This poses questions around whether or not design professionals are well enough equipped to build models that are robust and no more complex than required to answer the design question being investigated, and if so, can they interpret and translate the simulation outputs into useful design action.

## 5.7 Regulation and Requisites

Research progress on both the theoretical and modelling side has extended the potential areas of analysis, allowing the evaluation of a range of different aspects and the introduction and the calculation of new performance metrics. To a certain extent this has supported the introduction of more detailed and more demanding performance requisites, the evaluation of which require the adoption of more and more detailed calculation methods and more and more frequently requiring the use of simulation. Nevertheless, this activity has been generally limited to larger buildings, with special relevance in terms of consumption and/or impact on users either by number or by requisites. In addition, the application of simulation has been considered as the elective solution to evaluate and optimize the performance of new or deeply renovated buildings. Finally, while the introduction of new metrics and requisites has undoubtedly promoted the development or upgrade of existing calculation tools or suites, it might be disputed that this has equally supported better awareness in the appropriate use of simulation or in the realization of its real potential in terms of optimization of the design and operation of buildings generally.

# 5.8 Extremization of Performance, Emersion of Competing/Overlapping Areas, and Necessity for MOO

The increase in the number and thresholds for performance targets has led to an escalation in complexity of the analysis required due to the growth in emphasis on the conflicts and interactions between different objectives and to a more unstable balance among them. An extremization of the relevance of energy or resource efficiency has highlighted critical impacts on the occupants' comfort and satisfaction, also because of a higher level of expectation associated with higher performance design standards. In such cases, the use of advanced simulation approaches has proved to be irreplaceable, while still limited to larger or more crucial applications.

### 5.9 Information Availability and BIM

This final trend seems to be an outlier, in that unlike the others it has reached the wider audience of professionals, following long term discussion within the research community. Building Information Modelling (BIM) comprises information collection and exchange in a structured form, allowed by the introduction of the building information models. One of the perceived limitations of BPS has been the availability and reliability of large quantities of data, and the expectations are high that BIM, as an information organizational and sharing platform, can bring new life to BPS. For this to come to fruition, the focus would have to shift to the interoperability of tools, which in turn would contribute significantly to an increase in the efficiency of the entire process, including the simulation. However, difficulties in achieving such a complete seamless interoperability seems to occupy the ongoing discussion. Notwithstanding the fact that while information and its quality tend to increase with the development of the project, and ignoring all concerns about accuracy and reliability of BPS in the earlier design phases, a question remains about the efficacy and more generally, the point or purpose of BPS.

### 5.10 Business Integration

Adopting a computational approach to design could make a valuable contribution to the mitigation of climate change impacts and the wider goals of sustainable development. In order for this to happen, the tools need to be fully assimilated into the design process. Such integration would require a paradigm shift in the way designers do business, in short a complete change of mindset. From clients to designers, and project managers to contractors to manufacturers, those responsible for the design and delivery of buildings face many pressures and are often reluctant to tackle the challenges associated with adopting new methods into an already complex process; in spite of the fact that new and impending legislation now requires that these issues be addressed. In addition, the costs associated with staff training and maintaining up to date equipment and applications in a fastevolving technology area, places an additional burden on those practices that want to develop and maintain an in-house simulation capability, and so it is not always straightforward to adopt new methods, despite the apparent potential benefits. But the BIM experience indicates that this is possible.

### 6. And so?

So, what is still lacking or what can contribute to a larger diffusion of BPS in professional practice? Rather than a conclusive and comprehensive identification, it might be worth suggesting ideas and areas for further investigation by the IBPSA community. Here are some:

- Costs vs benefits: Would a reduction in cost make the use of BPS more intrinsic in design practice? Being simulation a time intensive activity, how could its costs be reduced? Are there other cost items in the desing and building process that could be saved and reinvested in simulation? To what extent the revenues from the simulation results or the model itself could compensate for these higher costs?
- Is there scope to improve the relationship between tool vendors and tool users through CPD, in-house support workshops and summer schools, for example? And could this be extended to educational institutions?
- Integration and adaptation of simulation tools with/during the design and operation phase: it is a priority to address the detail/accuracy paradox and to use only the level of detail strictly necessary, as increasing the number of uncertain parameters does not necessarily improve accuracy, rather it may do the increase uncertainty. That said, performance evaluation to conduct comparative assessments in the early design phase does not require accuracy in absolute terms. Synthetic/lumped parameters may be used instead of more detailed description, yielding useful results. However, it should be remembered that lower-level models may need to be easy to scale up or refined in a seamless way.
- Different business models/Innovation of building design and operation processes: is it

enough to move from a linear to an iterative model, or is it necessary to proceed further towards a multi-directional/integrated approach? Based on this perspective, all design team professionals may be called upon to contribute to the definition of the optimal design or to the revision of it. Efficient data interchange is key to enabling the iterative approaches that require to be implemented. Nevertheless, even through multiple iterations, the whole process remains mostly linear if the decision-making is not open to a more shared approach to participation. This begs the question, to what extent can BIM promote a change of paradigm in which professional competences are contributing in a multidirectional/integrated way? How could the synergy between BIM and BPS reduce the scale or the complexity of the projects to which BPS is actually contributing? And, finally, will the inclusion of BPS in the loop change how buildings are designed or will it still remain an accurate and sophisticated way to calculate some performance metrics and inform the final decision?

- Different interpretations/understanding of the value of simulation: is the objective to produce simulation results only, or is there additional value in the model itself? In other words, once the process is over, the model is among the outcomes, and if we recognise the value in this, could the building model be used to make the overall effort more profitable? Is there a way to maximize the benefits from this?

Extension of the number of beneficiary users: not only can BIM aggregate the contributions from different professionals but also provide contributions to multiple users/uses. Extending the horizon of BPS to wider use of resources, including information models, may increase the convenience and therefore the attraction of investing in the development of BPS models. The current trend from BIM to Digital Twins may suggest that a circularity is possible for information models as well as for physical resources.

- Education: simulation as virtual Problem Based Learning (PBL) environment. An overlooked value of simulation is the role it can play in educating new generations of professionals. If PBL is gaining the limelight in the discussion about effective educational approaches, there are areas like Building Physics in which the temporal and spatial scale of the object of interest cannot fully be explored and experienced directly. Providing a deeper understanding of the inner processes occurring within the different subsystems and components of a building, offering a tangible way to check the effects of design choices or configurations will drastically enhance the competence of the professionals who are called to develop and manage more and more challenging solutions to trade-off between extreme performance requisites in the context of complex and contrasting objectives (Beausoleil-Morrison, 2021).

# 7. Conclusion

The adoption of Building Performance Simulation (BPS) in professional practice presents significant opportunities for improving the design and performance of the built environment. However, several barriers must be addressed to realize its full potential. These include the complexity of simulation tools, the need for specialist knowledge, the lack of a consolidated design integration approach and possibly the business model and value chain in the construction sector. To overcome these challenges, it is essential to integrate further BPS into the design process, provide adequate training and support for practitioners, and develop userfriendly interfaces that facilitate the use of simulation tools. However, fostering a collaborative approach among design professionals also by promoting the use of BPS in educational institutions, and changing the rules of the game are needet to fill the gap between BPS popularity in research and starvation in practice. By addressing these issues from a cultural perspective, BPS can play a crucial role in achieving sustainable development goals and reducing the environmental impact of the built environment.

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