Purdue University

Purdue e-Pubs

International High Performance Buildings Conference | School of Mechanical Engineering

2022

District-level validation of a shoeboxing algorithm for Urban Building Energy Modeling

Federico Battini

Giovanni Pernigotto

Andrea Gasparella

Follow this and additional works at: https://docs.lib.purdue.edu/ihpbc

Battini, Federico; Pernigotto, Giovanni; and Gasparella, Andrea, "District-level validation of a shoeboxing algorithm for Urban Building Energy Modeling" (2022). *International High Performance Buildings Conference*. Paper 394.
https://docs.lib.purdue.edu/ihpbc/394

This document has been made available through Purdue e-Pubs, a service of the Purdue University Libraries. Please contact epubs@purdue.edu for additional information.
Complete proceedings may be acquired in print and on CD-ROM directly from the Ray W. Herrick Laboratories at https://engineering.purdue.edu/Herrick/Events/orderlit.html

District-level validation of a shoeboxing algorithm for Urban Building Energy Modeling

Federico BATTINI[1]*, Giovanni PERNIGOTTO[2], Andrea GASPARELLA[3]

[1]Free University of Bozen-Bolzano, Faculty of Science and Technology,
Bolzano, Italy
Tel: +39 0471 017888, Fax: +39 0471 017009, email: federico.battini@natec.unibz.it

[2]Free University of Bozen-Bolzano, Faculty of Science and Technology,
Bolzano, Italy
Tel: +39 0471 017632, Fax: +39 0471 017009, email: giovanni.pernigotto@unibz.it

[3]Free University of Bozen-Bolzano, Faculty of Science and Technology,
Bolzano, Italy
Tel: +39 0471 017200, Fax: +39 0471 017009, email: andrea.gasparella@unibz.it

* Corresponding Author

ABSTRACT

In the framework of Urban Building Energy Modeling, several procedures have been proposed to reduce the computational burden to evaluate the thermal behavior of multiple buildings. In a previous work, we presented a novel simplification algorithm capable of abstracting a randomly-shaped building into a representative shoebox. Differently from most of the approaches available in the literature, the proposed method is supposed to go beyond the preliminary assessment of the buildings' performance in the early design stage or on an annual basis. Indeed, it makes it possible to predict accurately not only the annual or seasonal energy needs but also the hourly thermal load and indoor temperature profiles. In addition to that aspect, the proposed algorithm has been specifically developed to deal with buildings of complex shape and geometry, as they are common in the European building stock, accounting for adjacencies and reciprocal shading effects.
After a first validation step carried out at single-building level, the proposed algorithm has been tested on many fictional parametrically-generated neighborhoods and several climates. In such a way, it has been possible to assess the reliability of the algorithm at city scale, with the goal to understand whether the application at urban level, characterized by multiple mutual interactions among buildings, could undermine its accuracy. Furthermore, the role played by solar radiation modelling in the framework of the shoebox simplification and its impact on the outcome of the algorithm have been discussed, presenting two alternatives with different accuracy levels.
As a whole, the algorithm showed to be effective in estimating hourly and annual thermal loads and indoor temperatures in district-scale simulations, reducing up to 30 times the simulation time for the considered configurations.

1. INTRODUCTION

Urban Building Energy Modelling *UBEM* represents the most recent development of Building Performance Simulation *BPS*. Indeed, the main feature of *UBEM* is the analysis on a larger physical domain, encompassing groups of buildings, districts, or whole cities. Among the methodologies that can be employed to estimate the energy use of buildings at urban scale, *UBEM* is the one having the greatest level of flexibility as it can consider new technologies and different energy efficiency designs (Johari *et al.*, 2020). In this way, it is possible to assess the buildings' energy performance at urban scale to drive energy policies for reducing the greenhouse gas emissions of the building stock.

The increase of the size of the simulation domain, however, brings a series of issues which prevents the application of the very same models and methods used in *BPS* because they would require too much time and information. Furthermore, the interactions among buildings (e.g., heat transfer through adjacent components, mutual radiative exchanges, shadows cast by adjacent building, solar radiation reflections, etc.) make the characterization of the boundary conditions more complex compared to single-building analyses. Combining both aspects, it looks clear that *UBEM* is more computationally demanding compared to traditional *BPS* (Reinhart and Davila, 2015). To cope with that, several approaches have been proposed in the literature to simplify models and simulation domains (Abbasabadi & Ashayeri, 2019). The most interesting methodologies aim at converting the geometrical massing into simplified energy models, rather than the fully detailed traditional model employed in *BEM*.
The first work going in this direction has been proposed by Dogan and Reinhart (2013), who developed an automated workflow to convert architectural massing models into sets of thermal shoebox models. Such procedure is known as Shoeboxer algorithm (Dogan and Reinhart, 2017) and it is employed in the urban modeling interface *umi* (Reinhart *et al.*, 2013) to estimate the thermal performance of the buildings in the model. Starting from the tridimensional massing model, the Shoeboxer computes the incident solar radiation on the envelope of each building and performs a clustering analysis to find the regions experiencing similar solar loads. For each cluster a shoebox thermal zone is created and placed in correspondence of the point on the façade whose radiation value is closest to the cluster's mean. For each shoebox, only the visible external shading surfaces are included into the thermal model. To obtain the overall building demand, the results of every shoebox are aggregated and weighed according to the related cluster area.
Later, Zhu *et al*. (2019) developed a new method called Building Blocks Energy Estimation *BBEE* based on the typical shoebox zone concept proposed by the Shoeboxer. The *BBEE* is built on top of the hypothesis that the energy needs of a building is close to the sum of each part of it. More specifically, the *BBEE* method consists in the *BBEE* algorithm which is coupled with an energy database of typical zones. Thus, the *BBEE* method employs the *BBEE* algorithm to transform complex building forms into an assembly of typical zones, coded according to their properties. Finally, instead of performing energy simulations, the method relies on the database to retrieve the energy use of each typical zone and sums them up to get to the final building's needs.
More recently, İşeri and Dino (2020) proposed another method that reorganizes the building geometries with functional clustering and radiation analysis scaling. At first, an adapted version of the solar radiation analysis performed in the Shoeboxer is implemented to group the buildings' units according to the radiation values on the envelope. Afterwards, the clustered units are further subdivided depending on their position in the building, i.e., ground, middle and top floor, and their space conditioning.
Finally, Zhu, *et al*. (2021) proposed a hybrid metamodel-based method to be used in the early design stage to find high-performance building forms. The method subdivides the building into several zones as metamodels and estimates the total energy needs by summing up the results of all metamodels. Differently from other metamodels, it accounts for the surrounding shading and reflection effects by using the received solar radiation values as inputs. Moreover, GPU acceleration technology is used to speed up the radiation calculation, and the accuracy of the metamodels is improved by implementing a machine learning algorithm screening framework.
The aforementioned methodologies showed how it is possible to introduce simplifications in *UBEM* to reduce the computational time of the simulation. Nonetheless, there is still room for improvement, especially for what regards the spatial and temporal resolution of the outcome, e.g., properly predicting hourly temperature profiles permits to perform thermal comfort evaluations at urban scale. Indeed, given that *UBEM* is a relatively new field of research, a well-established approach to optimize its computational efficiency has still to be found (Hong *et al*., 2019).
In a previous work, the authors presented a novel simplification algorithm capable of abstracting a randomly shaped building into a representative shoebox with a thermal zone per floor (Battini *et al*., 2021a). Differently from most of the approaches available in the literature, the proposed method has been development not only for the assessment of the buildings' performance in the early design stages or on an annual basis. Indeed, it makes it possible to accurately predict not only the annual or seasonal energy needs but also the hourly thermal loads and indoor temperature profiles. Even though the algorithm has been already validated for stand-alone buildings, it has been designed to be employed for urban level simulations. Therefore, in this work, the approach has been tested on many neighborhoods' configurations and several climates to assess its reliability at city scale.

2. METHODOLOGY

The methodology for assessing the performance of the proposed shoeboxing algorithm at urban scale consists of three parts: (i) overview on the simplification procedure, (ii) development of a set of fictional districts for testing, and (iii) simulation and comparison.

2.1 Shoeboxing algorithm

In this work, two workflows have been followed to perform the simplification. At first, the standard procedure accounting for the self and context shadings by means of an annual radiation analysis has been followed. Then, an improved and more detailed approach capable of accounting for the obstructions on a monthly basis has been pursued. The two procedures are presented in the following.

2.1.1 Basic shoeboxing algorithm description: A detailed description of the workflow employed to develop the algorithm can be found in a previous work by the authors (Battini *et al.*, 2021a). Nonetheless, the steps to take in order to employ the approach for simplifying buildings into representative shoeboxes can be summarized as follows:

1. *Shoebox generation*: starting from the three-dimensional building massing, three geometrical indicators able to meaningfully represent the building are computed. A system of three equations in three unknowns (i.e., the three indicators and the three shoebox dimensions) is solved to obtain the simplified model's dimensions prior performing the simulation. The representative shoebox is generated according to the dimensions found and it is characterized by the same window-to-wall ratio and floor height as the starting building. Also, the thermophysical properties are assigned accordingly.
2. *Contextual- and self-shading incorporation*: to account for the reduced amount of incoming solar radiation due to the building's self-shadings and surroundings also in the simplified model, a portion of the windows is substituted by an opaque surface characterized by the same thermal transmittance of the window. To properly size the shading surfaces, a direct radiation analysis is performed on both the starting geometry and the resulting shoebox according to the all-weather Perez sky model. For sake of simplicity, only window surfaces are considered for the detailed massing while the entire geometry is considered for the shoebox. The average annual beam radiation is computed for every orientation and floor, and the equivalent obstruction ratios obtained. For every window of the simplified model, the opaque area is calculated from the corresponding obstruction ratio. The opaque surfaces are modelled as elements having the same base of the window, while the height is calculated to match the equivalent area previously found.
3. *Adjacent buildings inclusion*: building adjacencies are treated as adiabatic surfaces. The presence of adjacencies is checked for each floor and orientation, and adiabatic ratios are computed. Adiabatic ratios can range between 0 and 1, i.e., surfaces can be totally exposed to the external environment or be completely adiabatic. As for windows, the adiabatic areas of the shoebox's surfaces are computed from the adiabatic ratios. Adiabatic surfaces have the same height of the parent surface and the base length calculated to match the equivalent area obtained.

For both obstructions and adjacencies, since a shoebox can have only four vertical surfaces, the orientation of the façades of the starting building are considered with a ± 45° tolerance range in order to aggregate walls with similar orientations. Windows and their corresponding obstruction surfaces are only applied to non-adiabatic façades.
The shoeboxing algorithm has been developed employing Rhinoceros as CAD tool, its plug-in Grasshopper, and EnergyPlus as *BPS* engine. More specifically, customized Grasshopper components written in Python programming language have been utilized. RhinoCommon API (Robert McNell & Associates, 2021) has been used for the geometrical modeling and Ladybug Tools core SDK (Ladybug Tools LLC, 2021) to perform the radiation analysis and the conversion into thermal models. Figure 1 shows an example of shoeboxes with the related boundary conditions.

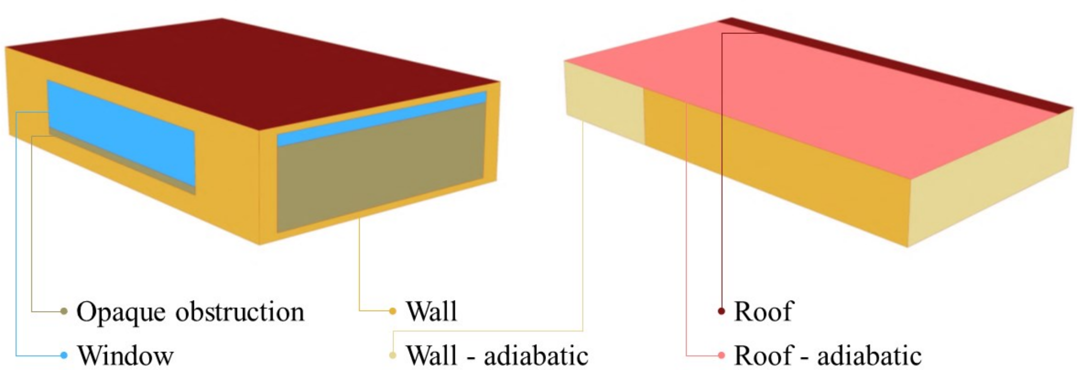


Figure 1: Example of shoeboxes

2.1.2 Improved and more detailed shoeboxing procedure: In a previous work by the authors (Battini *et al.*, 2021b), it has been proven that buildings' geometrical details and context have a greater impact on the cooling needs than on the heating ones. In order to improve the prediction accuracy of the shoebox models, especially for what regards the cooling demand, a different approach has been tested to size the opaque elements obstructing solar radiation on windows. The second step of the basic workflow has been adapted to account for the global radiation instead of the direct one; then, monthly solar radiation analyses have been employed instead of an annual one. To accomplish this step, the radiation analysis has been performed using EnergyPlus for consistently sizing the shoebox's obstructing surfaces by employing the same modeling tool as for the simulation. Differently from the basic procedure in which the radiation analysis and energy simulation have been carried out with two different engines.

To complete the process, in both workflows detailed (i.e., the starting building) and simplified (i.e., the resulting shoebox) models are automatically exported as .idf files and prepared for the simulation by means of Python scripts with the aid of the library Eppy (Philip, 2020), a scripting language for EnergyPlus input and output files. Both detailed and simplified models have one thermal zone for each floor. Nonetheless, the zoning discretization is not a built-in feature of the algorithm, thus it can be changed if needed. For what regards the second procedure, since each month has a specific set of obstruction ratios, 12 different simplified .idf files, differentiated by the size of the obstructing surfaces, are generated. This is necessary due to a limitation of EnergyPlus which does not accept to schedule variable values for this feature. Then, to properly compare the outputs of the simplified models with those of the detailed ones and save computing time, the simulations of the shoebox models are performed just for the month of interest starting one week before the first day of the month, in order to avoid the initial conditions to lead to misleading results.

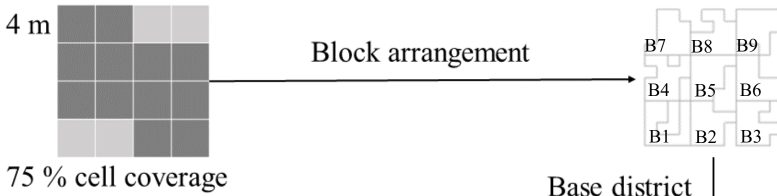
2.1 Districts for testing

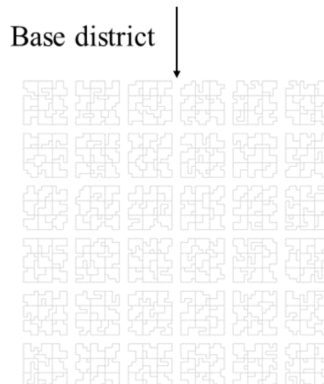
Testing the algorithm at the urban scale aims to explore as much as possible the space of the solutions for the shoeboxes. Therefore, it has been decided to create fictional districts to assess the capabilities of the procedure. A literature review has been performed to find workflows capable of creating from scratch neighborhoods of complex and different building shapes.

Lyu *et al.* (2019) developed nine Local Climate Zone models to find a correlation between sky view factor and microclimate. The models have the same simulation area and represent typical districts of the considered case study. Natanian *et al.* (2019) created an automated workflow for performance-driven urban design to evaluate the performance of both building and urban design parameters of residential and office buildings. Pomponi *el al.* (2021) analyzed the life cycle greenhouse gas emissions of cities decoupling density from tallness. They collected several inputs for real-world neighborhoods to create synthetic urban environments. Trepci *et al.* (2021) systematically evaluated the impact of the urban surroundings on the energy performance of buildings in a hot climate environment by applying different contexts to base case models changing the context's distance and height, as well as the model orientation. Shi *et al.* (2021), with the aim of investigating interactions between solar energy use and urban design, developed the Urban Block Generator to parametrically model typical vernacular block typologies featuring various combinations of block dimensions, building patterns, floor area ratios, and site coverage. In the mentioned studies, even though several metrics have been used to build up the districts, buildings have simple or repetitive shapes and have mainly rectangular footprints. Moreover, individual buildings or building blocks are repeated to obtain generate neighborhoods.

Since the target of this work are complex shaped buildings, a more viable solution is the Building Modular Cell *BMC* technique introduced by Javanroodi *et al.* (2018) to generate buildings based on a cuboid module according to a series of form generation rules. The *BMC* has already been used to enhance the energy efficacy of high-rise building in urban areas (Javanroodi *et al.*, 2019) and to develop the Urban Cell concept (Perera *et al.*, 2021), creating neighborhoods based on realistic morphological parameters. To create buildings, the *BMC* uses a 4x4 grid of cells along with a coverage indicator and two basic decision constrains: (a) the selected cells must be connected from their sides only (no corners), and (b) only one shape must be obtained from the grid (two or more separate footprints from one grid are not allowed).

In this study, a base district similar to the Urban Cell has been created and then modified as parametrically as possible to explore a wider space of the solutions. The district is a 6x6 grid of blocks composed by 9 buildings each, resulting in 324 buildings. Buildings' blocks are separated by fictional streets with the same width for the entire district. The buildings' footprints have been generated by adapting the *BMC* technique using a 4x4 cells grid having 4 m as side length for each cell and employing a cell coverage ratio of 75 %, in order to ensure touching buildings in each block. The variables that have been parametrically edited to create the batch of districts for the test of the algorithm are the buildings' height and scale, and the street's width.





Variables	
Buildings' height	1, 2, 3 and 4 floors
Street width	10, 20, 30 and 40 meters
Buildings' scale	1, 2, 3, and 4
Climate	Bolzano, Denver, Messina
Combinations	
324 buildings per 64 district	
20736 building to simulate for each climate	

Figure 2: Base district generation process, district variables and combinations

Changing the three variables, it is possible to move from a very dense urban setting with small buildings to a less dense one with large massings, allowing to properly evaluate which are the algorithm's strength and weaknesses for different urban layouts. In each model, buildings have the same height and they can be 1, 2, 3 or 4 floors tall, given a floor height of 3 m. Moreover, buildings have been scaled by a factor equal to 1, 2, 3 or 4. Finally, the street's width have been set equal to 10, 20, 30, or 40 meters. Combing all variables leads to 64 districts to be simulated, thus 20 736 buildings in total. The district generation process, a visualization of the base district's buildings footprints and the variables' ranges coupled with the resulting combinations are reported in Figure 2.

2.1 Simulation and comparison

The 64 districts have been simulated in the three climates of Bolzano and Messina, Italy, and Denver, U.S. Bolzano and Messina have been chosen to have both heating- and cooling-dominated climates respectively, while Denver has been selected since it is usually employed for validating *BPS* tools, and it is characterized by large daily temperature variations. Detailed and simplified models according to the shoeboxing algorithm have been simulated for every district in each climate.

As regards detailed models, in order to consider only the part of the district relevant for each building, the surrounding context has been taken into account up to a distance equal to the length of the blocks' diagonal. All models have been characterized by the same energy-related properties, as in the previous work on stand-alone buildings (Battini *et al*, 2021a).

The outputs of detailed and simplified models have been compared to assess the algorithm performance. Even though both temperature and energy needs differences have been evaluated, in this paper, the comparison has been carried out only for what regards the energy demand to properly discuss the procedure's goodness and reliability at building level. Thus, the energy needs have been analyzed at annual and hourly scale. Annually, absolute and relative differences between detailed and shoebox models have been calculated, while the Root Mean Square Error *RMSE* has been employed to assess the performance at hourly scale.

3. RESULTS AND DISCUSSION

3.1 Overview

The energy needs differences between detailed and simplified models are presented as boxplots for all three climates, given the large amount of data analyzed. At first, the results from the standard shoeboxing procedure with one fixed opaque obstructing surface are presented. Then, the outcome for the improved configuration with monthly opaque shadings is reported. For both methodologies, the introduction of the shoeboxing algorithm has reduced the energy simulation time from 10 to almost 30 times depending on the district, regardless of the differences between the models. In this way, it has been possible to reduce the time required to simulate a district from several hours to tens of minutes in the worst case.

3.2 Basic simplification results

The comparison of energy needs has been performed for all 64 districts simulated in the three climates of Bolzano, Denver and Messina. First, the differences have been reported for all simulated buildings without considering individual districts, buildings or blocks. Then, the analysis has increased the level of detail to identify the conditions leading to the poorest predictions.

Figure 3 shows the relative annual differences for all buildings in all districts for the three considered climates. Overall, the heating demand is the better predicted output yielding results within ±20 % in all three climates neglecting outliers (defined as the points lying outside 1.5 times the interquartile range past the low and high quartiles), and, thus, its accuracy of this kind of simplification can be considered acceptable. Moreover, heating boxplots are often narrower, meaning that the prediction is consistent for all buildings. On the other hand, the cooling demand experiences larger deviations. For all three climates, only half of the buildings are within ±20 % deviation. Nonetheless, the remaining part of the studied buildings yields much larger differences, even ±100 %. The considerations related to the annual differences can be extended to the hourly deviations reported in Figure 4 by the *RMSEs*. Indeed, the *RMSEs* for the heating demand are much lower compared to the ones of the cooling demand.

In Figure 5 and Figure 6 the relative annual differences and *RMSEs* have been grouped by building position in the blocks for a sample district. From the obtained boxplots, it is clear that their position in a block does not influence the deviations in the three climates. The same process has been followed to check the influence of the blocks' position in the district obtaining the same outcome.

From this first comparison, the basic configuration of the shoeboxing algorithm shows to be reliable enough when employed for assessing the heating demand, regardless the considered climate. However, it is still not able to ensure high accuracy when adopted for the cooling needs estimation in all the possible cases. To understand which are the conditions in which the accuracy of the procedure drops, a more in-depth analysis has been performed to check the variables employed in generating the districts leading to the poorest predictions.

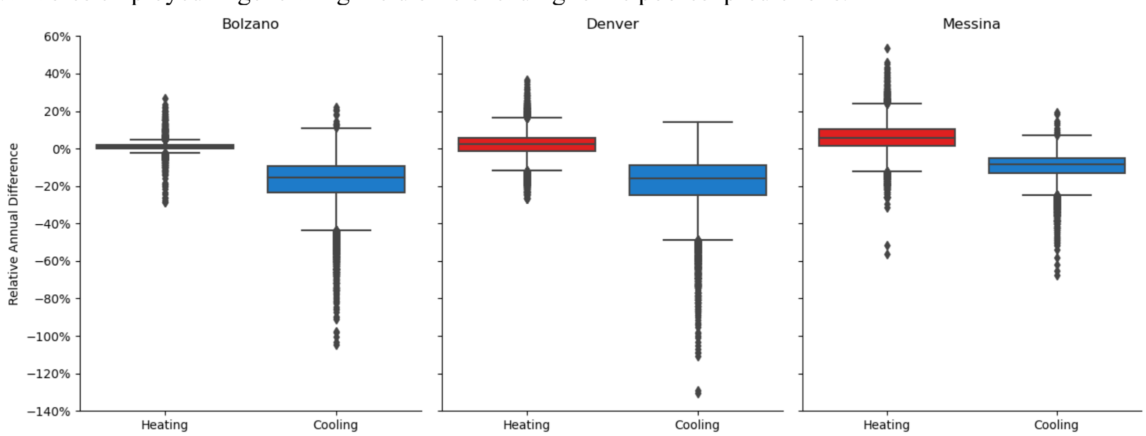


Figure 3: Boxplots reporting annual heating and cooling needs relative differences for all buildings in all districts in the three climates

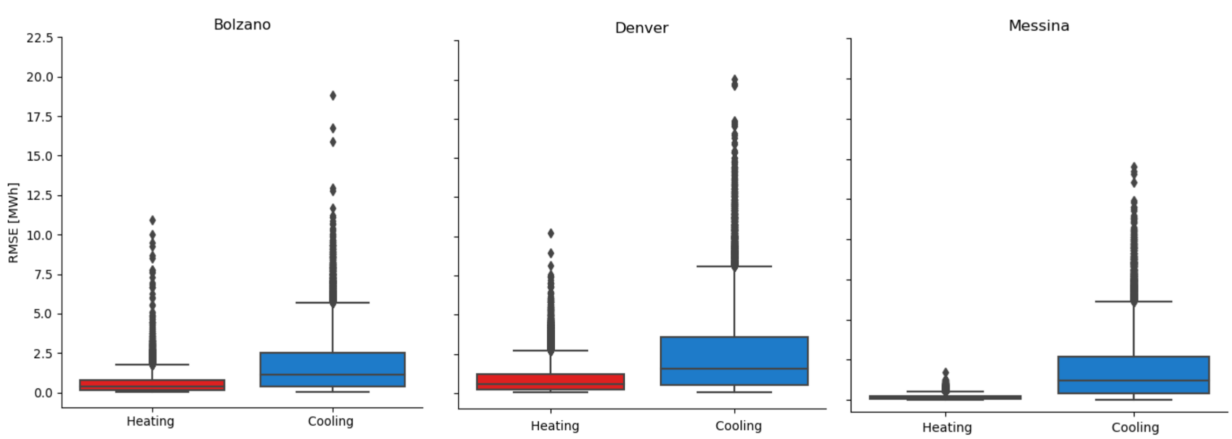


Figure 4: Boxplots reporting hourly heating and cooling *RMSEs* for all buildings in all districts in the three climates

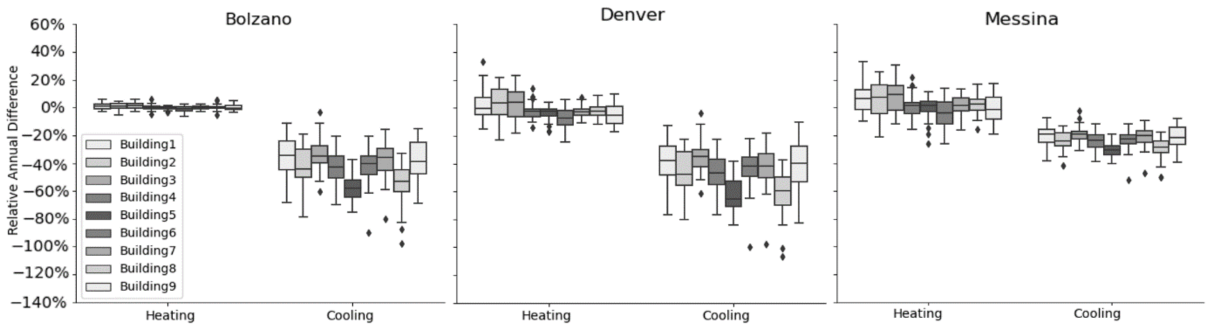


Figure 5: Relative annual differences in the three climates for the district with buildings of 4 floors, scaled by a factor of 1, and with a street width of 10 m

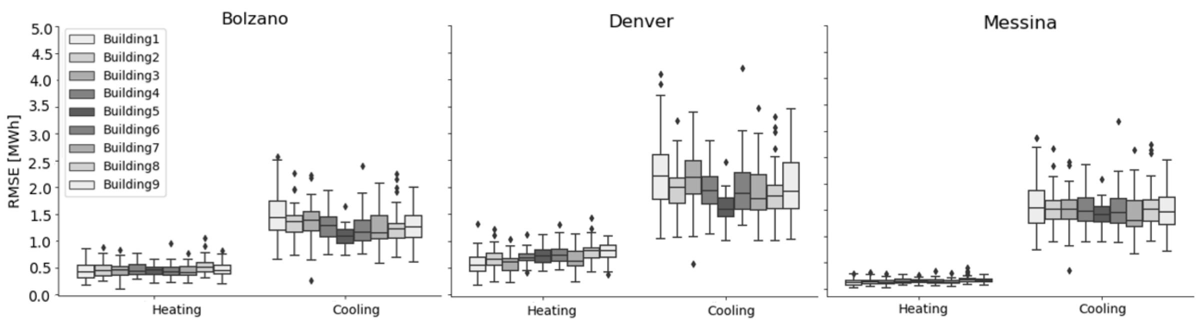


Figure 6: *RMSEs* in the three climates for the district with buildings of 4 floors, scaled by a factor of 1, and with a street width of 10 m

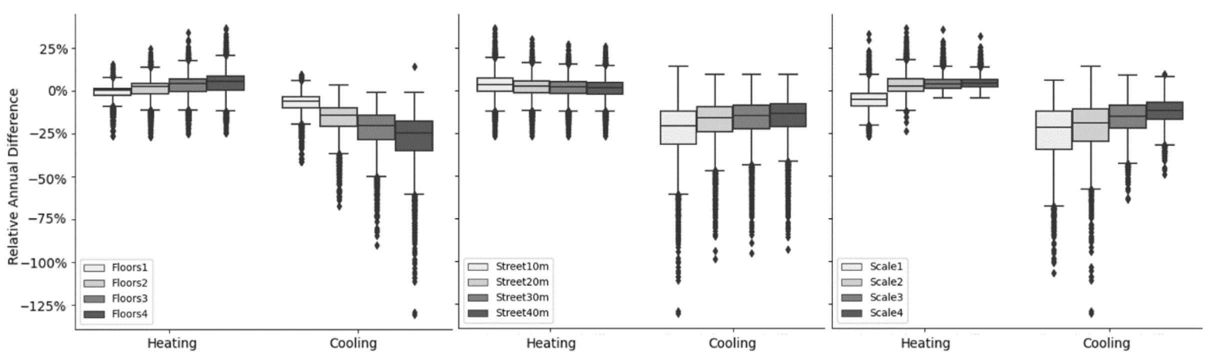


Figure 7: Relative annual differences boxplots for all districts in the climate of Denver, with buildings' deviations grouped according to the building height, street width and building scale

Specifically, the results of annual relative differences have been grouped according to the three variables utilized to create the districts: buildings' scale and height, and street width. The results are consistent in all the three climates and, as an example, the boxplots for the climate of Denver are reported in Figure 7. From Figure 7 it is possible to see that the largest differences occur for smaller and taller buildings with smaller street widths. Indeed, taller buildings obstruct more the radiation on the lower floor resulting in larger differences. In the same way, smaller street widths lead to a denser urban context shading more radiation on all buildings. Moreover, smaller buildings have poorer predictions because they have a smaller volume, in fact the impact of the solar radiation entering the thermal zone on the air-node heat balance is greater respect to larger ones. Hence, considering all the above, the worst prediction accuracy occurring for the cooling needs seems to be correlated to the modelling of the solar radiation entering into the thermal zones. For this reason, an improved solution accounting for the radiation on a monthly basis has been tested.

3.3 Improved simplification results

To assess the improvements of the shoeboxing algorithm with the new shading configuration, instead of running again all 64 districts, only the two districts yielding the worst overall prediction accuracy have been selected.
Among all districts, the two districts experiencing the poorest predictions have both buildings of 4 floors and a street width of 10 m. As mentioned before, districts with smaller buildings are those with the largest differences (Figure 5 and Figure 6), thus districts with buildings scaled by a factor of 1 and 2 have been selected. These two districts have been simulated in the three climates.
Figure 8 and Figure 9 show the comparison in accuracy prediction between the basic simplification procedure and the improved one for the two districts considered in the three climates. The results show that sizing the obstruction opaque surface monthly remarkably reduces the differences, both annually and hourly. The cooling needs estimation has even become more accurate than the heating one with annual cooling relative differences within ± 20 % for every building in both districts, independently of the considered climate. The cooling *RMSEs* are comparable to the heating ones. In general, the new approach improved the prediction accuracy of the shoeboxing algorithm for all the considered targets, as shown not only by the lower deviations on both hourly and annual basis, but also by the much narrower boxplots. In the basic procedure, the cooling demand was generally underestimated by the shoeboxes, while for the heating demand a clear trend was not detected, with heating needs either over or underestimated. Differently, in the improved approach, while the cooling demand neglecting outliers is generally overestimated, the heating demand predictions are mainly underestimated, and they also show differences larger than 20 %.

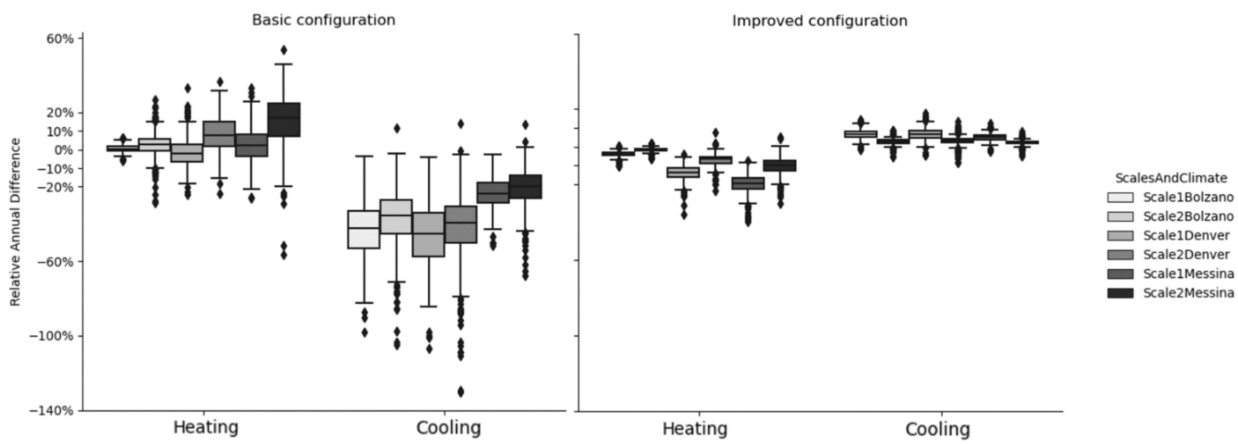


Figure 8: Relative annual differences comparison for the two districts considered in the three climates between the basic algorithm configuration and the improved one

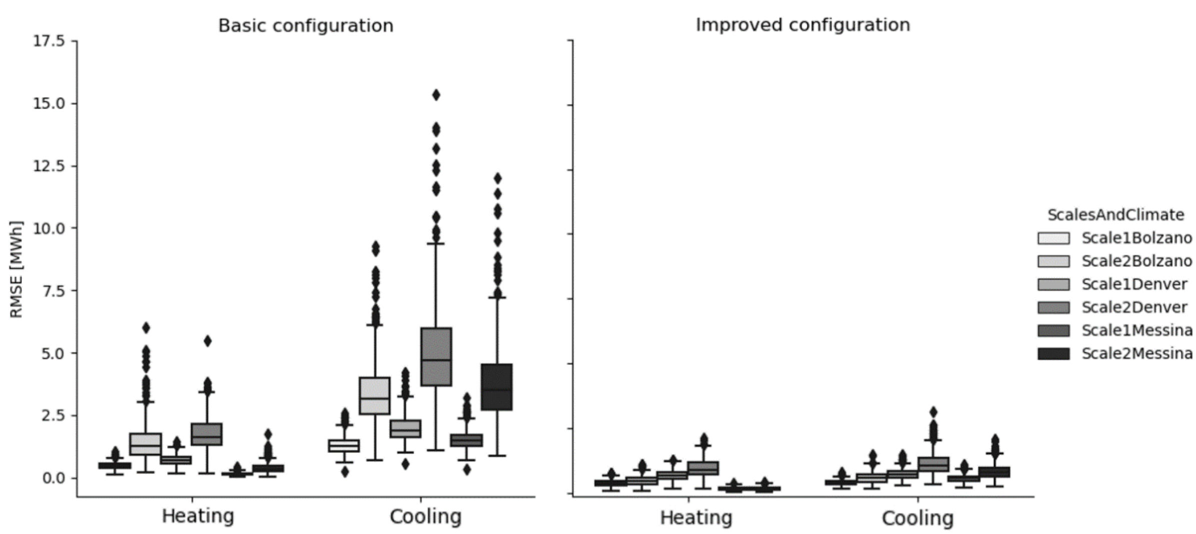


Figure 9: *RMSEs* comparison for the two districts considered in the three climates between the basic algorithm configuration and the improved one

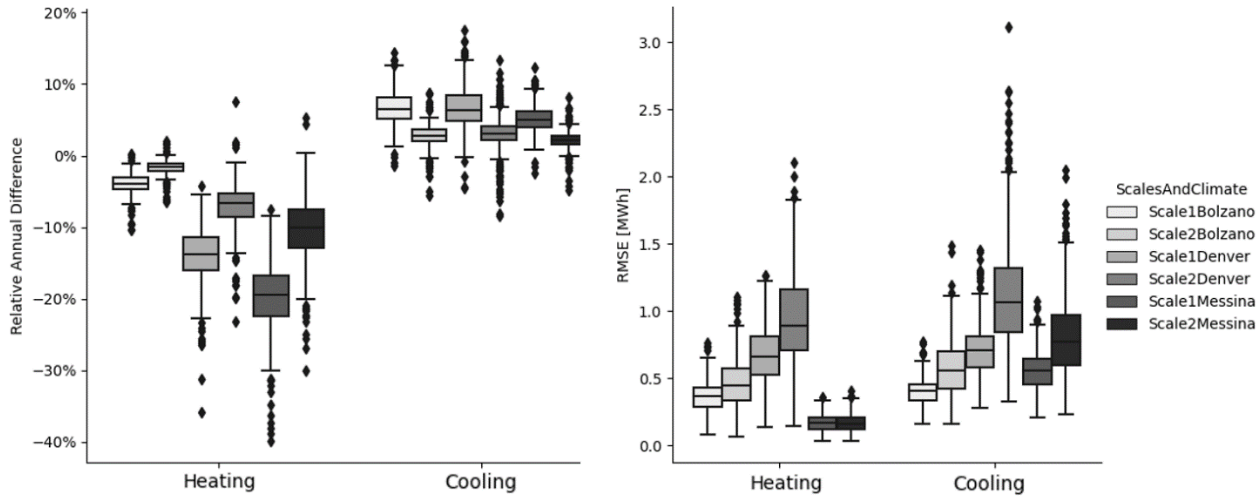


Figure 10: Detail on the differences of the improved configuration for the two districts considered in the three climates

Overall, the heating demand prediction has improved with respect to the basic procedure but not as much as the cooling one. Figure 10 reports more in detail the hourly and annual differences occurring in the six cases. The *RMSEs* boxplots highlight that the deviations between heating and cooling are comparable for all cases, excepts for Messina in which the heating demand magnitude is very low.
To conclude, the results obtained by a more detailed modelling of the incoming radiation have improved more than any other solution (e.g., changing the grid-spacing used for the radiation analysis or employing opaque elements instead of shading surfaces outside the window for casting the solar radiation) the algorithm's accuracy. More specifically, since the deviations are similar in the considered cases, the algorithm's performances are less dependent on the external boundary condition as it is for the basic configuration. It is also expected that the improvements achieved in the two analyzed districts will be confirmed in the remaining ones, already yielding better results. As for now, the improved shoeboxing algorithm is capable of properly predicting the energy needs of complex shaped buildings at the urban level, even in a wide range of conditions that could undermine its accuracy.

4. CONCLUSIONS

In this work, a novel simplification algorithm to reduce the computational cost of building energy simulations at the urban scale has been tested to evaluate its accuracy at the district level. The algorithm consistently simplifies every building in an urban model into a representative shoebox and accounts for the building's surroundings and adjacencies. Since the way in which the incoming solar radiation is modelled has a major effect on the outcome of the simplification approach's accuracy, two solutions to consider the building's self and context shadings have been investigated. The impacts of obstructions have been considered by means of opaque surfaces reducing the transparent building envelope generated according to obstruction ratios resulting from a radiation analysis. At first, such obstructions have been created from an annual direct radiation analysis. Then, an improved configuration considering monthly global radiation has been employed. The algorithm has been tested by means of a set of fictional districts, featuring complex shaped buildings arranged in blocks, that have been built to explore as much as possible the space of the solutions. To assess the algorithm's performance under different boundary conditions, three different climatic conditions have been used. For every building in each district, detailed and simplified energy models have been compared on hourly and annual basis in terms of heating and cooling needs.
Regardless of the kind of adopted radiation modelling (i.e., direct on annual basis or global on monthly basis), the algorithm has been able to cut the energy simulation time up to 30 times. The basic algorithm has proved to be effective in estimating the heating needs. However, it has not provided the same level of accuracy and reliability for what regards the cooling demand. For this reason, the improved methodology has been applied to the two districts yielding the worst results. Accounting for the solar radiation on a monthly basis significantly improved the cooling predictions, while still obtaining adequate results for the heating needs. Moreover, the results obtained were characterized by similar deviations regardless of the considered climate, making the algorithm's performance independent by external

boundary conditions.

To conclude, the shoeboxing algorithm showed to be adequate in predicting the energy needs of buildings of complex shapes at the urban level, even at fine time scale such as hourly. Further studies will be carried out in order to fully test the improved algorithm and to look for further improvements by studying outliers.

REFERENCES

Abbasabadi, N., & Ashayeri, M. (2019). Urban energy use modeling methods and tools: A review and an outlook. *Building and environment 161*. doi: https://doi.org/10.1016/j.buildenv.2019.106270

Battini, F., Pernigotto, G., & Gasparella, A. (2021a). Development of a shoeboxing approach for Urban Building Energy Modeling. *International High Performance Buildings Conference*, (p. 385). Purdue.

Battini, F., Pernigotto, G., & Gasparella, A. (2021b). A parametric analysis of the impact of thermophysical, geometry and urban features on the energy demand of a simplified building shoebox model. *Building Simulation 2021.* Bruges.

Dogan, T., & Reinhart, C. (2013). Automated conversion of architectural massing models into thermal 'shoebox' models. *Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28*, (pp. 3745-3752). Chambéry.

Dogan, T., & Reinhart, C. (2017). Shoeboxer: An algorithm for abstracted rapid multi-zone building energy model generation and simulation. *Energy and Buildings, 140*, 140-153. doi: https://doi.org/10.1016/j.enbuild.2017.01.030

Hong, T., Chen, Y., Luo, X., Luo, N., & Lee, S. (2019). Ten questions on urban building energy modeling. *Building and Environment, 168*. doi: https://doi.org/10.1016/j.buildenv.2019.106508

İşeri, O. K., & Dino, İ. G. (2020). An Algorithm for Efficient Urban Building Energy Modeling and Simulation. *2020 Proceedings of the Symposium on Simulation for Architecture and Urban Design*, (pp. 455-462).

Javanroodi, K., Mahdavinejad, M., & Nik, V. M. (2018). Impacts of urban morphology on reducing cooling load and increasing ventilation potential in hot-arid climate. *Applied Energy*, 714-746.

Javanroodi, K., Mahdavinejad, M., & Nik, V. M. (2019). A novel design-based optimization framework for enhancing the energy efficiency of high-rise office buildings in urban areas. *Sustainable Cities and Society*.

Johari, F., Peronato, G., Sadeghian, P., Zhao, X., & Widén, J. (2020). Urban building energy modeling: State of the art and future prospects. *Renewable and Sustainable Energy Reviews*. doi: https://doi.org/10.1016/j.rser.2020.109902

Ladybug Tools LLC. (2021, July 20). Retrieved from Ladybug Tools: www.ladybug.tools

Lyu, T., Buccolieri, R., & Gao, Z. (2019). A Numerical Study on the Correlation between Sky View Factor and Summer Microclimate of Local Climate Zones. *Atmosphere*.

Natanian, J., Aleksandrowicz, O., & Auer, T. (2019). A parametric approach to optimizing urban form, energy balance and environmental quality: The case of Mediterranean districts. *Applied Energy*, 113637.

Perera, A. T., Javanroodi, K., Wang, Y., & Hong, T. (2021). Urban cells: Extending the energy hub concept to facilitate sector and spatial coupling. *Advances in Applied Energy*, 100046.

Pomponi, F., Saint, R., Arehart, J. H., Gharavi, N., & D'amico, B. (2021). Decoupling density from tallness in analysing the life cycle greenhouse gas emissions of cities. *npj Urban Sustainability*, 33.

Reinhart, C., & Davila, C. (2015, December 2). Urban building energy modeling - A review of a nascent field. *Building and Environment, 97*, 196-202. doi: https://doi.org/10.1016/j.buildenv.2015.12.001

Reinhart, C., Dogan, T., Jakubiec, J., Rahka, T., & Sang, A. (2013, August). Umi - an Urban Simulation Evironment for Building Energy Use, Daylighting and Walkability. *13th Conference of International Building Performance Simulation Association.* Chambéry, France: IBPSA.

Robert McNell & Associates. (2021, June 14). *RhinoCommon API*. Retrieved from Rhino Developer Docs: https://developer.rhino3d.com/api/RhinoCommon/html/R_Project_RhinoCommon.htm

Shi, Z., Fonseca, J. A., & Schlueter, A. (2021). A parametric method using vernacular urban block typologies for investigating interactions between solar energy use and urban design. *Renewable Energy*, 823-841.

Trepci, E., Maghelal, P., & Azar, E. (2021). Urban built context as a passive cooling strategy for buildings in hot climate. *Energy and Buildings*, 110606.

Zhu, P., Yan, D., Sun, H., An, J., & Huang, Y. (2019). Building Blocks Energy Estimation (BBEE): A method for building energy estimation on district level. *Energy and Buildings, 185*, 137-147.

Zhu, S., Ma, C., Zhang, Y., & Xiang, K. (2021). A hybrid metamodel-based method for quick energy prediction in the early design stage. *Journal of Cleaner Production, 320*.