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ON THE IMPROVEMENT OF WHOLE-BUILDING PERFORMANCE SIMULATIONS THROUGH MULTI-OBJECTIVE OPTIMIZATION

Cassiana Fagundes da Silva
Lucas Camilotti
Roberto Zanetti Freire
Industrial and Systems Engineering Graduate Program (PPGEPS), Polytechnic School (EP), Pontifical Catholic University of Parana (PUCPR). Rua Imaculada Conceição, 1155, Prado Velho, Postal Code: 80215-901, Curitiba, Brazil
cassiana.fagundes@pucpr.edu.br, lucas.camilotti@pucpr.edu.br, roberto.freire@pucpr.br

Abstract. *Building energy consumption has become a source of discussion and research. Research has been proposed to improve the usage of energy resources and provide better indoor air quality and thermal comfort for the occupants considering indoor environments. In this context, the development of computer programs capable of simulating the thermal and energetic performance of buildings has been evolving, providing engineers and architects with new approaches to try to reduce energy consumption and improve occupant satisfaction with the internal climatic conditions of an environment. The objective of this work is to present the integration of metaheuristic techniques for multi-objective optimization to the Domus building thermoenergetic simulation program, in addition to evaluating the relevant variables about improving the thermoenergetic performance of environments. For this, two environments were tested, the first being a test case based on BESTest, initially proposed by the International Energy Agency, and the second based on a real building, located in the city of Curitiba /PR. The results present show that the NSGA-II algorithm was better than the other algorithms tested using the adopted performance criteria. In the real case study, the NSGA-II algorithm showed good results, but the execution time was longer than that obtained in the test case, and comfort limits were determined according to the criteria established by INMETRO, 2012. The percentage of hours of comfort for the building was 56.7% and the annual thermal discomfort is 42.4% of the hours.*

Keywords: *building simulation, energy savings, DOMUS, thermal comfort*

1. INTRODUCTION

Building energy consumption is responsible for a considerable amount of total urban energy demand. Taking into account that the energy demand tends to increase over the next few decades and that people spend more than 80% of their time in indoor environments, both energy savings and thermal comfort associated with the environmental impact of buildings are widely been discussed in academic and industrial areas (Buonocore et al., 2019).

Several countries have developed regulations to reduce the energy demand of buildings. To provide continuous improvements related to energy efficiency, building subsystems have been also affected by those regulations, such as lighting, air conditioning, and envelope. Around the world, several countries have invested in the optimizing associated with the energy consumption of buildings.

In Brazil, according to recent data obtained from the Ministry of Mines and Energy (EPE, 2019), the demand for electrical energy shows a significant concentration in the consumption related to buildings mainly in the commercial, residential, and public sectors.

In Brazil, these studies are still very discreet, since the country, in its territorial extension, presents a very diversified bioclimatic zone. In this sense, this work aims to determine the potential for application of parameter optimization techniques when applied to energy efficiency problems and improvement of thermal comfort conditions inside environments, in the context of Brazilian buildings, to enhance the use of computer simulation of buildings.

In this way, this paper proposes a methodology for the maximization of thermal comfort and minimization of energy consumption of Brazilians buildings assuming a multi-objective optimization approach, where was proposed the integration between MATLAB and Domus, where, the Multi-objective Differential Evolution algorithm with Spherical Pruning (sp-Mode), Multi-objective Differential Evolution (MODE), Multi-objective Particle Swarm Optimization (MOPSO) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) were tested in two case studies.

This paper is structured as follows. Section 2 specifies the concepts and definitions of the thermal comfort, energy consumption, optimization, and criteria of performance analysis. In the literature review, the multi-objective optimization applied to thermal comfort and thermoenergetic performance of buildings is described (Section 3). The problem addressed as a case study, the objective functions, and the design variables, are presented in Section 4. Section 5 discusses the results and, in section 6, conclusions and future works are addressed.

2. CONCEPTS AND DEFINITIONS

2.1 Thermal Comfort

Thermal comfort problems have grown over the years and are associated with the time that occupants spend in naturally ventilated or artificially controlled environments. Thermal comfort is defined by (Fanger, 1970) as the sensation in which a person feels neither cold nor hot in the environment. That is, a person under these conditions is in thermal neutrality. Second (ASHRAE, 2005), thermal comfort is a condition or state of satisfaction about the environment in which the person is. Thermal comfort indices were developed from the need to understand the thermal sensations experienced by people exposed to the climatic variables of the environment.

The sensation of thermal comfort depends on the influence of variables that are grouped into two groups: environmental variables and personal variables. For the environmental variables, the climatic conditions of the evaluated environment are observed, which are the mean radiant temperature, the air temperature, the relative speed, and the relative humidity of the air (Fanger, 1970).

2.2 Energy Consumption

Global energy demand is growing rapidly and concerns about supply shortages, depletion of energy resources, and environmental impacts are in constant evidence.

As described by the United Nations in 2014, the significant increase in urbanized areas shows that by 2050 over 70% of the population will reside in urban centers. Because of this growth, there will be an equal increase in the urban density of buildings, directly influencing the internal characteristics of the environments, since the time spent by people inside them is quite significant (Sorrell, 2015). Buildings in the commercial and residential sectors have a considerable contribution associated with energy demand, reaching between 20% and 50% in developed countries, surpassing the large industrial and transportation sectors (Soares et al., 2013).

Given this scenario, companies are discussing ways and procedures to minimize the energy consumption of the buildings sector. In Brazil, the certification-labeling method RTQ-C, Technical Regulation of Quality for Energy Efficiency in Commercial, Services, and Public Buildings, developed as part of the PROCEL Edifica program, has the objective of certifying building regarding the energy consumption.

2.3 Multi-objective Optimization

The optimization process, in general, refers to the search for the best solutions for a specific problem. Analyzing the objectives associated with a problem, which are feasible considering the restrictions imposed or inherent to it, an optimization problem consists of maximizing or minimizing some function relative to some set of design (or control) variables, representing a range of choices available in a certain situation.

In the last decades, researchers have been carried out to develop methods that solve the challenge of finding solutions to optimization problems in a fast and efficient way (Bechikh, Datta, and Gupta, 2016). However, when the computational complexity is evaluated, it becomes difficult to find an optimal solution for a multi-objective problem, in a polynomial approximation of time, as a function of the number of instances of the problem (Rao, 2009).

Given this scenario, most of the real optimization problems in buildings are characterized by having several goals that must be achieved simultaneously, and these objectives are often conflicting, that is, there is no single solution that optimizes them all at the same time. Problems of this nature are called multi-objective optimization problems because they involve minimizing or maximizing simultaneously a set of objectives satisfying a set of restrictions.

A multi-objective problem can be defined as the simultaneous minimization for $2 \leq k \leq 4$ of functions (Kagami, 2019), as described in Eq. (1).

$$\min_{\boldsymbol{\theta}} \boldsymbol{F}(\boldsymbol{\theta}) = [F_1(\boldsymbol{\theta}), \dots, F_k(\boldsymbol{\theta})]. \tag{1}$$

Optimization vector or θ p-dimensional variables, as described in Eq. (2).

$$\boldsymbol{\theta} = [x_1, \dots, x_p]. \tag{2}$$

Restricted to a U universe of feasible solutions, in Eq. (3).

$$U = \begin{Bmatrix} \underline{x_1} < x_1 < \overline{x_1} \\ \underline{x_2} < x_2 < \overline{x_2} \\ \dots \\ \underline{x_p} < x_p < \overline{x_p} \end{Bmatrix}, \tag{3}$$

where $\underline{x_p}$ and $\overline{x_p}$ the lower and upper limits of the search space for the variable x_p. In the literature there are several techniques and algorithms created and adapted for multi-objective optimization problems, as describe in (Cui et al., 2017): MOPSO – Multi-objective Particle Swarm Optimization; NSGA-II – Non dominated Sorting Genetic Algorithm; MODE – Multi-objective Differential Evolution; sp-MODE – Differential Evolution Algorithm with Spherical Pruning.

2.3.1 Multi-objective Particle Swarm Optimization (MOPSO)

The Multi-objective Particle Swarm Optimization algorithm is an extension of the PSO algorithm and was proposed by (Coello and Lechuga, 2002). This is characterized by impressive maneuverability and convergence, which has been validated and applied widely by many researchers.

Each potential solution, which is called a particle, is compared to a flying bird within the search space. Each particle is characterized by its position, velocity, and past performance. The particles fly randomly and update themselves by their choice and social characteristics from other particles. There is an extra set called the external archive containing all the particle leaders. The archive will be updated at each iteration when the new leader particle is better than the old one. Finally, the external archive contains the output of the searching results.

2.3.2 Non dominated Sorting Genetic Algorithm (NSGA-II)

Developed by (Deb et al., 2002), the NSGA-II, as well as its first NSGA version, implements the concept of dominance, classifying the population in frontiers according to the degree of dominance. The NSGA-II has a better sorting algorithm, incorporates elitism, and no sharing parameter needs to be chosen. At each generation, the populations are combined and sorted according to the non-domination concept. The number of non-dominated points available after sorting may be greater than the population size N, which defines the number of elite points that are kept by the algorithm.

The algorithm selects the N least crowded solutions by using the crowding distance measure and rejects the rest of the non-dominated points. Due to these improvements, both convergence and spreading of the solution front are ensured, without requiring the use of any external population.

2.3.3 Multi-objective Differential Evolution (MODE)

This algorithm was proposed by (Robič and Filipič, 2005) was adapted from the classic Differential Evolution algorithm and proposes the Pareto approach to select the best individual. In MODE, an initial population is generated at random from a Gaussian distribution; all dominated solutions are removed from the population; if the number of non-dominated solutions exceeds some threshold, a distance metric relation is used to remove those parents who are very close to each other. Three parents are selected at random. A child is generated from the three parents and is placed into the population if it dominates the first selected parent; otherwise, a new selection process takes place. This process continues until the population is completed.

2.3.4 Differential Evolution Algorithm with Spherical Pruning (sp-MODE)

This algorithm was developed by (Reynoso-Meza et al., 2010) to overcome the two main problems associated with multi-objective optimization: i) to avoid premature convergence in the hyperspace of the optimal location, losing the description and generalization about the true Pareto front; and, ii) to find a set of solutions with greater diversity, generating a good discrete representation of the Pareto frontier.

Among the main features of sp-MODE, some can be highlighted: i) it uses as base the stochastic algorithm of Differential Evolution; ii) the method adopts an initial population to explore the search space to avoid convergence in sub-optimal spaces; iii) the best solutions are stored in a file guaranteeing the quality of the solutions since these are not lost in the process of evolution. The definition of Spherical Pruning, as well as the steps of the sp-Mode algorithm, are described in (Reynoso-Meza et al., 2010).

3. LITERATURE REVIEW

Several studies can be found focusing on multi-objective optimization applied to the energy efficiency of buildings. Some of these works are reviewed in the sequence of this section.

A powerful simulation-based approach focusing on multi-objective optimization of building energy efficiency and indoor thermal comfort associated with variables of the building envelope was presented in (Delgarm et al., 2016). The optimization method was developed by integrating a multi-objective artificial bee colony (MOABC) algorithm implemented in MATLAB with EnergyPlus, a whole-building energy performance simulation tool. The proposed optimization approach was applied to a single office room, and the decision variables, including the room rotation, window size, cooling, and heating setpoint temperatures, glazing, and wall material properties, were considered as decision variables.

In (Wu et al., 2017), a method for multi-objective optimization of building energy systems and directed to retrofitting in buildings. The strategy was designed to fit the diversity of existing buildings in terms of age, size, and utilization. It combines dynamic energy simulation to explore individual scenarios with energy hub optimization. The method is implemented in a case study of typical residential buildings in the Swiss village of Zernez, where the energy demands are simulated using Energy Plus software, and the optimization problem was solved with CPLEX.

In the work proposed by (Zhang et al., 2017), the use of simulation and optimization tools, based on genetic algorithms, were assumed to find the best balance between minimizing the use of energy for heating and lighting, reducing the time of discomfort in summer and maximizing the use of natural light. Different spatial configurations were investigated, including a single-sided, closed-sided, and double-sided corridors types in school buildings. The following passive design parameters were considered in the optimization analysis: orientation, room depth, depth of the corridor, and the window-wall ratio of different interfaces, glazing materials, and types of shading. Besides, other work using dynamic programming to minimize the cost function, representing peak-hour electricity tariff, with restrictions functions related to comfort and maximum heating power, was proposed in (Louadj et al., 2018).

Along with these previous works, it can be noted that the design parameters selected for this type of problem usually falls under building orientation, wall elements, external absorption of the walls, type of window, window shading fraction, infiltration rate on walls and openings, different roofs and floors, interior wall materials, window opening for natural ventilation, the solar incidence concerning different tropical climates, air conditioning systems control and parameters, glass properties, indoor temperature, relative humidity, and the number of air changes per hour (Ekici, 2019).

In the work presented in (Camilotti et al., 2019), the authors proposed the utilization of an approach involving whole-building energy simulation and bio-inspired metaheuristic optimization comparing four techniques: Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), and Competition over Resources (COR). The optimization problem was formulated to minimize energy consumption and building costs while maximizing occupants' thermal comfort. Results showed that it is possible to reduce energy usage, materials cost, and thermal comfort simultaneously. However, restrictions imposed on the problem can significantly reduce the optimization associated with these three objectives.

4. CASE STUDY

One way to evaluate the energy consumption of buildings is through the whole-building energy simulation. Some computational tools as Domus (Mendes et al., 2003), which was adopted in this work, are capable to predict the thermal performance of multi-zone buildings. Considering a lumped formulation for temperature, Domus includes loads associated with the building envelope (sensible and latent conduction heat transfer), furniture (sensible and latent), fenestration (conduction and solar radiation), openings (ventilation and infiltration) and heating, ventilation, and air conditioning (HVAC) systems. The Energy balance for a zone subjected to the loads previously mentioned is presented in Eq. (4).

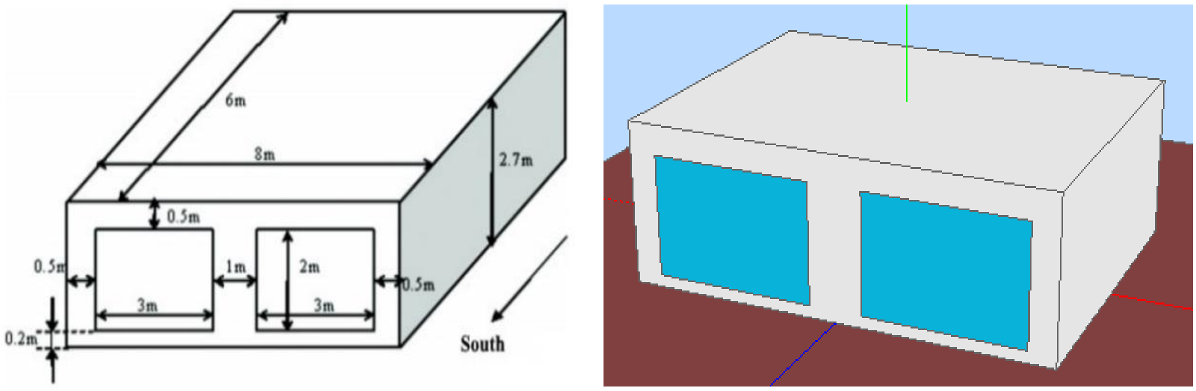
$$\dot{E}_t + \dot{E}_g = \rho_{air} \,.\, c_{air} \,.\, V_{air} \,.\, \frac{dT_{int}}{dt}\,. \qquad (4)$$

In the equation presented above, $\dot{E}_t$ is the thermal energy that crosses the building envelop (in W), $\dot{E}_g$ is the internal energy generation rate (W), ρ_{air} is the density of air (kg/m^3), c_{air} is the specific heat of the air (J/(kg.K)), V_{air} is the room volume (m^3), T_{int} is the room air temperature (K) and t is the time (s).

4.1 Model Description – Case Study 1

The case study one was modeled based on the International Energy Agency (IEA) architecture proposed in Annex 41 to analyze whole-building and energy simulation tools (Rode, Hens and Janssen, 2008). This building structure is a project to tackle several aspects related to humidity, air, and moisture, with one of them being related to the validation of aspects of models used by building simulation software around the world.

Figure 1 presents a building for the weather file of Curitiba of Paraná state in Brazil selected, along with its weather file. The city is located at a latitude of 25.43° S and longitude of 49.27° W. was considered, and the simulation period was defined as one year. The initial condition for the ambient temperature was set to 20°C, and the time step was set to 1 minute and the sampling time to generate data for this paper was set to 1 hour.



(a) (b)

Figure 1. The geometry of the BESTest building (Case Study 1): (a) with the measurements originally specified by the IEA; (b) replicated in the Domus computational tool.

In this case, the input variables established for the execution of the building model simulation were considering the requirements of the Brazilian construction standards. In this sense, five input variables were chosen (Table 1), constructive elements of the walls, constructive elements of the concrete slab, thickness of the concrete floor, external emissivity, and opening hours of the windows.

Table 1. Variables used in the optimization considering ranges of variation and type.

Name	Description	Type	Interval
Orientation	The orientation of the building in degrees	Continuous	[0, 360)
Walls pattern	Brazilian construction pattern used for the four walls	Discrete	[0, 30]
Celling pattern	Brazilian construction pattern used for the ceiling	Discrete	[0, 11]
Soil thickness	Variation in cm of concrete thickness	Continuous	[5, 25]
Offset open window	Start and end time shift for window opening[1]	Discrete	[0, 2]

(1) Hours of operation may vary from the specified, up to 08:00 - 16:00.

In this model, the building is occupied between 8:00 am and 12:00 am and from 1:00 pm to 5:00 pm. Thus, at times when the occupants are in the building, the occupation is maximum (100%) and at other times the building is considered unoccupied.

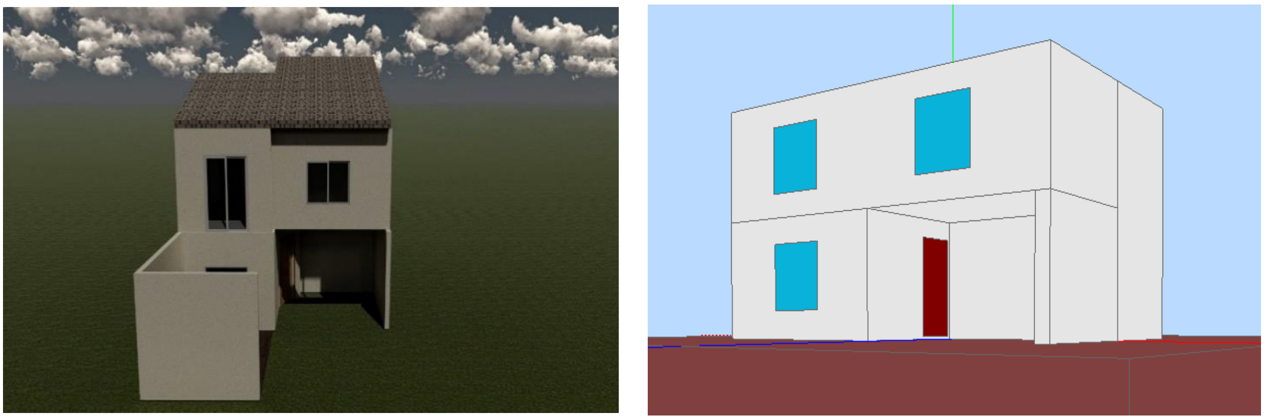
The building environment consists of four occupants, weighing 75 kg and 1.78 m high each, and with appropriate clothing for the local climate. Since the metabolic rate (M) for office activities performed by the four occupants is 1.2 W/m^2, and the clothing index of these occupants is 1.117 *clo*. For air velocity, a value of is assigned 0.01 m/s was assumed.

According to the recommendations of the RTQ-R (INMETRO, 2012), it is necessary to establish standards for the times of use of lighting and equipment for long-term environments. The equipment common to an office environment, such as computers, lighting, and printers is configured to operate in the interval from 8:00 am to 12:00 pm and from 1:00 pm to 5:00 pm, from Monday to Friday.

4.2 Model Description – Case Study 2

The building selected for the real case considers the premises established by NBR 15220-3 and NBR 15571-1. The lower floor has a toilet, a kitchen (Zone 2), and an integrated room for two environments (Zone 1), the building has a ceiling height of 2.70 m. This floor contains two sliding windows measuring 1.40 m x 1.10 m in the living room and kitchen, respectively, 4 opening doors in the dimensions of 0.80 m x 2.10 m, these being the entrance door, the toilet door, and the door, two kitchen doors (entrance and exit), in addition to the 1.40 m x 2.10 m sliding door, which allows an exit to the back of the building.

The floor plan of the upper floor consists of two bathrooms and three bedrooms. The dorms represented by Zones 4 and 5 contain a 1.40 m x 1.10 m corridor window, in addition to each having a 0.80 m x 2.10 m opening door. The bedroom represented in Zone 3 has a 1.40 m x 2.10 m sliding door. Figure 2 presents a building for the weather file of Curitiba cite, Brazil was considered, and the simulation period was defined as one year.



(a) (b)

Figure 2. The geometry of the real building (a) Case Study 2), and (b) replicated in the Domus computational tool.

The input variables established to perform the simulations of the real model incorporate the parameters used in Case Study 1 and added two more variables illustrated in Table 2.

Table 2. Variables used in the optimization considering ranges of variation and type.

Name	Description	Type	Interval
Window opening %	% ventilation opening of the window in relation to the floor	Discrete	[0, 2]
Window types	Three patterns the window	Discrete	[0, 2]

For the offset window-floor area ratio, it considered three scenarios, considering that for the Bioclimatic Zone 1, this percentage can vary from 15 to 25% (INMETRO, 2012), thus, this ventilation opening can vary by 15%, 20%, and 25%.

The pattern of occupancy of the environments in this case study was based on the description of the RTQ-R (INMETRO, 2012) which states "the minimum occupancy pattern of the bedrooms must be two people per room and the room must be used by all users dorms". Thus, as it has three bedrooms, it is considered that the building under study is inhabited by 2 people.

For the present analysis, the occupation schedules for the days of the week were considered, with the percentage of people available in the room and dormitories. Thus, there is an activity for watching the TV or sitting in the living room, with heat produced of 60 W/m^2 and for the dorms with activity sleeping or resting from the heat produced of 45 W/m^2. While the heat produced for the 108 W and 81 W skin area, respectively per room.

4.3 Objective Functions and Data Integration Mechanism

The test the optimization algorithms in the multiobjective optimization problem in buildings, three objective functions were initially chosen, the first is the evaluation of the degrees-hour of cooling, the second is the degrees-hour of heating, and the third o energy consumption. The cooling degree-hour indicator is calculated based on the sum of the temperature differences that are above the lower base temperature, as in Eq. (5).

$$F_1(\theta) = (T_o - 26°C). \tag{5}$$

While for the heating degrees, the sum of the temperature differences that are below the upper base temperature is performed, as in Eq. (6). It should be noted that for these calculations, the operating temperature was used as the base temperature.

$$F_2(\theta) = (18°C - T_o). \tag{6}$$

The model was simulated, obtaining the hourly operating temperature for all 8760 hours of the year. Since these temperatures were obtained by reports, generated by Domus, for each of the simulations. The monthly total energy demand can be extracted directly from the report and inserted in the objective function of the Eq. (7).

$$F_3(\theta) = (energy\_demand). \tag{7}$$

Integration with software DOMUS was held by DomusConsole.exe application, which is an application available on the Domus program for communicating with other computer programs bypassing the GUI. This console mode application was developed by the PUCPR Thermal Systems Laboratory to facilitate the integration of the Domus with other tools.

During the development of the integration module between Domus and MATLAB, several implementations were carried out to auto adjust the building parameters without using the program interface. These implementations were separated into MATLAB codes with extension ".m" and described below:

The file changemodifica.m implements the changes that must be made to the building file, that is, where the parameters of the input variables that must be changed and the values that they can assume are informed. The *confort.m* file allows the calculation of the objective functions for the degrees-hours of cooling and degrees of heating inside the building. For the calculation, a search mechanism was implemented to deal with the output files generated by the DOMUS software regarding the number of values outside the boundaries established in equations 7 and 8 are calculated. In the sequence, the results are added to the objective function.

The file consumption.m presented the total consumption value, generated by the simulation output file, is assigned the objective function for calculating energy consumption during the simulation period. The *execdomus.m* is a script that allows the DOMUS software to run without using the command line. This code enables the Domus execution inside MATLAB, where changes in the building parameters could be performed. The *ModelsBrasileiros_open.m* script permits the creation of a vector regarding all the constructive elements referring to the Brazilian models available in the Domus tool, including pre-defined multiple layer models for roofs and walls.

5. RESULTS

The results were divided into two case studies. In Case Study 1, it focuses on the integration of MATLAB with the Domus simulation software for the BESTest building and application on the four multiobjective algorithms, described in section 2.3, were compared for a multiobjective optimization problem in the context of Brazilian construction.

The parameters' settings are important, affecting the optimization performance. For different kinds of algorithms, it is hard to adjust every parameter equally. Here, the population size and the iteration number of each algorithm are both set to the same values, found in Table 3.

Table 3. Parameters setting of four algorithms

Algorithm	Options	Value
NSGA-II	Crossover probability	0.9
	Mutation probability	0.5
MOPSO	Acceleration coefficient c1	2
	Acceleration coefficient c2	1.8
	The initial weight value	0.9
	The initial final value	0.4
MODE	Subpopulation size	50
	Scaling factor	0.5
	Crossover probability	0.9
sp-MODE	Subpopulation size	50
	Scaling factor	0.5
	Crossover probability	0.9
	Maximum solutions Pareto	100

All experiment settings are identical to Case Study 1. Five design variables and three objective functions were used: cooling degrees, heating degrees, and energy consumption. For the building simulation and optimization parameters the Domus software, some parameters were configured. A one-minute step for both the simulation and sampling of the data was chosen. An initial temperature of 20 ºC, along with a humidity ratio of 50% were selected as well.

For the general parameters that are common to all algorithms, a population size of 50 individuals was selected. As a stop criterion, a limit of 100 iterations was considered. For specific algorithm parameters, a sensitivity analysis was performed to find a set that would generate the best possible results.

The criteria comparison used in the performance analysis of the four algorithms were based on three aspects (Hamdy, 2016): execution time, convergence to the optimal set, indicated by the normalized generational distance GD_n and diversity of solutions in the Pareto-optimal set, indicated by the normalized diversity metric DM_n. The GD_n indicates the average Euclidean distance between the best Pareto front and the optimal solution obtained by each algorithm.

Table 4 presents the four algorithms' performance comparison with three criteria and each algorithm is executed three times and results illustrated.

Table 4. Comparison with three criteria the four algorithms' performance.

Indicator	Algorithm	1	2	3	Average	Best
Time	MOPSO	843.87	913.56	950.43	902.62	843.87
	NSGA-II	1058.11	980.02	990.13	1009.42	980.02
	MODE	995.11	997.12	1010.15	1000.79	995.11
	sp-MODE	1279.72	1190.12	1043.98	1171.17	1043.98
GD_n	MOPSO	0.1853	0.2034	0.2312	0.2666	0.1853
	NSGA-II	0.2112	0.1812	0.1923	0.1949	0.1812
	MODE	0.2174	0.2209	0.2190	0.2191	0.2174
	sp-MODE	0.2113	0.2212	0.2337	0.2220	0.2113
DM_n	MOPSO	0.2634	0.2789	0.3091	0.2838	0.2634
	NSGA-II	0.1896	0.1789	0.1534	0.1739	0.1534
	MODE	0.2304	0.2532	0.2456	0.2430	0.2304
	sp-MODE	0.1197	0.1345	0.1899	0.1480	0.1197

Table 4 shows that MODE and NSGA-II have a similar best execution time (1009.42 min or so). The execution time de MOPSO ranges from 843 min – 950 min, and the best time is only 843,87 min. Comparatively speaking, sp-MODE costs the longest time to reach convergence (1043.98 min – 1279.72 min).

In terms of convergence, GD metrics were used, which is a measure minimization. If GD is equal to 0, all points in the approximation set generated belong to the frontier of Pareto. The GD allows us to observe if the algorithm converges to some region of the border of Pareto. The convergence of the obtained solutions (indicate by the GD_n), the NSGA-II obtains a better average/best GD_n (0.1949 and 0.1812) then the others, while the sp-MODE is still the worst (average: 0.2220; and best: 0.2113).

In terms of the diversity of the obtained solutions (indicated by the DM_n), sp-MODE, and NSGA-II have similar performances. Compared with them, the diversity of NSGA-II that Pareto solutions are tightly clustered with shows Figure 3.

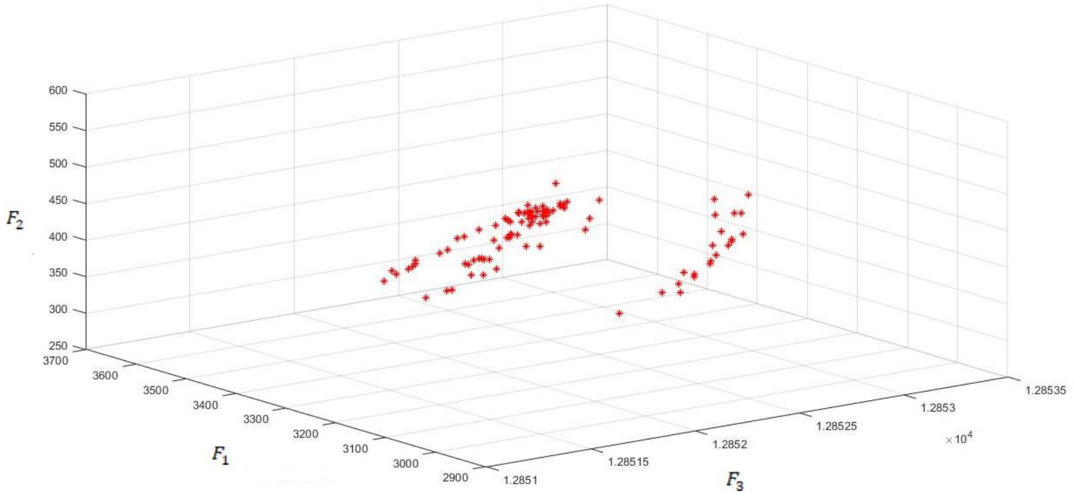


Figure 3. Pareto front for of the NSGA-II algorithms – Case Study 1.

About energy demand, it can be seen from the results that did not show provide great significant variations in the four algorithms, and value 12,852.28 W. From the results it can be noted that the approximated Pareto front took the form of two well-defined groups: i) one being clustered around an of 300 heating degree-hour, and ii) one more uniformly distributed throughout, at a value of 3,400 cooling degree-hour.

However, applying the comparison of performance criteria among the algorithms, it can be observed that the execution time of the MODE and NSGA-II algorithms are similar, with execution around 15 hours. The computer uses to tests execution was operational system Windows 10 64 bits with 16 GB memory RAM and processor Intel Core i7 – 7500U whit 2 cores.

Based on the results obtained in Case Study 1, it is noted that the NSGA-II algorithm showed better results among the four algorithms tested in the building optimization problem, both in terms of convergence and diversity. Thus, the NSGA-

II algorithm was chosen for the Case Study 2 experiment, as described in section 4.2 and Figure 2. The experiment adopted the same objective functions as case study 1, but two more parameters were added, as shown in Table 2.

In this experiment, it was observed that the values of degrees hour of cooling were lower than those presented in case study 1, for the two thermal zones evaluated (bedroom and living room). Analyzing the results obtained, windows with an opening area of 20% have better efficiency. This is because the loss of thermal heat due to increased ventilation is sufficient to supply the thermal gains caused by the increase in exposure of the environment to direct solar incidence.

The analysis of comfort was performed for the two zones (bedroom and living room), with medium-sized windows (20% opening area), with the lowest number of degrees of cooling time.

Thus, the percentage of the degree of comfort hours for the housing unit is 56.7% and the annual thermal discomfort is 42.4% of the hours. Of the total hours of discomfort, 29.8% are caused by cold and 12.8% are due to heat. It is also noted that the discomfort in the building occurs mainly in the summer.

6. CONCLUSIONS

This work presented a study focused on the optimization of a residential building, where three conflicting objectives were tackled simultaneously. Two case studies were proposed, where the first was proposed the integration of the thermo-energetic simulation software to MATLAB, to validate the use of metaheuristic optimization algorithms added to the software. Four algorithms were tested: MOPSO, NSGA-II, MODE, and sp-MODE and compared based on performance criteria: time execution, GD_n, and DM_n.

Results show that for case study 1, the NSGA-II algorithm presented better results about the convergence and diversity presented in the Pareto border and being replicated to the case study 2 experiments.

In the case of Case 2, a real building was used, and two zones were analyzed to degrees of cooling and heating, as well as energy consumption. The comfort limits were determined according to the criteria established by RTQ-R (INMETRO, 2012). The percentage of hours of comfort for the building was 56.7% and the annual thermal discomfort is 42.4% of the hours.

As future work, it aims at inserting new input variables into the residential building problem to analyze their behavior in the thermal comfort of its occupants.

7. ACKNOWLEDGEMENTS

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