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

Jacopo Vivian – University of Padua, Italy – jacopo.vivian@unipd.it
Enrico Prataviera – University of Padua, Italy – enrico.prataviera@unipd.it
Gianmarco Bano – University of Padua, Italy – gianmarco.bano@studenti.unipd.it
Angelo Zarrella – University of Padua, Italy – angelo.zarrella@unipd.it

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 CO_2 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 CO_2 emissions.

Part of
Pernigotto, G., Ballarini, I., Patuzzi, F., Prada, A., Corrado, V., & Gasparella, A. (Eds.). 2025. Building simulation applications BSA 2024. bu,press.
https://doi.org/10.13124/9788860462022

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).

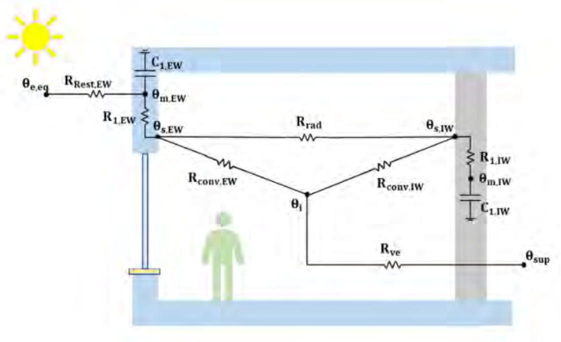

Fig. 1 - Representation of the equivalent electrical circuit of the 7R2C model proposed by VDI 6007

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 and 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 - 1.25 for 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.

$$\mathrm{CV_{RMSE}} = \sqrt{\textstyle\sum_{i=1}^{n} e_i^{\,2}/n}\,/\mu \quad (1)$$

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

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 μ 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_2 emissions. The study considered an emission factor of 0.260 kg/kWh for the electricity consumed and 1.983 kg/Nm^3 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).

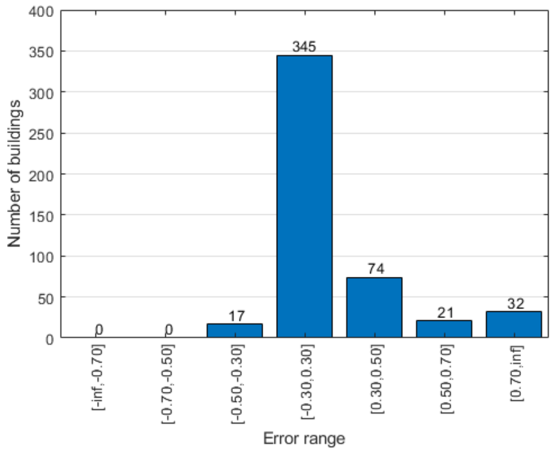

Fig. 3 – Distribution of the errors in the annual gas consumption before model calibration

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.

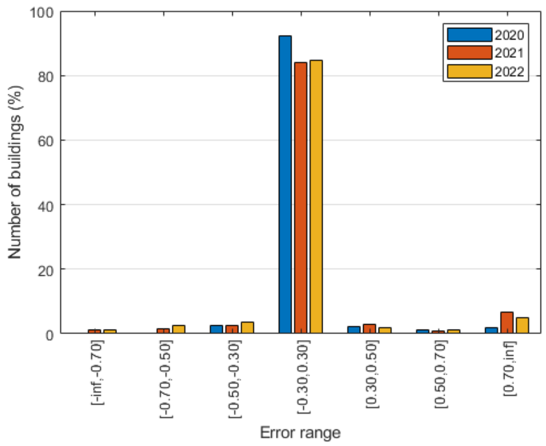

Fig. 4 - Distribution of the errors in the annual gas consumption after model calibration

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.

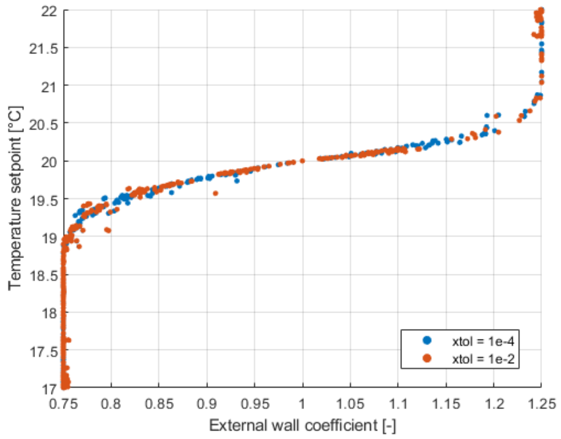

Fig. 5 – Calibrated parameters with different exit criteria

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_{MAE}	CV_{RMSE}	Comp. time (min)
10^{-4}	19.0%	46.1%	209.1
10^{-3}	19.0%	46.1%	181.7
10^{-2}	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^{-4}). 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_{MAE} 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.

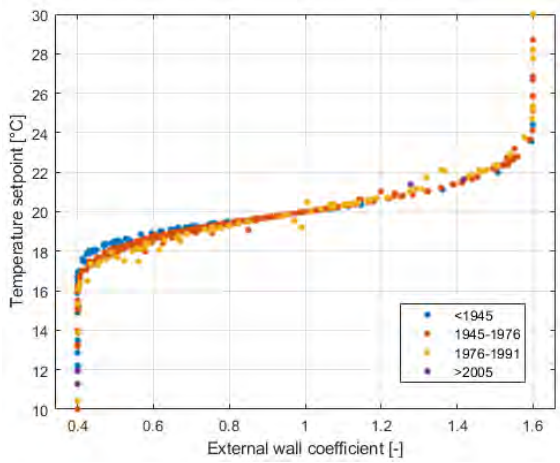

Fig. 6 – Calibrated parameters on extended domain

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_2 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_2 emissions) and on the right axis (CO_2 emissions compared to the total). The orange and green lines represent the effect of the corresponding building renovation scenarios on the overall CO_2 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 CO_2 emissions (i.e. 60% of CO_2 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_2 emissions reduction that can be achieved by Scenario 2 is higher than that of Scenario 1: if all buildings underwent renovation, CO_2 emissions would be 47.1% of today's emissions in Scenario 1 and only 21.2% in Scenario 2.

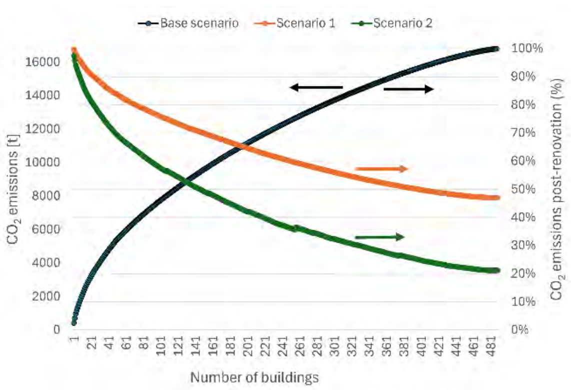

Fig. 7 – Decarbonization chart for different renovation scenarios

6. 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 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 CO_2 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.

Acknowledgement

The authors would like to thank ANACI Padova and the technical Institute G.B. Belzoni for providing the initial dataset. The authors are particularly grateful to Giorgio Cambruzzi (ANACI Padova) for his commitment.

References

Branch, M.A., Coleman, T.F. and Li Y. 1999. "A Subspace, Interior, and Conjugate Gradient Method for Large-Scale Bound-Constrained Minimization Problems." *SIAM Journal on Scientific Computing* 21 (1): 1–23. https://doi.org/10.1137/S1064827595289108

Cerezo Davila, C., Reinhart, C.F., and Bemis, J.L. 2016. "Modeling Boston: A Workflow for the Efficient Generation and Maintenance of Urban Building Energy Models from Existing Geospatial Datasets." *Energy* 117 (December):237–50. https://doi.org/10.1016/j.energy.2016.10.057

Chen, Y., Deng, Z., and Hong, T. 2020. "Automatic and Rapid Calibration of Urban Building Energy Models by Learning from Energy Performance Database." *Applied Energy* 277 (November):115584. https://doi.org/10.1016/j.apenergy.2020.115584

Dilsiz, A. D., Ng, K., Kämpf, J., and Nagy, Z. 2023. "Ranking Parameters in Urban Energy Models for Various Building Forms and Climates Using Sensitivity Analysis." *Building Simulation* 16 (9): 1587–1600. https://doi.org/10.1007/s12273-022-0961-5

Dilsiz, A. D., Nweye, K.E., Wu, A.J., Kämpf, J., Biljecki, F., and Nagy, Z.. 2023. "How Spatio-Temporal Resolution Impacts Urban Energy Calibration." *Energy and Buildings* 292 (August):113175. https://doi.org/10.1016/j.enbuild.2023.113175

D.P.R. n. 412. 1993. https://www.gazzettaufficiale.it/eli/id/1993/10/14/093G0451/sg

European Commission. Joint Research Centre. 2021. *Urban PM2.5 Atlas: Air Quality in European Cities: 2021 Report*. LU: Publications Office. https://data.europa.eu/doi/10.2760/356670

European Committee for Standardization. 2019. *EN 16798-1: Energy Performance of Buildings - Ventilation for Buildings. Part 1: Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings Addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics - Module M1-6*

European Environment Agency and European Environment Agency. 2022. "Urban Atlas Building Height 2012 (Raster 10 m), Europe - Version 3, Oct. 2022." https://doi.org/10.2909/42690E05-EDF4-43FC-8020-33E130F62023

Peel, M. C., B. L. Finlayson, and T. A. McMahon. 2007. "Updated World Map of the Köppen-Geiger Climate Classification." *Hydrology and Earth System Sciences* 11 (5): 1633–44. https://doi.org/10.5194/hess-11-1633-2007

Prataviera, E., Vivian, J., Lombardo, G., and Zarrella, A. 2022. "Evaluation of the Impact of Input Uncertainty on Urban Building Energy Simulations Using Uncertainty and Sensitivity Analysis." *Applied Energy* 311 (April):118691.

https://doi.org/10.1016/j.apenergy.2022.118691

Sokol, J., Cerezo Davila, C., and C.F. Reinhart. 2017. "Validation of a Bayesian-Based Method for Defining Residential Archetypes in Urban Building Energy Models." *Energy and Buildings* 134 (January):11–24. https://doi.org/10.1016/j.enbuild.2016.10.050

Virtanen, P., Gommers, R., Oliphant, T.E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., et al. 2020. "SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python." *Nature Methods* 17 (3): 261–72. https://doi.org/10.1038/s41592-019-0686-2

Vivian, J., Zarrella, A., Emmi, G., and M. De Carli. 2017. "An Evaluation of the Suitability of Lumped-Capacitance Models in Calculating Energy Needs and Thermal Behaviour of Buildings." *Energy and Buildings* 150 (September):447–65. https://doi.org/10.1016/j.enbuild.2017.06.021

Zarrella, A., Prataviera, E., Romano, P., Carnieletto, L., and J. Vivian. 2020. "Analysis and Application of a Lumped-Capacitance Model for Urban Building Energy Modelling." *Sustainable Cities and Society* 102450. https://doi.org/10.1016/j.scs.2020.102450