Assessing the Performance of a Simplification Algorithm for Urban Building Energy Modeling in Multi-Objective Optimization

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Abstract

Urban Building Energy Modeling and Multi-Objective Optimization are two very computationally intensive applications of Building Performance Simulation. In this research, a simplification algorithm developed to speed up thermal simulations at urban scale was tested to assess its performance in optimization studies. Since the algorithm showed good accuracy at the individual building level, it was applied to standalone buildings, considering a set of energy efficiency measures and all the possible combinations of four objectives, i.e., heating and cooling needs, thermal comfort and costs. The algorithm showed adequate performance in finding the optima with the same inputs for most of the considered buildings and combinations of objectives in different climatic conditions, allowing the simulation time to be reduced to one third.

1. Introduction

In 1965, Gordon E. Moore stated that the number of transistors on an integrated circuit would have increased at a rate of roughly a factor of two per year, at least over ten years (Moore, 1965). Nowadays, such a prediction, known as Moore's law, is still true, and it means that the power of computers is approximately doubling every couple of years. Thanks to such exponential increases in computing resources, two fields of Building Performance Simulation *BPS* have been gaining more and more interest in recent years: Multi-Objective Optimization *MOO* and Urban Building Energy Modeling *UBEM*. Rather than offering a one-design solution, *MOO* provides the flexibility of choosing from a set of optimal solutions with a more realistic decision-making process (Costa-Carrapiço et al., 2020). On the other hand, *UBEM* aims at finding an aggregated and simplified way of estimating the operational energy needs of groups of buildings, overcoming the limitations of single building modeling (Reinhart & Davila, 2015).

The major computational cost of *MOO* and *UBEM* is the main drawback that they have in common. Regardless of other technical aspects, such as the modeler's skills and knowledge, being too computationally demanding is the first hurdle preventing their widespread employment in common practice. In addition, it is also the main reason why most of the *UBEM* studies present in the literature investigate retrofit or design scenarios (Ang et al., 2020) rather than performing *MOO*. Haneef et al. (2021) carried out one of the few studies combining *UBEM* and *MOO*. Considering a residential district of around a hundred buildings, they examined different sets of renovation measures for the building envelope and found the Pareto front with regarding three objectives, i.e., energy, economic and sustainability performances.

In a previous work (Battini et al., 2021), we proposed a simplification algorithm for *UBEM* to speed up the simulation time limiting the accuracy loss at hourly and building scale. The algorithm simplifies any arbitrarily shaped building into a representative shoebox to estimate the building's indoor temperatures and thermal loads. Since the procedure showed good precision in assessing the building's performance at individual level, it could also be used to expedite other aspects of *BPS,* such as *MOO*. Given these premises, the aim of the present work is to assess the capabilities of the simplification in performing *MOO*. A batch of standalone buildings were selected to test the procedure and they were simulated in three climates. The optimization was carried out considering energy efficiency measures

Part of
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pertaining only the building envelope respect to up to four objectives, i.e., heating needs, cooling needs, indoor thermal comfort, and economic performance. The objectives were considered one, two, three and four at a time, in order to evaluate the algorithm's reliability with all possible target combinations.

2. Methodology

2.1 Simplification Algorithm

The simplification, or "shoeboxing", algorithm is capable of converting a building of any shape into a shoebox. Thus, from a detailed or starting model, a simplified or shoebox model is obtained. The process to be employed for simplifying each building present in an urban model into its representative shoebox has three steps:

1. *Shoebox generation*: by solving a non-linear system of three equations in three unknowns, the dimensions of the shoebox are found from the starting building geometry.
2. *Radiation modeling*: opaque surfaces are placed on a portion of each window of the simplified model, in order to reduce the amount of incoming radiation and reproduce the effect of the contextual and self-shadings simulated in the detailed model. To size such equivalent shading surfaces, a radiation analysis is performed on both models to compute obstruction ratios for each orientation and floor.
3. *Building adjacency*: adiabatic surfaces are used to account for adjacent buildings.

A more in-depth description of the shoeboxing process can be found in a previous work by the authors (Battini et al., 2021). Once obtained, detailed and simplified models are characterized by the same non-geometrical features.

The procedure does not depend on specific tools to be developed, hence it can be reproduced with any software having the right capabilities. In this work, Rhinoceros and Grasshopper were employed for the geometrical conversion, Ladybug Tools SDK was used for creating the energy models, and EnergyPlus was utilized as *BPS* tool. The programs were coupled by automating the entire process thanks to custom-made Python scripts.

2.2 Multi-Objective Optimization

2.2.1 Buildings selection for testing

The simplification algorithm developed was first tested on 3072 buildings of complex shape built out of polyominoes (Golomb, 1994) to guarantee complex and non-repetitive shapes. Moreover, to assess its prediction capabilities under different boundary conditions, every building geometry obtained and its related simplified model were simulated in three climates, i.e., Bolzano and Messina, Italy, and Denver, US.

Since performing a *MOO* is already largely computationally and time-consuming, a set of buildings were chosen from the ones already generated. Fig. 1 reports the boxplots for the relative annual differences between detailed and simplified models in the three climates. The results are reported as a function of the number of floors of each building and show how, for both targets, the simplified model prediction always falls within ± 20 % difference. Five buildings for each target (i.e., heating and cooling) were chosen for each climate, thus thirty building were used in the *MOO*. In order to employ representative buildings in this work, starting from the relative annual differences obtained by the previous study, buildings corresponding to the minimum, first quartile, median, third quartile and maximum difference were selected. In this way, it was possible to study buildings whose performances are different but also representative of the batch which they were picked from. Among the starting 3072 possibilities, Fig. 2 reports the buildings selected for the analysis. Instead of simulating all buildings in the three climates, each building was simulated in the same climate from which it was selected. Thus, ten buildings were simulated per each climatic condition.

2.2.2 Optimization

The aim of the present optimization is to test whether the detailed and simplified building models' non-dominated solutions match in terms of inputs. Thus, the optima found should have the same values for the inputs rather than the outputs.

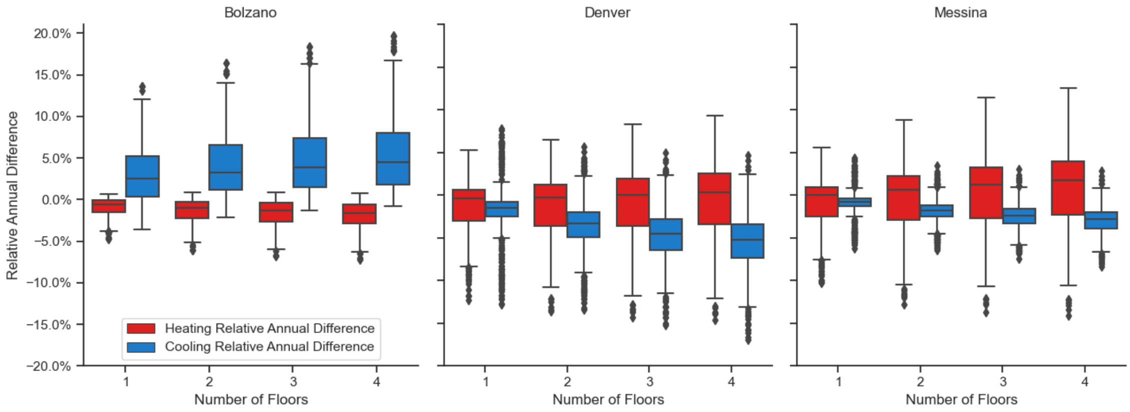

Fig. 1 – Boxplots for annual heating and cooling needs relative differences depending on buildings' number of floors for the entire building

Since the algorithm was developed for urban scale applications, the variables considered in this first study only focus on the envelope. Since in *UBEM*, the information regarding the systems is usually not available, retrofit or design scenarios mainly pertain to the buildings' envelope. Thus, three variables were considered:

- insulation type: all external opaque surfaces are characterized by the same composition, three types of insulation were selected, i.e., XPS, mineral wool, and cellulose fiber.
- insulation thickness: the thickness of the type of insulation varied from 2 to 20 cm with a step of 2 cm.
- type of window: five different types of windows were chosen, such as double glazing with air filling, double glazing with argon filling and high solar factor, double glazing with argon filling and low solar factor, triple glazing with argon filling and high solar factor, and triple glazing with argon filling and low solar factor.

In Table 1, the variables considered are reported along with their properties and related investment costs. As far as insulation is concerned, the investment cost per square meter was computed in function of the thickness *s* according to the formulas reported for each type of material. The investment costs considered in this study for the opaque and transparent envelope are the same as those employed by Haneef et al. (2021) and Pernigotto et al. (2017). Given the low number of combinations, a full factorial analysis was carried out and all possibilities were simulated.

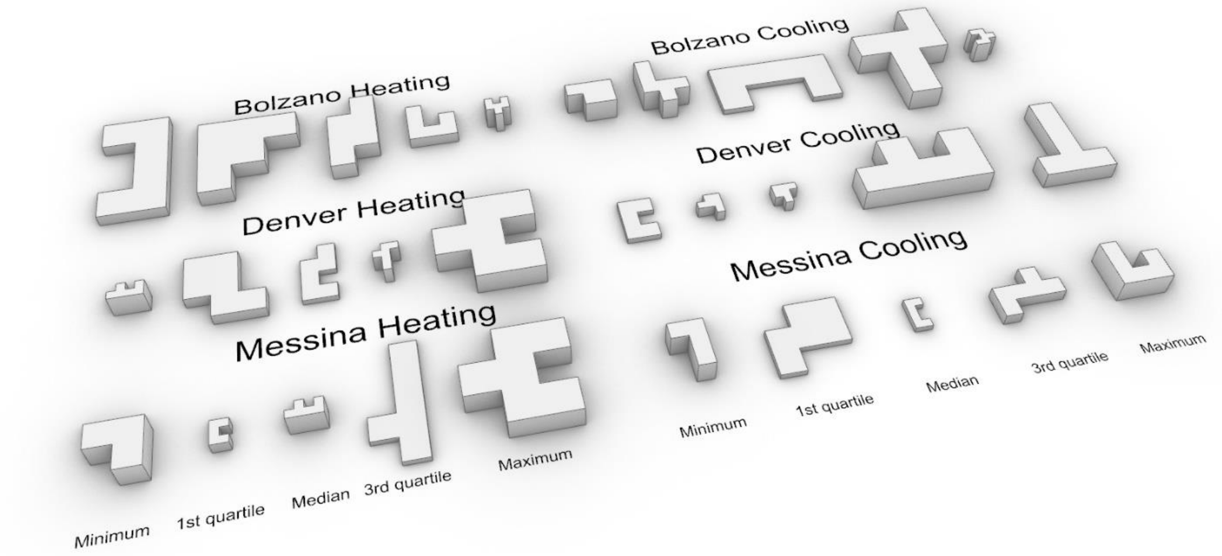

Fig. 2 – Selection of buildings for each target and climate

Table 1 – Variables for *MOO*

Insulation				
Insulation	Thermal conductivity [W m^{-1} K^{-1}]	Density [kg m^{-3}]	Specific heat [J kg^{-1} K^{-1}]	Investment cost [€ m^{-2}]
XPS	0.035	30	1450	112.5 · s + 55.6
Mineral wool	0.038	130	1030	213.6 · s + 70.2
Cellulose fiber	0.045	160	2000	363.7 · s + 74.6

Windows			
Window	Glass transmittance [W m^{-2}K^{-1}]	SHGC [-]	Investment cost [€ m^{-2}]
Double glazing air filling	2.72	0.76	247.30
Double glazing argon filling high SHGC	1.14	0.61	404.33
Double glazing argon filling low SHGC	1.10	0.35	439.06
Triple glazing air filling high SHGC	0.61	0.58	477.65
Triple glazing air filling low SHGC	0.60	0.34	454.49

Thus, the real Pareto solutions were found, since no optimization algorithm was used.

To test the simplification capabilities as broadly as possible, the heating demand, cooling demand, thermal comfort and economic performance were considered as the objectives to be minimized. The heating and cooling needs were accounted as annual energy needs expressed in megawatt hour by summing up the hourly needs. Thermal comfort was evaluated as the annual average of the hourly results for the Predicted Percentage of Dissatisfied *PPD*, since it is one of the suggested methods by UNI EN ISO 7730 (UNI, 2006) for long-term evaluations of comfort conditions. The costs were considered by computing the Net Present Value *NPV* of the building by means of an economic analysis with a lifespan of 30 years according to UNI EN 15459-1 (UNI, 2018). The optimal solutions were found for all the possible combinations of objectives, thus from one at a time to all four together, resulting in 15 combinations. In this way, it was possible to assess the performance of the procedure with a variable number of objectives and non-dominated solutions.

For each case, the optimal solutions found for the detailed and simplified models were compared. First, the total number of optima was counted. Then, it was checked for the presence of non-matching solutions as follows: (i) the solutions that were found as optima for the detailed model which were dominated for the simplified one were counted as optima not found, (ii) the solutions that were labeled as non-dominated for the simplified model that were not optima for the detailed one were considered as wrongly found optima. On top of these two absolute values, for each combination of objectives, the error rate in performing a right choice or a wrong choice with respect to the total number of real optima was computed.

3. Results and Discussion

Even though the aim of this work is to assess if the detailed and simplified models result in having the same input values for the optimal solutions, the simulation outputs for heating and cooling needs, and the *PPD* for the detailed and simplified models were visually compared.

Fig. 3 and Fig. 4 show that the simplified models tend to underestimate the heating needs and overestimate the cooling ones. Such behavior was present also in the previous work from which the buildings were selected. However, since prior to this research the algorithm was tested focusing mainly on the buildings' shape rather than varying the thermophysical properties of the envelope, it was not possible to state that such a tendency could be true in all cases. Fig. 5 reports the boxplots with the *PPD* distribution for all the combinations for the buildings considered. Compared with the thermal needs, the distributions of the annual average *PPDs* for the simplified and detailed models are much more similar.

From Figs. 3, 4 and 5, it is clear that the differences between detailed and shoebox models are independent of the starting building's shape. Thus, to be consistent with previous research, the results for the optimization were compared in the three climates to assess the procedures' weaknesses more in detail.

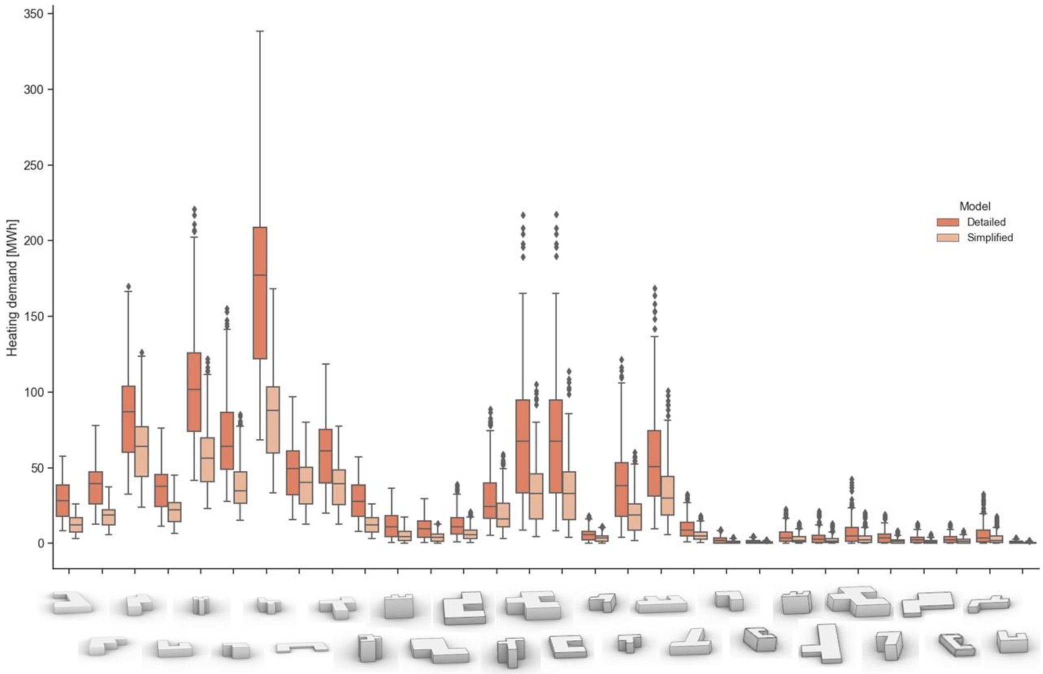

Fig. 3 – Annual heating needs boxplots for detailed and simplified models of each building for all input combinations

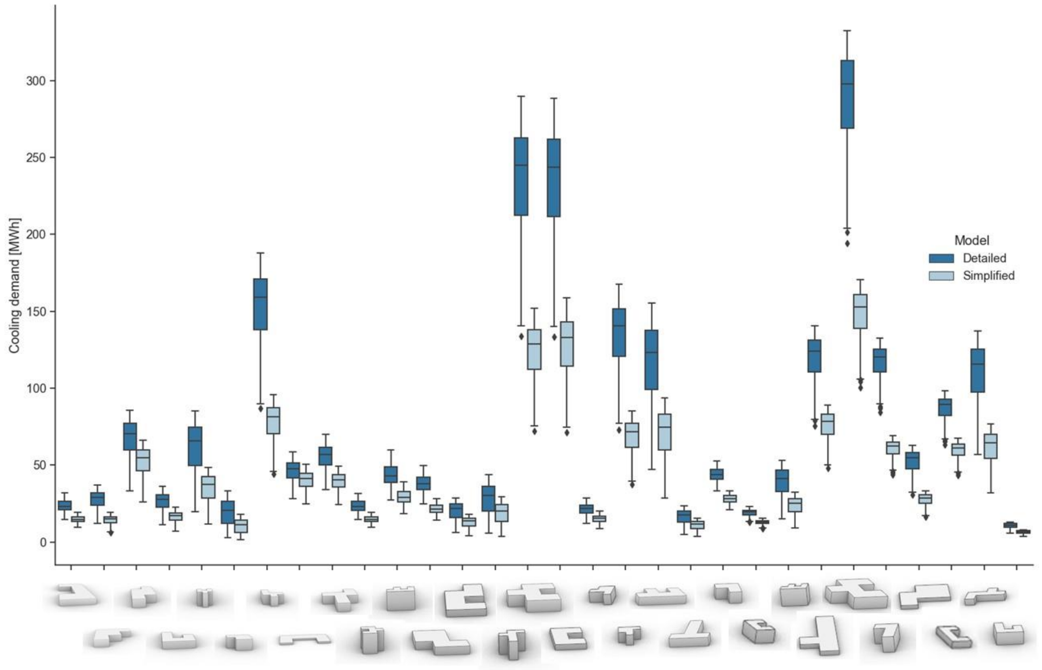

Fig. 4 – Annual cooling needs boxplots for detailed and simplified models of each building for all input combinations

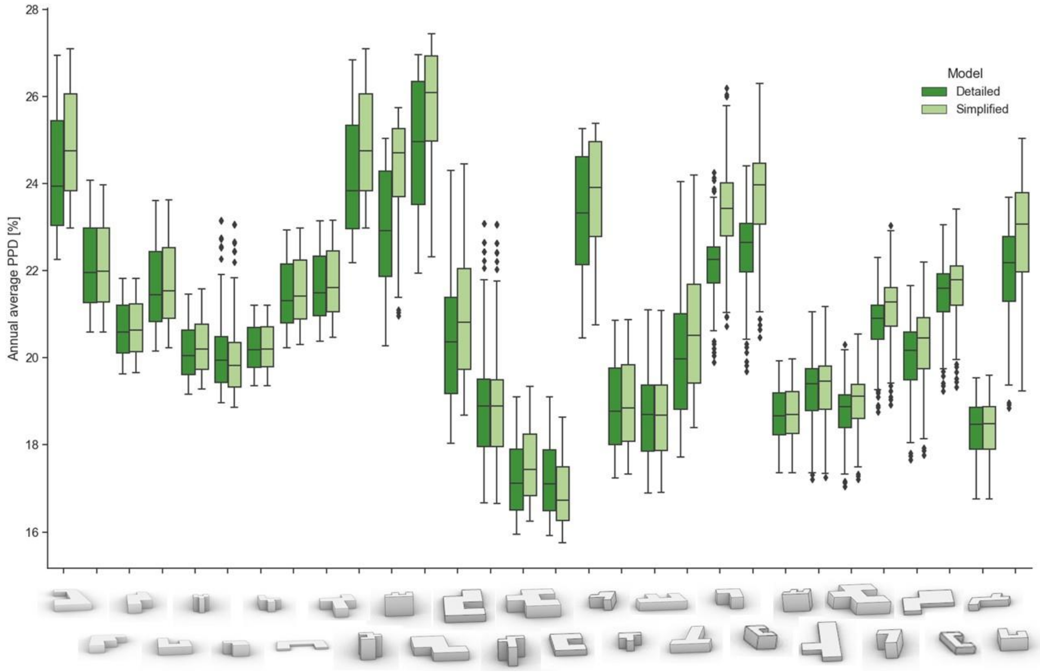

Fig. 5 – *PPD* boxplots for detailed and simplified models of each building for all input combinations

Table 2 reports the results for all combinations of objectives in the three climates. To visually understand in which cases the algorithm is performing better, the cells reporting the objectives considered were color-coded according to the right or wrong error rates. The combinations of objectives were colored in green if both error rates were lower or equal to 10 %, yellow if at least one of them was larger than 10 % and lower or equal to 20 %, and red if at least one of the two errors was greater than 20 %. In this way, it is possible to have a quick understanding of the reported tabular results.

The number of optimal solutions found for the detailed models is greatly affected not only by the number of objectives but also by the type of objectives considered. When antagonist objectives such as heating and cooling are in the same optimization problem, the number of optimal solutions increases much more compared with other cases. Since the *NPV* is related to both heating and cooling annual needs, including the economic performance leads to an increase of optima as well. Even though from Fig. 5 it seems that, for detailed and simplified models, the distributions for the annual average thermal comfort could be similar, Table 2 reports higher error rates when thermal comfort is included among the objectives, mainly for the climates of Bolzano and Denver. Generally, in all climates, low error rates are reported when having one, three or four objectives. Thus, the algorithm’s performance in finding the right optimal solutions is more accurate when there is a unique solution (i.e., one objective) or the number of optima is very large.

In the climate of Bolzano, the higher error rates occur when the economic and comfort objectives are optimized. When they are coupled with the cooling needs for the simplified models, not every optimum is found. On the other hand, coupling them with the heating needs leads to mainly wrongly labeled optima. As far as the climate of Denver is concerned, the results obtained are very similar to those of Bolzano. Even though thermal comfort and costs still yield the least accurate outcomes, there is an overall reduction of the error rates, except for the analysis with thermal comfort as sole objective.

Finally, the climate of Messina is the one yielding the most accurate optimization predictions, even for the heating demand, which is not a target output for this type of climate. Overall, for standalone buildings, the algorithm is three times faster in performing energy simulations for the buildings considered. Thus, the time required to run an optimization for each of these buildings was cut to one third. Even though, in some cases, the errors are still not negligible, the algorithm’s performance in finding a set of optimal solutions is adequate for the purpose.

Table 2 – Optimal solutions comparison in the three climates

Objectives	Total real optima	Total not found optima	Total wrongly labeled optima	Right choice error [%]	Wrong choice error [%]	Average number of optima
Bolzano						
Heating	10	0	0	0.00	0.00	1.00
Cooling	10	0	0	0.00	0.00	1.00
Costs	10	0	0	0.00	0.00	1.00
Comfort	10	4	4	40.00	40.00	1.00
Comfort-Costs	115	36	28	31.30	24.35	11.50
Cooling-Comfort	101	19	0	18.81	0.00	10.10
Cooling-Costs	169	13	0	7.69	0.00	16.90
Heating-Comfort	99	2	50	2.02	50.51	9.90
Heating-Cooling	289	0	0	0.00	0.00	28.90
Heating-Costs	353	1	42	0.28	11.90	35.30
Cooling-Comfort-Costs	403	52	0	12.90	0.00	40.30
Heating-Cooling-Comfort	299	0	1	0.00	0.33	29.90
Heating-Cooling-Costs	1025	5	0	0.49	0.00	102.50
Heating-Comfort-Costs	503	0	52	0.00	10.34	50.30
Heating-Cooling-Comfort-Costs	1047	5	1	0.48	0.10	104.70
Denver						
Heating	10	1	1	10.00	10.00	1.00
Cooling	10	0	0	0.00	0.00	1.00
Costs	10	2	2	20.00	20.00	1.00
Comfort	10	4	4	40.00	40.00	1.00
Comfort-Costs	332	50	17	15.06	5.12	33.20
Cooling-Comfort	153	16	1	10.46	0.65	15.30
Cooling-Costs	80	5	0	6.25	0.00	8.00
Heating-Comfort	87	5	16	5.75	18.39	8.70
Heating-Cooling	256	8	2	3.13	0.78	25.60
Heating-Costs	405	8	14	1.98	3.46	40.50
Cooling-Comfort-Costs	477	56	1	11.74	0.21	47.70
Heating-Cooling-Comfort	259	8	3	3.09	1.16	25.90
Heating-Cooling-Costs	912	13	3	1.43	0.33	91.20
Heating-Comfort-Costs	578	9	31	1.56	5.36	57.80
Heating-Cooling-Comfort-Costs	918	13	3	1.42	0.33	91.80
Messina						
Heating	10	0	0	0.00	0.00	1.00
Cooling	10	1	1	10.00	10.00	1.00
Costs	10	0	0	0.00	0.00	1.00
Comfort	10	0	0	0.00	0.00	1.00
Comfort-Costs	38	0	0	0.00	0.00	3.80
Cooling-Comfort	15	0	1	0.00	6.67	1.50
Cooling-Costs	30	2	0	6.67	0.00	3.00
Heating-Comfort	284	1	1	0.35	0.35	28.40
Heating-Cooling	290	1	3	0.34	1.03	29.00
Heating-Costs	615	5	7	0.81	1.14	61.50
Cooling-Comfort-Costs	38	0	0	0.00	0.00	3.80
Heating-Cooling-Comfort	297	0	1	0.00	0.34	29.70
Heating-Cooling-Costs	1014	6	7	0.59	0.69	101.40
Heating-Comfort-Costs	1067	4	6	0.37	0.56	106.70
Heating-Cooling-Comfort-Costs	1081	3	4	0.28	0.37	108.10

4. Conclusion

In this work, the performance of a simplification algorithm developed for *UBEM* was tested in order to speed up the simulation time of building-level *MOO*. From a previous study, a group of buildings was chosen to perform a *MOO*, and energy efficiency measures and four objectives were selected. Heating and cooling needs, thermal comfort and investment costs were considered as objectives. To test the capabilities of the simplification in finding the right optimal solutions, all possible combinations of objectives were counted, and the buildings were simulated in three different climates.

Overall, it was possible to reduce to one third the thermal simulation time, obtaining adequate results for almost all combinations of objectives, regardless of the climatic condition considered. More specifically, the error rates in choosing the right optima were lower than 10 % for more than half of the combinations of objectives considered. Except for four cases, it was always possible to limit the error rate to maximum 20 %. Nonetheless, since the optimal solutions are related to the prediction accuracy of the algorithm, improving the precision of the simplification procedure will lead to more exact solutions. For this reason, a new configuration of the algorithm modeling the incoming radiation on a monthly basis is under development by the authors.

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