ARQUITETURA REVISTA

v.17 n.2 2021
DOI: 10.4013/arq.2021.172.03

ANALYSIS OF THE PERFORMANCE OPTIMIZATION PROCESS OF HOUSING UNITS USING HONEYBEE

ANÁLISE DO PROCESSO DE OTIMIZAÇÃO DO DESEMPENHO DE UNIDADES HABITACIONAIS COM USO DO HONEYBEE

Íris Loche[1]
Joyce Correna Carlo[2]

Abstract

The Simulation-Based Optimization (SBO) method differs from conventional design methodology, as its main focus is the building's performance, without failing to take into account the traditional aspects of design. When associated with parameterization, it can be explored to create solutions appropriated for specific shape and performance criteria. This method is achievable through the interoperability between digital performance and modeling software, such as Grasshopper, a parametric modeling plug-in for Rhinoceros, and HoneyBee, a plug-in for Grasshopper that connects the parameterized model to Energy Plus. Octopus is a plug-in connected to Grasshopper that allows trade-offs between variables to be combined by genetic algorithms and indicates modifications to the model based on the data provided. This study aims to analyze the thermal performance optimization process of an autonomous housing unit through the SBO method. Shape variation parameters were evaluated in function of thermal performance criteria depending on two objectives: reducing the cooling and heating degree-hours. The results enabled the shape analysis of the models and the identification of predominant characteristics of best and worst solutions for winter and summer conditions, as well as a study of simulation controlling termination criteria.

Keywords: Parameterization, Thermal Performance, Simulation-based Optimization; Grasshopper; Octopus

Resumo

O método de Otimização Baseada em Simulação (OBS) difere-se da metodologia convencional de projeto, tendo seu principal foco no desempenho ambiental de edificações, porém sem desconsiderar os demais aspectos tradicionais do projeto. Quando associado à parametrização, pode ser explorado para criar soluções adequadas aos critérios formais e desempenho pré-determinados. Este método é possível através da interoperabilidade entre programas de desempenho e modelagem digital, como Grasshopper, um plug-in de modelagem paramétrica para o Rhinoceros, e o HoneyBee, plug-in para Grasshopper que conecta o modelo parametrizado ao Energy Plus. O Octopus é o motor de otimização conectado ao Grasshopper que toma decisões das variáveis a combinar por algoritmos genéticos, e propõe alterações no modelo com base nos dados fornecidos. Este estudo objetiva analisar o processo de otimização do desempenho térmico de uma unidade habitacional pelo método de OBS. Parâmetros de variação formal da unidade foram analisados em função de critérios de desempenho térmico, condicionados a dois objetivos: reduzir os graus-hora de resfriamento e graus-hora de aquecimento. Os resultados permitiram análises formais dos modelos e identificação das características predominantes das melhores e piores soluções para as condições de inverno e verão, além de um estudo do critério de parada da simulação.

Palavras-chave: Parametrização, Desempenho térmico, Simulação baseada em Otimização, Grasshopper, Octopus

[1] Universidade Estadual de Campinas, orcid.org/0000-0003-4117-0367, i229320@dac.unicamp.br
[2] Universidade Federal de Viçosa, orcid.org/0000-0003-3868-0307, joycecarlo@ufv.br

INTRODUCTION

Since the 1980s, with the development of computational technology and the growing demand for energy-efficient buildings, there has been great progress in the design process. From this context, a method known as Simulation-Based Optimization (SBO) has emerged, which differs from conventional design methodology as its main focus is on buildings' performance, without failing to consider other traditional design aspects, such as composition and spatiality (1). This type of architectural project design is an effective approach to efficient designs, and when associated with parameterization, can be used to create appropriated solutions to predetermined shape and performance criteria.

Parameterization and digital manufacturing have aided architects and engineers in developing a new way of constructing, meaning that architectural design does not limit the volume and spatial arrangements to subjective relationships, limited to the architect's repertoire. This type of modeling has enabled the development of more organic and complex forms based on the creation of rules, restrictions, and relations between the elements. To create this network of connections, the geometry is composed of parameters and hierarchies, which facilitate manipulation according to the need of each user (2).

Based on the combination of pre-determined parameters, parametric modeling provides several design solutions that are subsequently selected and evaluated according to the predefined judgment criteria for meeting one or more objectives (2). Thus, performance-based design has become an effective method to aid the design of energy-efficient buildings, allowing the parameterization of the shape linked to simulation to intervene in the design from the very first stage of its development (3).

Decisions taken early on in the design are those that most impact the final costs and energy performance of the building (4). Thus, Oxman (5) introduces the concept of "performative generative design", in which performance becomes the determining element in the creation or modification of the architectural form. Rather than creating the architectural point of view as a starting point for the design, "performative design" is based on the ability to find a way to arrive at unexpected and unique design solutions (6). This new method of design not only implies significant changes in traditional design practices, revising design attitudes and means of action, but also allows us to contemplate aspects of form and function at the same time as solving design problems.

Currently, the software most widely used by architects for shape modeling do not allow the input of information to evaluate the building performance, and thus, the simulation is performed after the final design of the project in other software specifically used for performance evaluation (7). If the design does not reach the desired level, it must be remodeled and altered to adapt it to higher levels of performance, which may cause an undesired extra effort to the process, distancing architects and professionals from their use. Thus, the importance of simulation from the initial stages of design is reinforced.

According to Gossard; Lartigue and Thellier (8), improving the buildings' thermal performance can be achieved in two ways: trial and error, which means an improvement achieved through failures; or an algorithm-based approach to optimization, a more efficient method. The trial-and-error method can create acceptable solutions, but the latter, because it is based on global search, is more likely to indicate the best solutions for a design (9). Performance-based architectural design is therefore an effective approach to the design of more efficient solutions, as long as obstacles to interoperability are overcome, which has been occurring in the last decades (3).

There are different ways of setting parameters for a project, one of which is through scripts to program complex algorithms. There are currently several software with friendly interfaces that facilitate the use and development of scripts without the need for previous programming knowledge, with a simpler language. For example, Grasshopper is a parametric modeling plug-in for the software Rhinoceros and HoneyBee is a plug-in for Grasshopper that connects the shape parameterization of Rhinoceros to the Energy Plus performance analysis software. Octopus is the optimization engine connected to Grasshopper that makes the decisions of the variables to combine and changes the shape of the model in Rhinoceros based on the data provided by Energy Plus (10).

Optimization processes aim to improve the performance of buildings based on deciding on a condition considered satisfactory. According to Nguyen, Reiter, Rigo (1), the optimization can be classified according to the number of objective functions, and it can be mono or multi-objective. The multi-objective optimization or Pareto optimization is more interesting because, in addition to approaching more real problems - since designers usually need to deal with conflicting design criteria - multi-objective optimization seeks the balance between the defined objectives (11). In this simulation method, the designer is free to choose one or more solutions that are interesting for his design in a visual and quantitative analysis of each solution related to the objectives.

A widely used optimization approach is through genetic algorithms, a method based on the process of natural selection mimicking biological nature. The algorithm modifies the individual solutions based on crossing the best cases of one generation to create the next generation repeatedly until the end of the simulation, the stopping criterion of which is the convergence of the graph or a pre-set number of generations (11). The stopping criterion is an obstacle for those working with the SBO method. According to Fonseca et al. (12), the user can stop the optimization process when it reaches the number of generations pre-set by the user or by observing if the values of the objective function do not present significant variations (when the optimization reaches convergence).

Octopus is a plug-in developed for Grasshopper that enables this type of multi-objective optimization and works through genetic algorithms (10). It offers the user the possibility of working with two or more objectives, the third being diversity of parameters. Its advantage is to maximize the distance of each solution to all other solutions in the genetic space, preventing the algorithm from fixing on or locking in local solutions (10). The plug-in also allows users to graphically visualize the optimization convergence based on the Pareto Front, which is constituted by a set of optimum solutions according to the objectives set for the optimization (13).

When working with the Simulation-Based Optimization, Santana and Carlo (14) and Santana (15) studied this method applied to multi-objective simulations aiming to optimize the thermal performance of a housing unit for both winter and summer conditions. Santana and Carlo (14) studied a low geometric complexity model, composed of one thermal zone and a small number of variables, to verify the efficiency of the SBO method in searching for optimum solutions, using the performance criteria prescribed in the Technical Regulation of Quality for Energy Efficiency of Residential Buildings (RTQ- R) (16). The authors showed that, when compared to the base-case, the annual degree-hours decreased by around 15% for the optimum solutions. Santana (15) applied the same method for a more complex model, a housing unit with eight thermal zones. By considering the room's depth and width as variable parameters, the impact of the shape on the building thermal performance was evaluated through the identification of the optimum solution's prevailing geometric characteristics.

Likewise, Acar; Kasha, and Tokgoz (17) and Fonseca et al (12) performed a multi-objective optimization aiming to reduce the construction costs and improve the thermal performance of a residential building. The authors were able to select optimum solutions from the Pareto Front, showing that the SBO method can be a powerful tool to be used in the early design stages of architectural projects. Furthermore, Salata et al. (18) pointed out the SBO method as a potential tool for energy requalification of existing buildings. The authors conducted a multi-objective optimization aiming to reduce the annual energy demand, construction costs, and greenhouse gas emissions of a residential building. Through this method, they were able to identify the most advantageous retrofitting interventions for nineteen European cities with different climates.

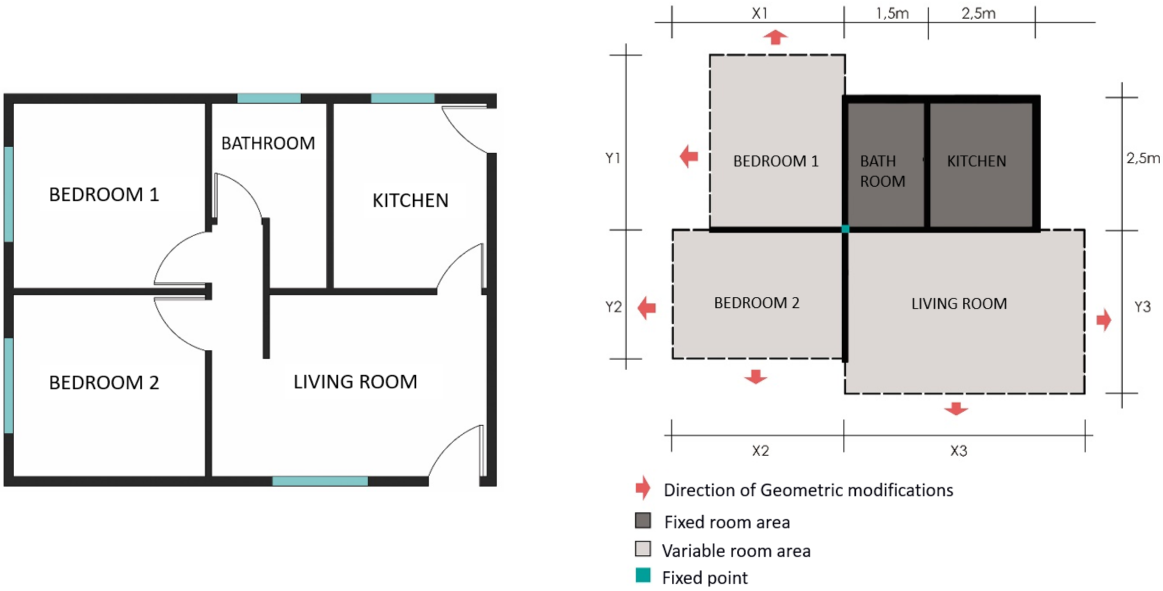
METHODS

Representative model definition

The representative model developed for this study is a single-family housing unit based on the standards established by Santana (15). The model is formed of a single story consisting of 5 rooms: 2 bedrooms, 1 living room, 1 bathroom, and 1 kitchen (Figure 1). It was considered that in its surroundings there would be no obstructions shading the building. It was established that certain characteristics of the building remained constant so that those linked to the shape decision making were analyzed. This was based on the premise that building parameters can only be evaluated when the other parameters (which will not be analyzed) are considered efficient in order to avoid masking results (19). Thus, the constants of this model follow that prescribed to reach level A according to the RTQ-R (16).

Geometric variations were set only for the long term occupancy rooms (Bedrooms and Living room). To establish their minimum areas the Building Work Code for São Paulo, Brazil, was used (20). Windows were defined as the minimum area required for ventilation according to the São Paulo building work code (minimum 15% of the room's floor area), but also taking into consideration the minimum value suggested by the RTQ-R (minimum of 17% of the room's floor area) (Table 1). For those rooms with constant areas, an opening with an area of $1m^2$ for the kitchen and bathroom was defined (Figure 1 and Table 1).

Figure 1: Housing- unit representative model in the study



(a) Base case floor plan (b) Rooms geometric variations

Table 1: Variable parameters: minimum and maximum dimensions of prolonged stay rooms

	Room	Variable	Mín value (m)	Max values (m)	Type	Nature
1	Bedroom 1	X1	2.0	6.0	Continuous	Dependent
2		Y1	2.6	6.0	Continuous	Independent
3		Window-to-floor ratio	17%	90%	Continuous	Dependent
4	Bedroom 2	X2	2.1	6.0	Continuous	Independent
5		Y2	2.5	6.0	Continuous	Dependent
6		Window-to-floor ratio	17%	90%	Continuous	Dependent
7	Living Room	X3	4.1	6.0	Continuous	Independent
8		Y3	2.6	6.0	Continuous	Independent
9		Window-to-floor ratio	17%	90%	Continuous	Dependent
8	All rooms	Height	2.5	4.0	Continuous	Independent

The decision on the type of roof and construction materials was based on Santana (15), where the percentage of the roof slope is dependent on the variation of the height of the ridge and the material used varies according to its slope. Two types of material were used for the roof: ceramic tile and fiber cement tile. The material adopted for the walls was a mortar-coated ceramic block. The slab chosen was a concrete slab and the material used for the floor was composed of concrete, mortar plaster, and ceramic. The thermal properties of the material are based on NBR15220 (21).

Representative model parameterization

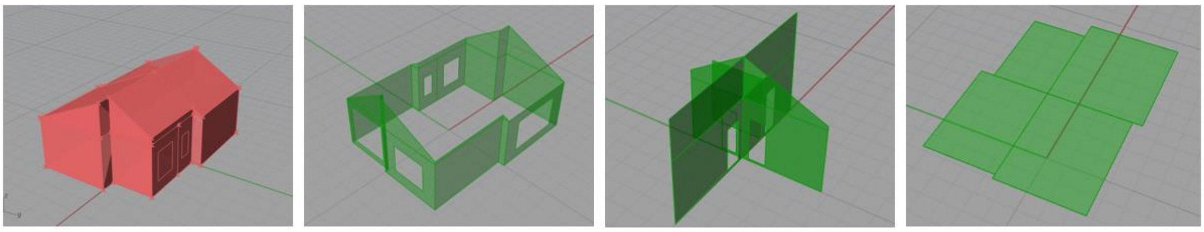
The representative housing unit was modeled in Grasshopper and connected to the HoneyBee plug-in to analyze its thermal performance (figure 2). The model was divided into nine thermal zones, three for long-term occupancy rooms (bedroom 1, bedroom 2, and living room), two for transient occupancy (kitchen and bathroom), and four for the roof attic (two for each side of the roof). The location determined for the model was the city of São Paulo (SP), which was included in the script as an "epw" file using a tool from the LadyBug plug-in, complementary to Honeybee.

To identify the internal walls, floor, ceiling, and external walls of the model, each face of the room was modeled separately, and when assembled, they create a room corresponding to a thermal zone (Figure 2). With the change in size between the rooms (Figure 1b), sometimes one part of the wall may be larger than the wall of the adjacent room and sometimes it may be smaller than the wall of the surrounding room. Thus, when the wall is larger than that of the adjacent room, two surfaces are automatically created for the same face: an inner and an outer surface. With this variation generated for the faces of each room, the HoneyBee plug-in is not able to create a "closed" thermal zone, generating an error. Because of this limitation, constraints on the measurements ensured that the number of surfaces of each room remained constant. Thus, it was decided that:

$y3>y2$ | therefore, the wall of the living room would receive the sun from the East and would prevent bedroom 2 from receiving the sun from the West.

$x2>x1$ | As y2 has previously been restricted, x2 is free, as is y1, while x1 is restricted.

Figure 2: Representative model created through Grasshopper and Honeybee



(a) Representative model parameterized through grasshopper

(b) Faces identified as external walls through Honeybee

(c) Faces identified as internal walls through Honeybee

(d) Faces identified as ground floor through Honeybee

Multi-objective optimization

The objective of the optimization was to find the lowest value possible for cooling degree-hours (DHc) and heating degree-hours (DHh) with a base temperature of 26ºC and 18ºC, respectively. The outputs of the simulation were given in hourly operative temperature (OT) for the period of one year. The adopted conditions for the objectives were:

Objective 1: Temperatures higher than 26º are filtered and then the equation is applied: $DHc = \Sigma \ (OT - 26^{o})$

Objective 2: Temperatures lower than 18º are filtered and then the equation is applied: $DHh = \Sigma \ (18^{o} - OT)$

Thus, the results of DHc and DHh were connected to the Octopus optimization engine as objective functions, in addition to the 11 geometric variables. As a third objective, the diversify parameters option was added to the simulation.

RESULTS AND DISCUSSION

Analysis of simulation stopping criteria

One of the challenges in simulation-based optimization (SBO) is deciding on the stopping criteria. As the number of generations needed to find an optimum solution for the established objectives was unknown, the criteria of observing the convergence in the graphs were used, combined with exhaustive creation of generations.

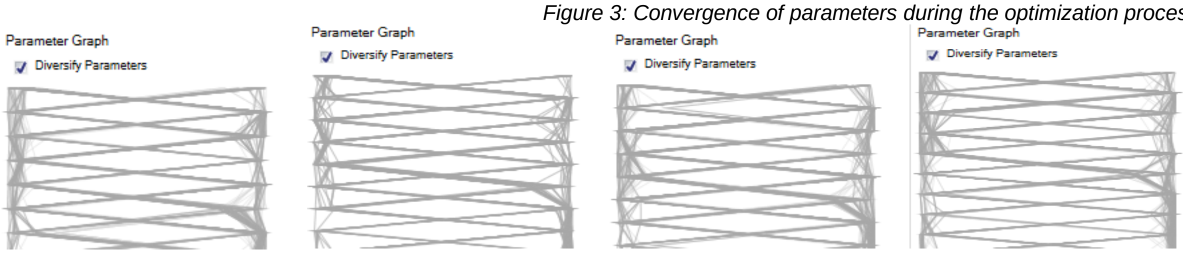
To analyze the results, the Octopus optimization engine was up and running for 240 hours (10 days), obtaining a total of 294 generations and 21,887 scenarios. During the 10 days of simulation, pauses were made to collect the results obtained and to observe progress in the convergence of the data (Table 2, Figures 3 and 4). Figure 3 indicates convergence of the parameters and Figure 4 indicates the oscillation of the objectives. Moreover, we also analyzed the results of the Pareto Front at each pause, to analyze whether there was a considerable difference in the scenarios generated between the pauses. Tables 3, 4, 5, and 6 represent the values of DHc and DHh of the scenarios composing the Pareto Front identified in each pause.

When analyzing the convergence in Figure 3, we can see that it is only in the fourth pause that the graph does not show inconstancy in the oscillation of the objectives (Figure 4). However, when analyzing the values that the Pareto Front described in Tables 3 to 6, from the first pause to the fourth pause, the difference found is only 2.8 º Ch for DHh and 0.4º Ch for DHc. Thus, it can be seen that 87 generations were enough to obtain significant results. Therefore, we can conclude that the criterion of convergence of parameters (Figure 3) is more appropriate for visual analysis in monitoring optimization than oscillation of the objectives (Figure 4).

Table 2: Pauses made during the convergence.

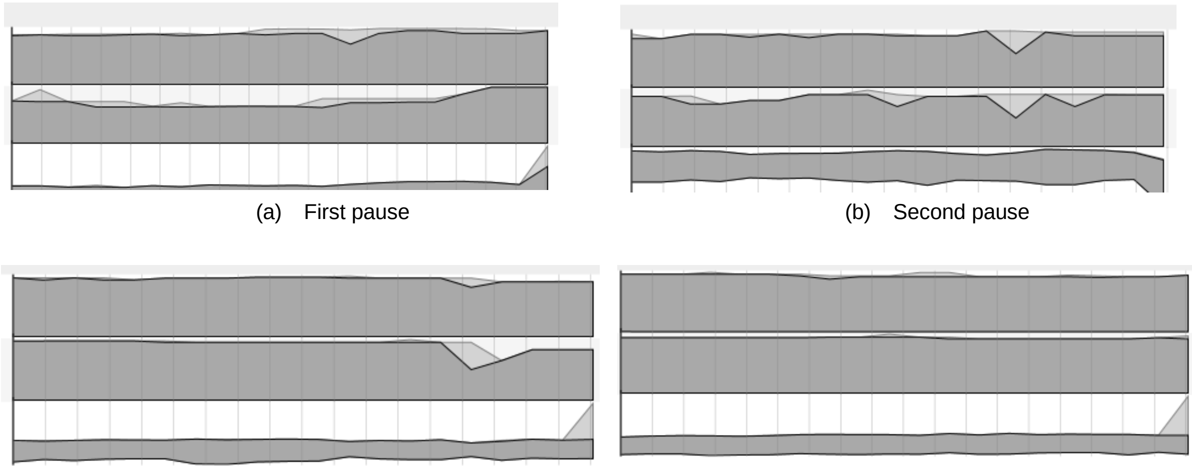
Pauses	Optimization duration	Number of generations	Number of scenarios
1	71 hours	87	4655
2	97 hours	116	7004
3	193 hours	237	17010
4	239 hours	294	21887

Figure 3: Convergence of parameters during the optimization process



(a) First pause (b) Second pause (c) Third pause (d) Fourth pause

Figure 4: Oscilation of the objectives during the optimization process



(a) First pause

(b) Second pause

(c) Third pause

(d) Fourth pause

Table 3: 1st pause made during the optimization process

Case	Generation	DHh	DHc
1	86	4365	667.6
2	86	4367	667.1
3	86	4369	667.3
4	86	4370	667.1
5	86	4378	667.0
6	86	4379	666.9
7	86	4380	666.6
8	86	4381	666.3
9	86	4382	666.0
10	86	4383	665.8
11	86	4386	665.7
12	86	4388	665.6
13	86	4391	665.5

Table 4: 2nd pause made during the optimization process

Case	Generation	DHh	DHc
1	116	4365	667.6
2	116	4367	667.3
3	116	4369	667.1
4	116	4371	666.9
5	116	4373	666.8
6	116	4378	666.8
7	116	4380	666.4
8	116	4381	666.3
9	116	4382	666.0
10	116	4383	665.9
11	116	4385	665.8
12	116	4386	665.6
13	116	4387	665.5
14	116	4389	665.4

Table 5: 3rd pause made during the optimization process

Case	Generation	DHh	DHc
1	237	4365	667.6
2	237	4367	667.3
3	237	4369	667.1
4	237	4371	666.9
5	237	4372	666.7
6	237	4380	666.4
7	237	4382	666.0
8	237	4383	665.8
9	237	4384	665.7
10	237	4387	665.5
11	237	4389	665.3
12	237	4392	665.2
13	237	4395	665.1

Table 6: 4th pause made during the optimization process

Case	Generation	DHh	DHc
1	294	4365	667.3
2	294	4365	667.6
3	294	4367	667.1
4	294	4369	666.9
5	294	4371	666.7
6	294	4372	666.4
7	294	4374	666.0
8	294	4376	665.8
9	294	4380	665.7
10	294	4382	665.5
11	294	4383	665.3
12	294	4385	665.1
13	294	4387	665.2
14	294	4390	665.3

To confirm the analysis of the simulation stopping time, previous studies which performed simulations with the Octopus optimization engine were analyzed (12, 15). Table 7 shows the characteristics of each study and the number of generations created to reach simulation convergence. It can be seen from Table 7 that in the study by Fonseca et al. (12), the number of generations created to reach convergence of optimization was 99 generations, which is closer to the number of generations obtained in the first pause of this study. In Santana (15), due to presenting computational difficulties in optimization, the study only reached 12 generations, and results were validated through a Surrogate Model (model reduced to essential characteristics to minimize computational expenditure in the process).

Table 7: Comparison of simulation time in previous studies

Reference	Variable parameters	Thermal zones	Number of Generations	Population size
This study	11	9	87 / 294	4655 / 21887
Fonseca et al. (12)	8	10	99	19800
Santana (15)	9	8	12	1495

After verification and checking of convergence of the optimization in the first pause, the results of the first 87 generations were adopted, analyzing the space of solutions and the Pareto Front, represented in Figures 5 and 6. It was noticed that the results converged to a point, where it is not possible to identify a Pareto Front. When approaching area 1, where the best cases are found, the point of convergence becomes a curve. However, the variation of the solutions from the Pareto Front is not significant - 665º Ch to 667º Ch for DHc and 4365º Ch to 4391º Ch for DHh – which implies in a series of equivalent performance solutions.

Figure 5: Pareto Front - best cases (area 1) and worst cases (area 2)

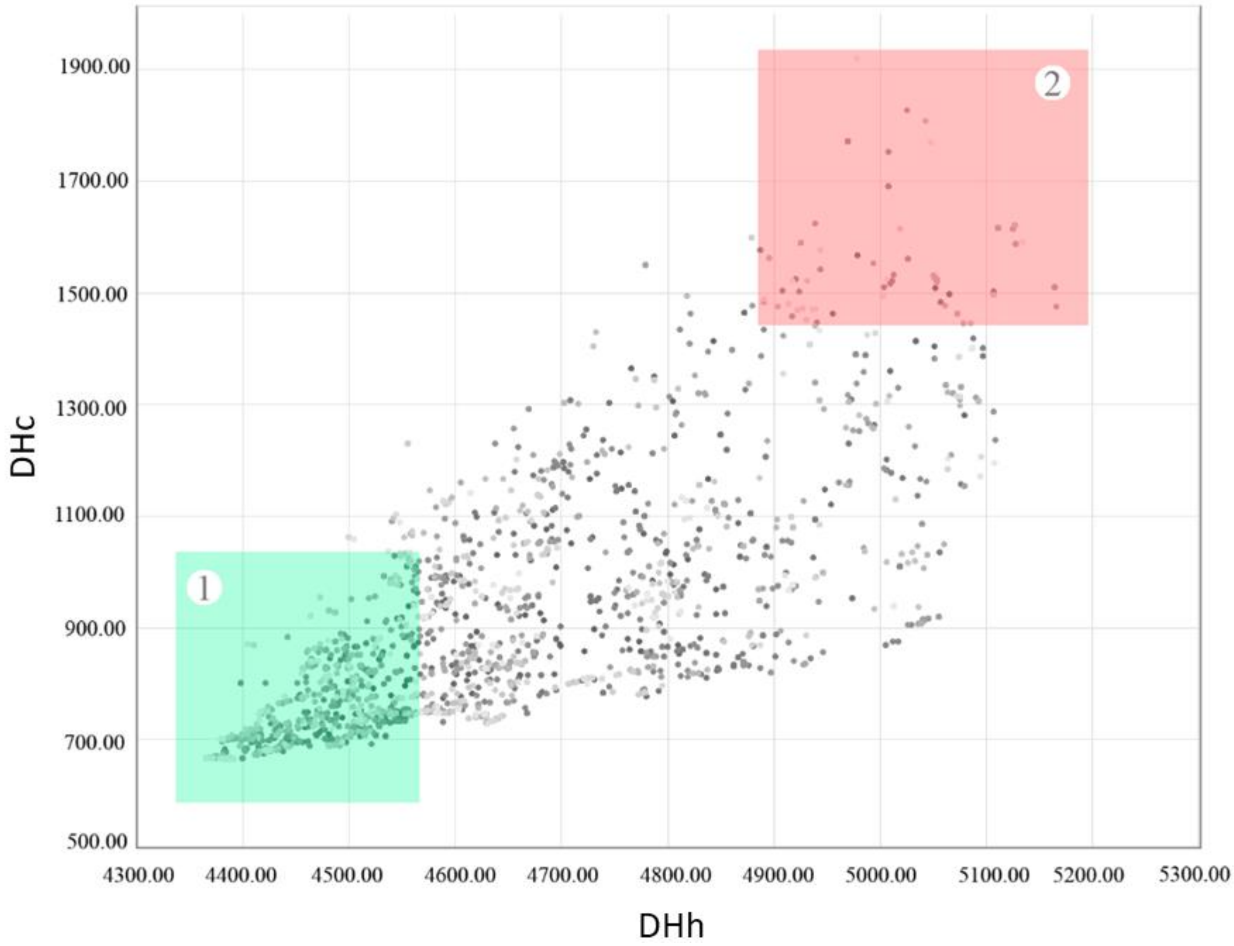
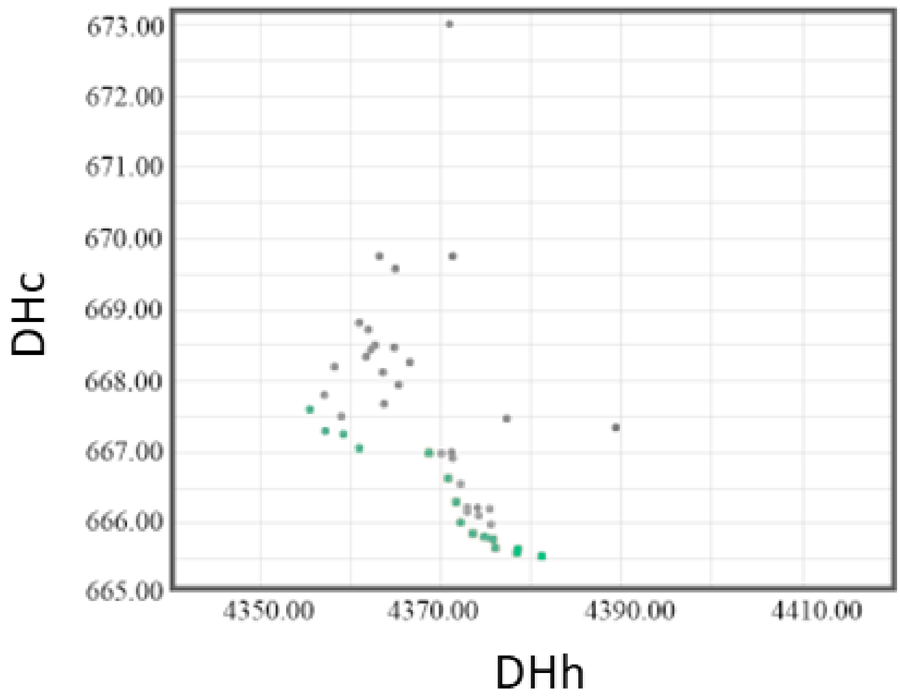


Figure 6: Zoom in area 1, showing the Pareto Front



From analyzing all cases obtained up to generation 87, based on the DHc results, it was observed that, according to the RTQ-R (16), only 48.4% of the results presented a level of efficiency A, 51.2% level B, and 0.4% level C. Results indicated that the construction materials and colors/solar absorptance indicated by the RTQ-R alone were not enough to ensure level A for all the scenarios.

By analyzing the best cases obtained in the Pareto Front, thirteen models were identified (Figure 7). All of the models were classified as level A and geometric similarities were identified. For all the solutions presented in the Pareto Front, there was a relation between the ceiling height and rooms' area. When the model presented a large room area, the ceiling height was low and vice versa, which was determinant for good thermal performance. For DHh, results showed that the models presented smaller floor areas when compared with the solutions found for DHc. Also, the larger the area of contact with the ground, the greater its contribution to cooling the internal rooms, which justifies small areas for the rooms optimized for DHh. Openings were set through optimization as predominantly medium, and larger when located in east-facing bedrooms.

The best cases selected for DHc presented as dominant characteristics: larger floor areas, smaller openings, high ceilings, and steep roofs, due to the height of the ridge. By analyzing the geometry with the best solutions found in the Pareto Front, the interval between the solutions was narrow: from 2ºCh for DHc and 25ºCh to DHh. Thus, simultaneous analysis for DHc and DHh was possible, with a great similarity between the cases C, I, K, and M, which were positioned at the beginning, middle, and end of the curve (Figure 8).

To represent the worst solutions, 8 cases were selected from area 2, identified in Figure 5 (Figure 9). If we consider model C as representative of the Pareto Front and model N of the worst cases, we can see that the latter is composed of wide glazed areas that receive high incidence of solar radiation and rooms with larger areas than the models in the Pareto Front (Figure 10)

Figure 7: Best cases found in optimization (area 1 highlighted in figure 5)

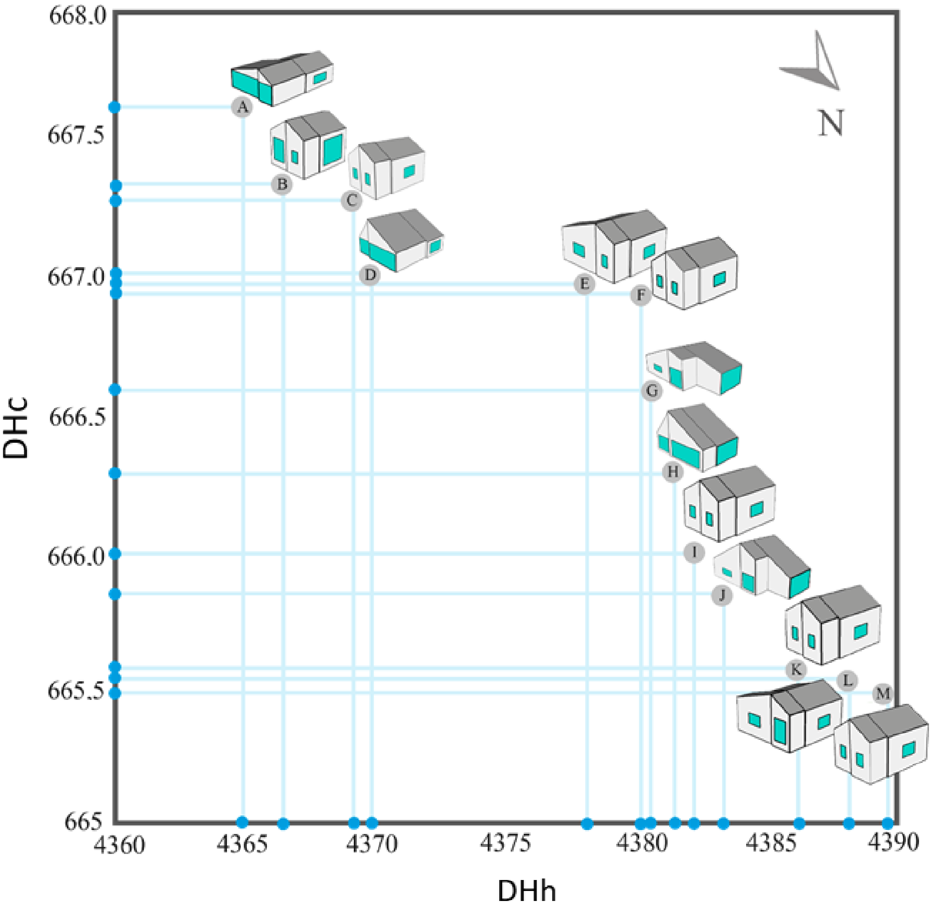


Figure 8: Similarity of the C, I, K, and M models

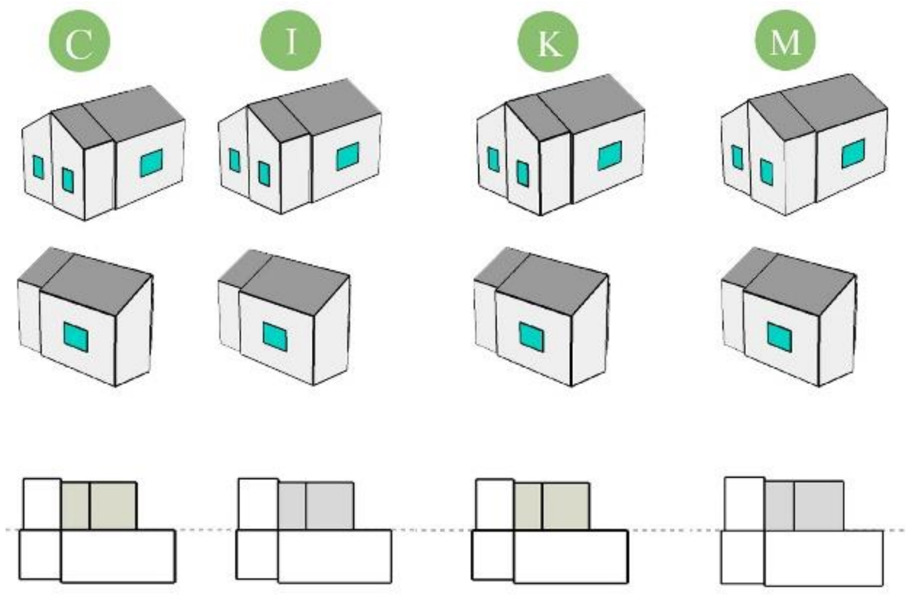


Figure 9: Worst cases found in optimization (area 2 highlighted in figure 5)

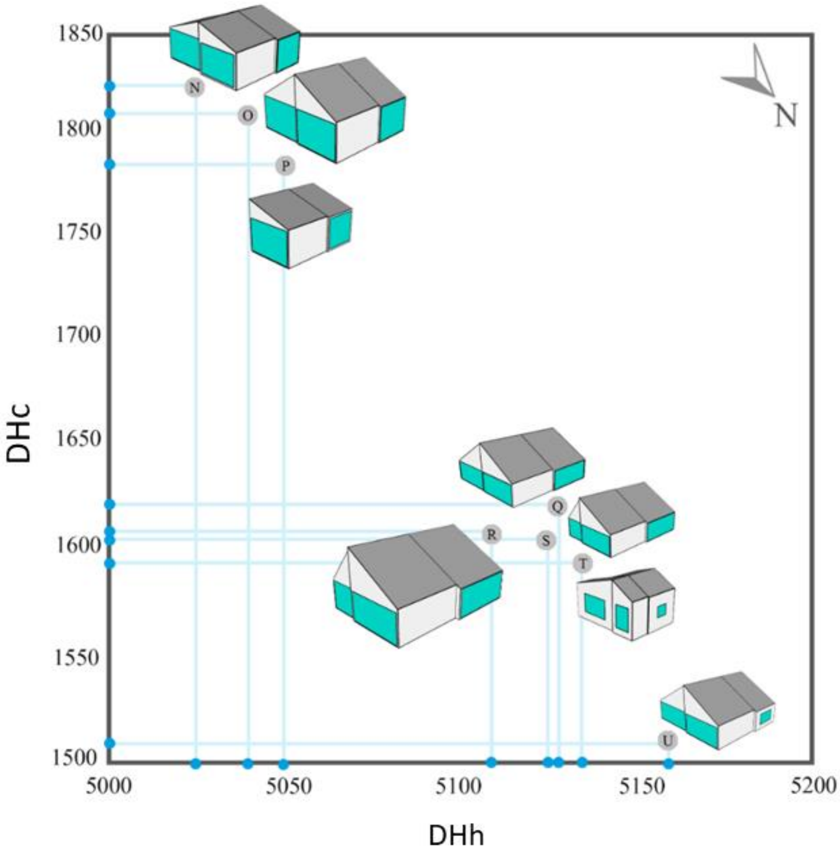
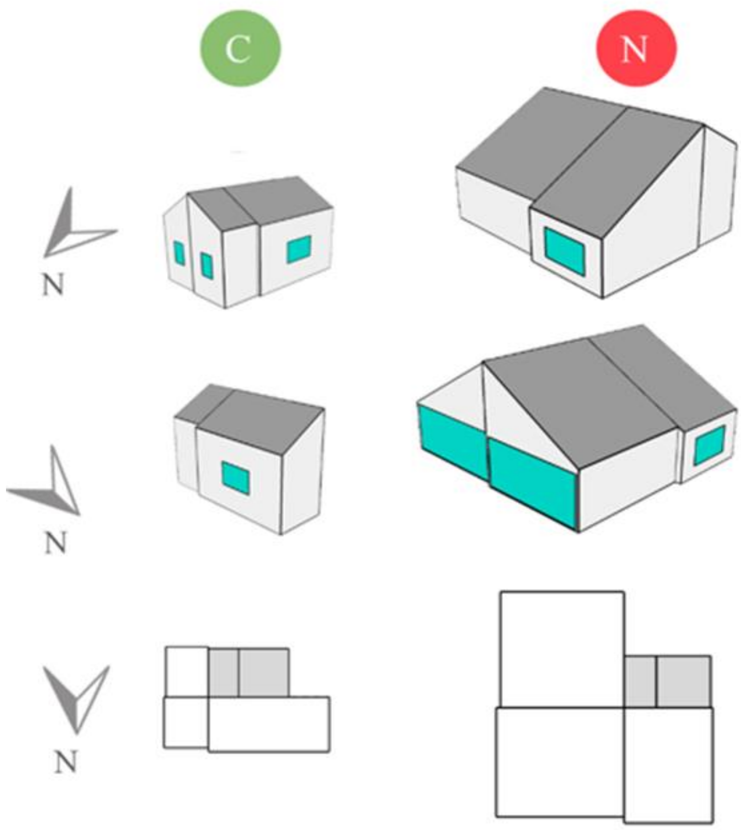


Figure 10: Comparison between the best and worst solutions found



CONCLUSION

In this study, the process for optimizing a housing unit was approached, varying geometric parameters while considering materials, colors, and window frame models as constants. The universe of solutions presented maximum values close to 1920º Ch for Cooling Degree-hours (DHc); 5164º Ch for Heating Degree-hours (DHh) and minimums around 665º Ch for cooling and 4365º Ch for heating. The fixed parameters values, chosen based on those recommended to achieve level A according to the RTQ-R, were not sufficient to ensure that all solutions reached level A but prevented the cases from reaching very low levels such as D or E, with only 0.4% of cases reaching level C.

Divergent characteristics were observed for DHc and DHh in the Pareto Front, such as the size of opening areas and room areas, although a combination of high ceiling height with smaller room areas and vice versa was identified for all cases. Although this divergence occurred between the characteristics, four similar models were observed in the Pareto Front: models C, I, K, and M. These models presented in common the high ceiling, steep roof due to the height of 3.3m from the ridge, small rooms and openings located in all solar orientations. The worst cases can be seen visually, for larger models regarding the floor area. In addition, they present larger areas of window opening.

In general aspects, concerning most impacting geometric parameters in the building, the thermal performance can be partially predicted based on the literature, such as the impact of the area in contact with the ground and large areas of glazed openings. However, although the majority of the cases on the Pareto Front have common characteristics, there are still geometric conformations that differ from the predominant ones that also present good results, thus emphasizing the importance of the use of the thermal simulation for the design of energy-efficient buildings starting from the design stage.

Regarding the study of stopping criteria, by analyzing the results of the pauses, it was observed that 87 generations, 4655 individuals, were enough for the convergence, even if, visually, the objective functions still presented some oscillations.

The optimization process was described in the methodology. Its tools were found to be user-friendly from the point of view of the architects and do not require in-depth knowledge of programming, but the accessibility of the usual architectural design process is still low considering the entire modeling process of a housing unit. Besides the tools used for the purpose of this study, the plugin also offered many other possibilities that can be used in greater depth to optimize other objectives.

ACKNOWLEDGMENTS

This research was made with the support of the Brazilian National Council for Scientific and Technological Development (CNPq).

REFERENCES

1. NGUYEN, Anh Tuan, REITER, Sigrid and RIGO, Philippe. A review on simulation-based optimization methods applied to building performance analysis. *Applied Energy*. 2014. Vol. 113, p. 1043–1058. https://doi.org/10.1016/j.apenergy.2013.08.061
2. FLORIO, Wilson. Modelagem Paramétrica, Criatividade E Projeto: Duas Experiências Com Estudantes De Arquitetura. *Gestão e Tecnologia de Projetos*. 2012. Vol. 6, p. 43-66.
3. ATTIA, Shady, HENSEN, Jan L.M., BELTRÁN, Liliana and DE HERDE, André. Selection criteria for building performance simulation tools: Contrasting architects' and engineers' needs. *Journal of Building Performance Simulation*. 2012. Vol. 5, no. 3, p. 155–169. https://doi.org/10.1080/19401493.2010.549573
4. ØSTERGÅRD, Torben, JENSEN, Rasmus L. and MAAGAARD, Steffen E. Building simulations supporting decision making in early design - A review. *Renewable and Sustainable Energy Reviews*. 2016. Vol. 61, p. 187 - 201. https://doi.org/10.1016/j.rser.2016.03.045
5. OXMAN, Rivka. Theory and design in the first digital age. *Design Studies*. 2006. Vol. 27, no. 3, p. 229–265. https://doi.org/10.1016/j.destud.2005.11.002
6. ANDRADE, Max and RUSCHEL, Regina. Projeto performativo na prática arquitetônica recente. *Vitruvius* [online]. 2012. Ano 13, no.150.07. Available from: http://www.vitruvius.com.br/revistas/read/arquitextos/13.150/4587. [Accessed 08 January 2020].
7. SHI, Xing and YANG, Wenjie. Performance-driven architectural design and optimization technique from a perspective of architects. *Automation in Construction*. 2013. Vol. 32, p. 125–135. https://doi.org/10.1016/j.autcon.2013.01.015
8. GOSSARD, D., LARTIGUE, B. and THELLIER, F. Multi-objective optimization of a building envelope for thermal performance using genetic algorithms and artificial neural network. *Energy and Buildings*. 2013. Vol. 67, p. 253–260. https://doi.org/10.1016/j.enbuild.2013.08.026
9. MAGNIER, Laurent. *Multiobjective Optimization of Building Design Using Artificial Neural Network and Multiobjective Evolutionary Algorithms* [online]. Master thesis. Concordia University, 2008. Available from: https://spectrum.library.concordia.ca/976218/
10. FOOD4RHINO. Octopus. [online]. 2020. [Accessed 5 August 2019]. Available from: https://www.food4rhino.com/
11. DOE, Robert and AITCHISON, Mathew. Multi-criteria Optimisation in the Design of Modular Homes. In: *33rd Annual Confrence of Education Research in Computer Aided Design in Europe* (eCAADEe 33). Vienna, Austria, 2015. p. 1-9
12. FONSECA, Ligiana Pricila Guimarães, NUNES, Vitor Dias Lopes, SANTANA, Laila Oliveira, CARLO, Joyce Correna and JÚNIOR, Kléos Magalhães Lenz Cézar. Otimização multiobjetivo das dimensões dos ambientes de uma residência unifamiliar baseada em simulação energética e estrutural. *Ambiente Construído*. 2017. Vol. 17, p. 267–288. https://doi.org/10.1590/s1678-86212017000100135
13. SILVA, Mario Alves, CARLO, Joyce and BOSCO, Luciana. Modelagem paramétrica e desempenho da edificação : otimização baseada em simulação luminosa e energética através de algoritmos genéticos. *Cadernos do PROARQ*. 2018. Vol. 30, p. 150-176.
14. SANTANA, Laila Oliveira and CARLO, Joyce Correna. Processo de otimização baseada em simulação do desempenho energético de um modelo de uma zona térmica. *Cadernos Proarq*. 2016. Vol. 27, p. 144–155.
15. SANTANA, Laila Oliveira. *Otimização Multiobjetivo da Geometria de Edificações através do RTQ-R, EnergyPlus e Algoritmos Genéticos* [online]. Master thesis. Universidade Federal de Viçosa, 2016.

16. INMETRO. Regulamento Técnico da Qualidade para o Nível de Eficiência Energética de Edificações Residenciais (RTQ-R). Rio de Janeiro, 2012. Portaria no. 18.

17. ACAR, Ugur, KASKA, Onder and TOKGOZ, Nehir. Multi-objective optimization of building envelope components at the preliminary design stage for residential buildings in Turkey. *Journal of Building Engineering*. 2021. Vol. 42. https://doi.org/10.1016/j.jobe.2021.102499

18. SALATA, Ferdinando, CIANCIO, Virgilio, DELL'OLMO, Jacopo, GOLASI, Iacopo, PALUSCI, Olga and COPPI, Massimo. Effects of local conditions on the multi-variable and multi-objective energy optimization of residential buildings using genetic algorithms. *Applied Energy* [online]. 2020. Vol. 260. https://doi.org/10.1016/j.apenergy.2019.114289

19. CARLO, Joyce Correna. *Desenvolvimento de Metodologia de Avaliação da Eficiência Energética do Envoltório de Edificações Não-residenciais* [online]. PhD thesis. Universidade Federal de Santa Catarina, 2008. Available from: https://repositorio.ufsc.br/xmlui/handle/123456789/91026

20. SÃO PAULO PREFEITURA. Código de Obras de São Paulo [online]. 2016. [Accessed 6 February 2020]. Available from: http://www.prefeitura.sp.gov.br

21. ABNT ASSOCIAÇÃO BRASILEIRA DE NORMAS TÉCNICAS. NBR 15220-3: Desempenho Térmico de Edificações. Rio de Janeiro, 2005.

Submetido: 17/02/2021
Aceito: 17/06/2021