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 expected 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

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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 (T_{in} in Fig. 2). However, in underfloor heating systems, the thermal contribution is applied to the innermost thermal node of the floor ($T_{f,in,ap}$ in Fig. 2) representing the inner layers from the tubes (Mugnini et al., 2021).

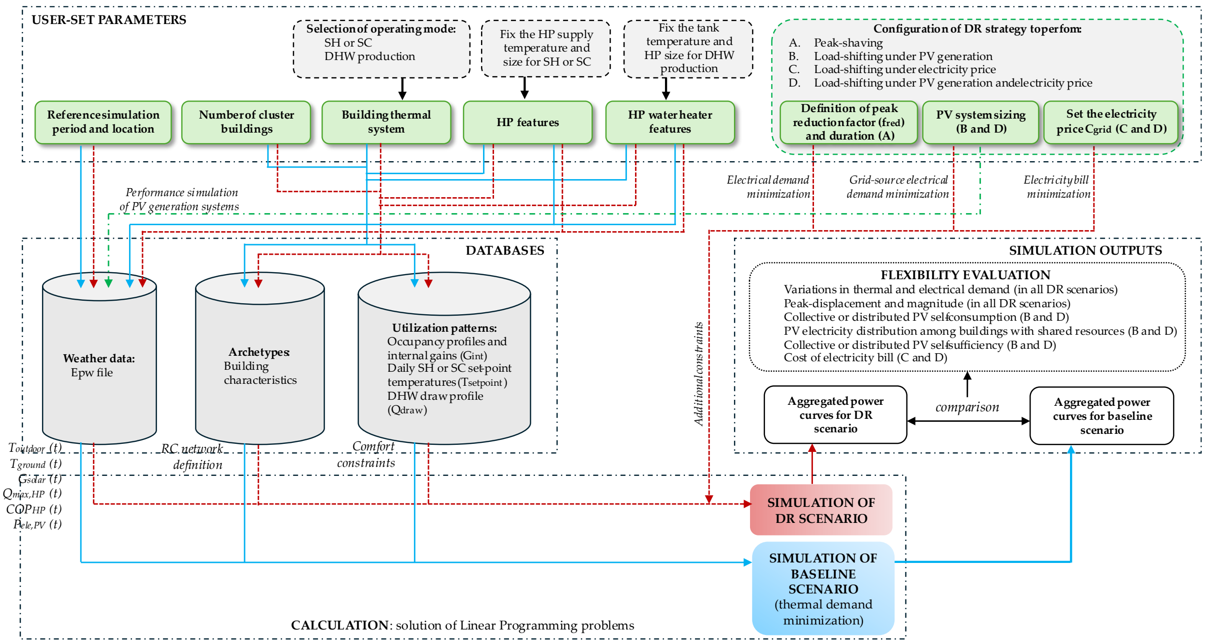

Fig. 1 - Schematic of ClustEnergy OpTool operation

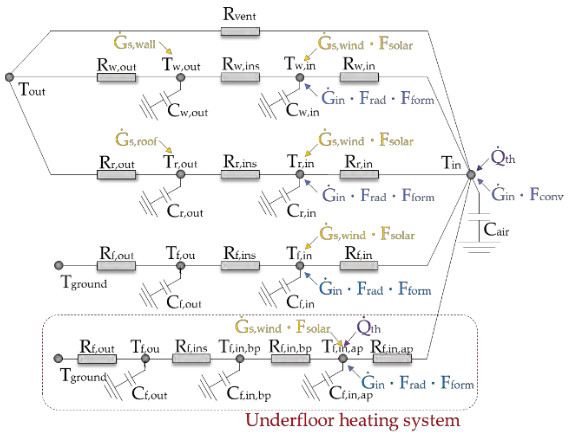

Fig. 2 – RC network model of a thermally insulated building with air emission system (Q_{th} applied to the indoor air thermal node) and underfloor heating system (Q_{th} applied to the to the innermost thermal node of the floor)

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:

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

Subject to the following constraints and bounds:

$$\forall t:\ T_{in}(t) \le T_{setpoint}(t) + \Delta T_{upper} \qquad (2)$$

$$\forall t:\ T_{in}(t) \ge T_{setpoint}(t) - \Delta T_{lower} \qquad (3)$$

$$\forall t:\ 0 \le\ Q_{th}(t) \le\ Q_{th,max}(t) \qquad (4)$$

Where $T_{setpoint}$ represents the user-set temperature in the thermostat. ΔT_{upper} and ΔT_{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:

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

where COP_{th} represents the Coefficient of Performance (COP) 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 (Q_{draw}) 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., Q_{tank}), directly supplied to the thermal node of the water tank (e.g., T_{tank}), 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:

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

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_{tank}) provided by the user (Eq. 10).

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

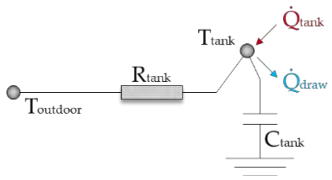

Fig. 3 – RC network model of a heat pump water heater

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

U-value ($Wm^{-2}K^{-1}$)	Area (m^2)	Volume (m^3)	Capacity (kW)	COP
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 pvlib (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 ($P_{ele,th,BL}$ and $P_{ele,tank,BL}$ 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 load-shifting 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 (f_{limit}). 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:

$$\forall b: 0 \leq \sum_b^N Cost_b \leq (P_{ele,b} - u_{PV,b} \cdot P_{gen,PV}) \cdot \mathrm{C}_{\mathrm{grid}} \quad (11)$$

where N is the number of buildings composing the cluster and u_{PV} is the utilization factor of centralized PV generation. C_{grid} 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:

$$\forall b: \sum_b^N u_{PV,b} \leq 1 \quad (12)$$

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 f_{limit}).

Table 2 – Number of archetypes composing the reference cluster and related HP characteristics referring to an ambient temperature of 35 °C and a supply temperature of 18 °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).

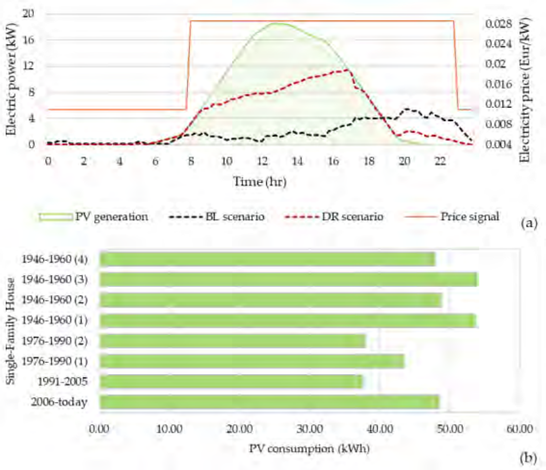

Fig. 4 – (a) Aggregate electric power trends for SC and DHW production during baseline and DR scenarios and (b) distribution of PV electricity among cluster buildings during DR scenario

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 decision-making 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).

References

Abd Alla, S., Bianco, V., Scarpa, F. and Tagliafico, L. A., Electrification of the Residential Heat Demand: An Analysis of the Power Market Potential to Accommodate Heat Pumps, *Thermal Science and Engineering Progress*, vol. 27, p. 101173, accessed August 27, 2023, January 1, 2022. https://doi.org/10.1016/J.TSEP.2021.101173

Arteconi, A. and Polonara, F., Assessing the Demand Side Management Potential and the Energy Flexibility of Heat Pumps in Buildings, *Energies*, vol. **11**, no. 7, p. 1846, July 14, 2018. https://doi.org/10.3390/en11071846

ASHRAE, Standard 140-2017 - Standard Method of Test for the Evaluation of Building Energy Analysis Computer Programs, 2020.

Awan, M. B., Sun, Y., Lin, W. and Ma, Z., A Framework to Formulate and Aggregate Performance Indicators to Quantify Building Energy Flexibility, *Applied Energy*, vol. 349, p. 121590, November 2023. https://doi.org/10.1016/j.apenergy.2023.121590

Boa Morte, I. B., Araújo, O. de Q. F., Morgado, C. R. V. and Medeiros, J. L. de, Electrification and Decarbonization: A Critical Review of Interconnected Sectors, Policies, and Sustainable Development Goals, *Energy Storage and Saving*, vol. **2**, no. 4, pp. 615–30, December 2023. https://doi.org/10.1016/j.enss.2023.08.004

Corrado, V., Ballarini, I., and Corgnati, S. P., National Scientific Report on the TABULA Activities in Italy, 2012.

DL, Attuazione Della Direttiva (UE) 2018/2001 Del Parlamento Europeo e Del Consiglio, Dell'11 Dicembre, Sulla Promozione Dell'uso Dell'energia Da Fonti Rinnovabili, 2021.

Enel, Enel Flex , 2024.

Ercoli, P., Mugnini, A., Caresana, F., and Arteconi, A., Flexible Heat Pumps in Clusters of Buildings: Energy Flexibility Quantification of Space Cooling Loads, *Proceedings of the 26th IIR International Congress of Refrigeration: Paris*, 2023.

Ercoli, P., Mugnini, A., Polonara, F., and Arteconi, A., Flexible Cooling Demand in Cluster of Buildings: Energy Flexibility Quantification in Presence of Central or Distributed Photovoltaic Generation, 2023.

F. Holmgren, W., W. Hansen, C. and A. Mikofski, M., Pvlib Python: A Python Package for Modeling Solar Energy Systems, *Journal of Open Source Software*, vol. **3**, no. 29, p. 884, September 7, 2018.https://doi.org/10.21105/joss.00884

IEA, Key World Energy Statistics 2021, Paris, 2021.

Mugnini, A., Ercoli, P., and Arteconi, A., ClustEnergy OpTool, 2024. Online: https://github.com/diismunivpm/ClustEnergy_OpTool

Mugnini, A., Polonara, F., and Arteconi, A., Energy Flexibility of Clusters of Buildings: Development of an Assessment Tool, 2021.

Python, Python, 1991.

Richardson, I., Thomson, M. and Infield, D., A High-Resolution Domestic Building Occupancy Model for Energy Demand Simulations, *Energy and Buildings*, 2008. https://doi.org/10.1016/j.enbuild.2008.02.006

RWTH-EBC, Districtgenerator, 2022.

RWTH-EBC, Richarsonpy, 2017.

UNI, UNI EN 15316-3-1:2008, Impianti Di Riscaldamento Degli Edifici - Metodo per Il Calcolo Dei Requisiti Energetici e Dei Rendimenti Dell'impianto - Parte 3-1, 2008.

Vigna, I., Pernetti, R., Pasut, W. and Lollini, R., New Domain for Promoting Energy Efficiency: Energy Flexible Building Cluster, *Sustainable Cities and Society*, vol. **38**, pp. 526–33, April 1, 2018. https://doi.org/10.1016/j.scs.2018.01.038

Wang, A., Li, R. and You, S., Development of a Data Driven Approach to Explore the Energy Flexibility Potential of Building Clusters, *Applied Energy*, vol. 232, pp. 89–100, December 2018. https://doi.org/10.1016/j.apenergy.2018.09.187