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CO-SIMULATION FOCUSED ON THE OPTIMIZATION OF ENERGY EFFICIENCY, THERMAL COMFORT AND COST OF BUILDINGS

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Abstract. *The global demand for electricity has increased in the last few decades and due to this factor, several countries are already assuming computational simulations in order to design energy efficient buildings with the objective of reducing energy demand of the sector. Based on three main objectives: i) the reduction of energy consumption; ii) the increase of occupants' thermal comfort; and iii) the reduction of costs associated with building materials; the present work presents an approach involving whole-building energy simulation and bio-inspired metaheuristic optimization. By comparing four techniques: Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), and Competition over Resources (COR), an approach to solve a multi-objective optimization problem in building design was proposed. Techniques to reduce the overall complexity of the problem are addressed in order to make the solution of this problem viable, and a comparison among all the algorithms is presented. Results show that it is possible to reduce energy usage, materials cost and thermal comfort simultaneously. However, restrictions imposed to the problem can significantly reduce the optimization associated to these three objectives.*

Keywords: *building simulation, cost reduction, energy efficiency, metaheuristic optimization, thermal comfort.*

1. INTRODUCTION

The constant increase in the energy consumption has already become a global scale problem, and in the electrical sector, Brazil is one of the affected, even considering its total primary energy supply main component being hydroelectric (Filho, 2009). This is a problematic scenario, which forces the compensation of energy supply by activating thermoeletric plants, those that are nonrenewable energy sources with higher operational cost, increasing the electric tariff.

Considering this scenario, several regulations are being created in order to reduce the energy consumption of sectors with increased energy demand. Buildings are responsible for the consumption of more than 45% of the electrical produced in Brazil (Empresa de Pesquisa Energética, 2018), and building energy simulations are being considered in the Brazilian energy certification program in order to reduce this number. Among all the available software for building energy analysis, it can be found in the specialized literature the EnergyPlus (Crawley *et al.*, 2001), WUFI® (Zirkelbach *et al.*, 2007), TRNSYS (Klein, 2004) and Domus (Mendes *et al.*, 2003), which was used in this study and actually is the official Brazilian tool for whole-building energy analysis.

Through parameter optimization, it is possible to address this problem, and several works using this approach exist in the literature, sometimes even considering multiple objectives. Delgarm *et al.* (2016a) proposed a study where the energy consumption was categorized into heating, cooling and lighting, and by finding a balance between them, the authors proved that it is possible to reduce the overall consumption during the year. Hamdy *et al.* (2016) presented an optimization problem focused on decreasing both the energy consumption and later life cycle cost associated with the design of a building, where a comparison was made among several evolutionary optimization algorithms and how well each of them performed. From an opposite perspective, Delgarm *et al.* (2016b) showed an approach aiming for the balance between energy consumption and thermal comfort, where results highlighted the potential of a significant increase in the comfort of the occupants by only increasing the electricity usage by a small amount. Bichiou and Krarti (2011) presented a study with the objective of reducing the life cycle costs of a building when five different locations were simulated considering distinct terrain and climate. Finally, the results in the study conducted by Griego *et al.* (2012) showed that optimization techniques can even be applied to reduce costs in the retrofitting of already existing buildings.

In the overall scenario, following the line of aforementioned works, parameter optimization proved to be a valid approach in helping to soften the problem associated to the increased energy demand of buildings. Each work presented optimization problems that were carried out under the most different constraints, and even though the distinct design parameters, the results obtained showed clear signs of improvement over the desired objectives.

However, these types of problems can quickly escalate in complexity. Depending on the amount and type of the design parameters chosen, it can lead to a significant number of available combinations (Hamdy *et al.*, 2016), and it may not be computationally viable, or even possible, to verify every possible solution. Furthermore, the use of classical optimization algorithms may be invalidated if there's a lack of a mathematical model, or due to the unknown behavior of the objective function, which could have several points of local maximum or minimum.

Based on relevant works mentioned previously, this study proposes the utilization of metaheuristic optimization techniques in order to minimize the energy consumption and building materials costs, and to maximize occupants' thermal comfort.

Next section describes the theoretical background associated to energy consumption, thermal comfort and building cost, the three optimization objectives that were proposed in this study. Section 3 gives an introduction to metaheuristic optimization and the algorithms used in this work. Section 4 presents the adopted case. Section 5 specifies the optimization problem, giving a more in-depth look into the selected design variables, objectives, algorithm parameters and the simulation process. In Sec. 6, the results of optimization for each algorithm are presented, where they are compared with one another. Finally, Sec. 7 concludes the work with a recapitulation of the covered topics and what is currently being done to improve the results of future related works.

2. THEORETICAL FRAMEWORK

In the specialized literature, specific studies can be found associating energy consumption, thermal comfort, and optimization applied to buildings. This section will cover these three topics separately.

2.1 Energy Consumption

Global energy consumption is growing rapidly (Quaschning, 2005), and concerns about supply difficulties, depletion of energy resources and environmental impacts are in evidence. Buildings from commercial and residential sectors have a considerable contribution associated to the energy demand, reaching between 20% and 50% in developed countries, surpassing the large industrial and transport sectors (Pérez-Lombard *et al.*, 2008; Peruzzi *et al.*, 2014; Soares *et al.*, 2013).

Based on these facts, governments have created regulations to evaluate the energy consumption in early stages of building design and also in existing buildings as a way to reduce energy demand of this sector. In the last decades, several researches have been carried out in order to find methods to solve the challenge of finding optimal or quasi-optimal solutions of engineering problems associated to buildings' energy consumption.

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. (1).

$$\dot{E}_t + \dot{E}_g = \rho_{air} \cdot c_{air} \cdot V_{air} \cdot \frac{dT_{int}}{dt} \tag{1}$$

In the equation 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 air ($J/(kgK)$), V_{air} is the room volume (m^3), T_{int} is the room air temperature (K) and t is the time (s).

2.2 Thermal Comfort

For most of the international standards, thermal comfort can be defined as "that condition of mind which expresses satisfaction with the thermal environment" (ISO, 2005; ASHRAE, 2005). Among several formulations to calculate thermal comfort, one widely used is the Predicted Mean Vote - PMV index, proposed by Fanger (1970), it is used to predict the average thermal sensation of a large group of people. The PMV can be described as a function dependent on physical variables related to the ambient where measurements are taking place, and personal variables related to the occupants of the evaluated environment.

Equation (2) shows the simplified form of Fanger's equation, which depends on four environmental variables and two personal ones.

$$PMV = f(T_{bs}, \phi, T_{rm}, v, M, I_{cl}) \tag{2}$$

In the above equation T_{bs} represents the indoor temperature (in ^oC), ϕ the indoor relative humidity ($\%$), T_{rm} the mean radiant temperature (^oC), v the air's speed (m/s), M the metabolic rate of the occupant (Met, which can be related to W/m^2), and I_{cl} the clothing coeffiencient (Clo, which can be related to m^2K/W).

In terms of thermal comfort measurements, the PMV, which was assumed in this work, is adopted specially when air conditioning systems are considered. It is an index that predicts thermal comfort according to a scale of thermal sensations based on 7 points, including very hot, warm, slightly warm, neutral (ideal), slightly cold, cold, and very cold.

2.3 Building costs

There are several factors associated with the total cost of a building as presented by Cunningham (2013), from those of which are directly related to the construction of the building itself to those that the building will generate during its lifetime. Therefore, the process of reducing costs is far more complex than a simple cutting without worrying about possible long-term problems.

In a greater scale, the cost reduction process could be considered an optimization problem, where the objective is to find the correct set of variables that will balance out the short-term and long-term costs. In the study presented by Asadi *et al.* (2012), this was performed by reducing the costs of retrofitting a home while assuring a reduced energy consumption for the following years.

3. METAHEURISTIC OPTIMIZATION

The optimization research field is vast and various techniques are available for distinct types of problems. In the engineering area, optimization problems can be defined as a search for the best solution, frequently considering restrictions. Problems of this type usually have limits to their variables, representing characteristics and physical limits of the system being optimized. Additionally, conflicting objectives are common task in this area (Blum and Roli, 2003). One example of this type of problem is the one proposed in this work, which associates three conflicting objectives: energy savings; thermal comfort; and materials costs.

In high complexity problems, several dimensions and costs associated with the calculation of the objective function can both affect and limit the choices for optimization techniques. Due to this fact, an approach based on bio-inspired metaheuristic optimization gives alternatives with a reasonable balance between exploration and exploitation of the search space in order to find an interesting solution for this type of problem.

The next subsections give a quick introduction about four meta-heuristic algorithms chosen in this study.

3.1 Genetic Algorithm

The Genetic Algorithm (GA), proposed by Goldberg (1989), is an evolutionary algorithm built to simulate the process of evolution and natural selection found in nature. It is an algorithm that works based on the principle that the most fitted individuals in a population will thrive and live to pass their genes to the next generation.

In the context of optimization, every solution, or set of variables, can be viewed as an individual of the population. Each gene represents a value associated with one of the variables in the set in order to compute a fitness. The fitness is associated to the objective function of the optimization problem. Each iteration of the algorithm can be seen as a generation of individuals that was born from their parents, those representing individuals of the last generation. Individuals of the current generation are chosen based on their fitness and have their genes combined in order to create a more fit descendant. The process of mutation also happens during this stage, guarantying that new variety is added to the gene pool from time to time. The mutation process helps to avoid stagnation and prevents the solution from being trapped in local minimum.

In the implementation used in this work, each gene is represented in a binary string, with the combination (crossover) and mutation operations happening at bit-level. The algorithm also has two configuration parameters, those dictating both chances for the crossover (Cr) and mutation (Mr) processes. The values for the previous mentioned variables lie in the interval $[0, 1)$.

3.2 Differential Evolution

The Differential Evolution (DE) was originally proposed by Storn and Price (1997). The method is similar to GA due to its evolutionary behavior. It uses the same principles, such as combination and selection, in order to create the individuals for the next generation.

The process begins with the selection of a parent solution, and a number of other distinct solutions. After that, the other solutions, except for one of them, have their difference weighted and added to the remaining one, which creates a mutant solution. After the previous mentioned process, the combination begins and both parent and mutant solutions have their genes combined based on a specified crossover rate, creating a child solution. In the final step of the algorithm, the child solution is compared with the parent to determine which one of them will continue to the next generation.

In order to generate relevant results for the optimization process, DE should be properly configured. In this case, the number of solutions used in the difference term or to which solution they will be added should be adjusted. A common setup for the algorithm, which was adopted in this work, is denominated "DE/rand/1/bin" and assumes one difference term (between two solutions) multiplied by the differential factor (F) and adds it to a third randomly selected one. In the end of the algorithm, both parent and mutant genes are combined based on binomial distribution considering the crossover rate (Cr) in the interval $[0, 1)$.

3.3 Particle Swarm Optimization

The Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart (1995), is an algorithm based on swarm-intelligence. It considers a set of individuals and their interactions in order to reach a certain objective.

Assuming a collective behavior of certain species in order to solve a task such as the search for resources, the algorithm considers that the population will work together towards that objective, achieving mutual benefit in the process.

The population of solutions are scattered across the search space, moving around in each iteration in order to find spots where the resources are more abundant (points which have a better performance over the objective function). To calculate their trajectory, the particles take three weighted factors into consideration: their last trajectory; the best point that they have come across; and the best point that the entire population has come across.

This study adopts the original simplified version of the PSO, which does not have any configuration parameters.

3.4 Competition Over Resources

The Competition Over Resources (COR), proposed by Mohseni *et al.* (2014), is also an algorithm that was inspired on the behavior of animal species. While the PSO algorithm is focused on how the individuals of a single group share information among each other in order to reach their mutual objective, COR focuses on how several groups of animals from the same species compete against each other for a territory with more natural resources.

The population of COR starts being divided into a certain number of groups, of which only the best solution in each group is kept. The algorithm then starts its iterative process by determining each group territory, which is calculated based on the euclidean distance among the best solution of each group. New solutions are generated for each group and are scattered inside its territory. Some solutions can rarely search outside its own territory in order to search for a spot with more resources. Once this step is over, the new best solutions for each group are updated, and the group with most resources in its territory, gains new members. In the opposite side, the one with least amount of resources loses some of its population. As the execution progresses, groups without resources are eliminated when the number of individuals falls below 2. At this time the best group is split into two groups, thus making sure the number of groups stays the same through the entire run.

The COR algorithm has 2 configuration parameters, Ng, the number of groups to be used, and Dr, the death rate.

4. CASE STUDY

A building structure was designed based on the evaluation o whole-building and energy simulation software presented in the Annex 41 of the International Energy Agency (IEA) (Rode and Woloszyn, 2007). The building geometry presented in Fig. 1 represents the BESTest 600FF case.

In the original case, the Denver weather file was assumed during the Annex 41. In this case, in order to assume a typical Brazilian climate condition, the weather data of Rondonópolis from the Mato Grosso State was considered. The city has a stable hot climate all year around, which helps to simplify the simulation process as will be described in Section 5.2.

The building was adapted to simulate a working office, assuming work equipment for a group of people. The list of equipment includes lighting, computers, a coffee machine, a printer and an air conditioning (AC) system, totaling a power demand of $3096\ kW$.

The occupancy pattern assumed was an 8-hour working day from Monday to Friday with an one hour lunch. The whole year was considered with a total of 255 working days. In this case, it was possible to calculate the maximum monthly energy consumption assuming all the equipment staying operational during the eight hours where the workers are in the building with exception of the AC system, that also functions during the break hour to maintain the temperature. The estimated monthly maximum electrical energy consumption was $555.6\ kWh$.

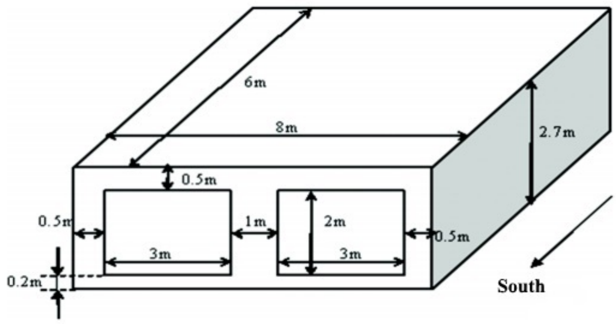

Figure 1. Building geometry: BESTest case

Four people dressed with adequate clothes to the local climate and performing office work were assumed in this study, resulting in a clothing index of $0.543\ Clo$ ($8.416 \cdot 10^{-2}\ m^2K/W$) and metabolic rate of $1.2\ Met$ ($69.9\ W/m^2$) (Fanger, 1970).

5. OPTIMIZATION PROBLEM

At first, the approach to the problem should be selected and that can be mono-objective or multi-objective. In this study, a mono-objective approach was chosen for its simplicity, removing the need of an an additional strategy for decision-making analysis of the obtained results. Instead, an aggregation function combining the optimized objectives was selected as it could directly provide a final solution for the problem.

The decision variables selected for the problem needed to be relevant enough to cause an impact on the measured objectives. For that reason, five variables that were dependent to at least one objective where chosen. These parameters were selected based on previous studies, presented by Delgarm *et al.* (2016c) and Bamdad *et al.* (2017), where results pointed to the ones with significant impact over the energy consumption, such as those involving the overall envelope of the building and some related to climatization. Table 1 shows their names, a brief description, type and their accepted intervals associated to this problem.

Table 1. Optimization variables.

Name	Description	Type	Interval
Orientation	Orientation of the building in degrees	Continuous	[0, 360)
Window size	Size of the frontal window$^{(1)}$	Continuous	[0, 1)
AC Schedule	Schedule of operation for the AC system$^{(2)}$	Discrete	[0, 4]
Walls pattern	Brazillian construction pattern used for the four walls	Discrete	[0, 30]
Ceiling pattern	Brazillian construction pattern used for the ceiling	Discrete	[0, 11]

$^{(1)}$ 0 indicates a $1m^2$ window, values closer to 1 indicate a window closer to $21.6m^2$ (area of the South wall)

$^{(2)}$ nine-hour schedules with 1 hour offset, from 5:00 - 14:00 to 9:00 - 18:00

5.1 Fitness Function Definition

The three established objectives are the energy consumption, thermal comfort and cost, the latter associated to the construction cost. Domus can already generate data for the energy consumption during the simulation period, and values for PMV thermal comfort index for every time step of the simulation. In order to evaluate occupants' thermal comfort sensation, the average of the absolute values of PMV obtained during the simulations was used.

For the construction cost, it was calculated manually, based on its dependent variables: window size, as that also determines the area of the wall; walls pattern; and ceiling pattern. A survey was conducted during July, 2018, on the same city used on the simulation, in order to estimate the prices of the 31 walls patterns and 12 ceiling patterns. Once the value for these 3 variables were established, they could be used as input in Eq. (3) to calculate the construction cost in Brazilian real ($R\$$).

$$f_3(\mathbf{x}) = (75.6 - 11.9x_2^2 - 8.7x_2) \cdot g_1(x_4) + 48 \cdot g_2(x_5) \tag{3}$$

In Eq. (3), $\mathbf{x}$ represents the solution vector specified by the optimization algorithm, x_2 is the window size, x_4 is the walls pattern and x_5 the ceiling pattern. g_1 is a function that takes into account the wall pattern and returns its cost per area ($R\$/m^2$), and g_2 does the same, but for the ceiling pattern. The coefficients for g_1 and g_2 represent the respective areas (m^2) for the walls and ceiling, where the first one depends on the window size and the later is always constant.

Once the values of these three objectives were obtained, they were normalized and combined according to Eq. (4). The values used for the normalization were the maximum values that each objective could assume, with the maximum energy consumption already calculated in Sec. 4, the maximum value on the PMV scale being 3, and the maximum possible cost being calculated utilizing the most expensive pattern for walls, ceiling and the smallest window size.

$$f(\mathbf{x}) = \frac{1}{3}\left(\frac{f_1(\mathbf{x})}{555.6} + \frac{f_2(\mathbf{x})}{3} + \frac{f_3(\mathbf{x})}{94358.4}\right) \tag{4}$$

In the equation above, $\mathbf{x}$ represents the solution vector, and f_1, f_2 and f_3 the three optimization objectives.

5.2 Simulation Process

Ideally, for an optimization that focuses on the reduction of the energy consumption, it would be desirable to run the simulations for the whole year, in order to capture the entire dynamic of the climate and its influence on building materials. However, such task would be exceedingly costly due to two factors: the time required for the simulation grows linearly with the simulation period; each evaluation of the cost function is equal to one complete simulation, and that population-based metaheuristic algorithms have to do this a number of times which is proportional to the population and iteration number. Taking these facts into account, it was decided to run the simulation for one month, the one whose values best approaches to the average monthly values for the yearly simulation, hoping to reduce the total optimization time by a factor of 12.

In order to make a fair comparison among all the algorithms, 500 random solutions where selected from the search space and simulated for the whole year. After that, the same solutions where used to simulate each of the 12 months separately. The monthly average of the consumption values for the yearly simulation was considered since we compared the yearly consumption to monthly ones. The values for the comfort, however, could be used directly since they already represent the mean PMV. The construction costs were also used right away since they were a one-time expense.

Finally, the converted average yearly values were plugged into the aggregated cost function. The values for each month were subtracted from the average yearly values, generating a residual error for each month, as show on Fig. (2).

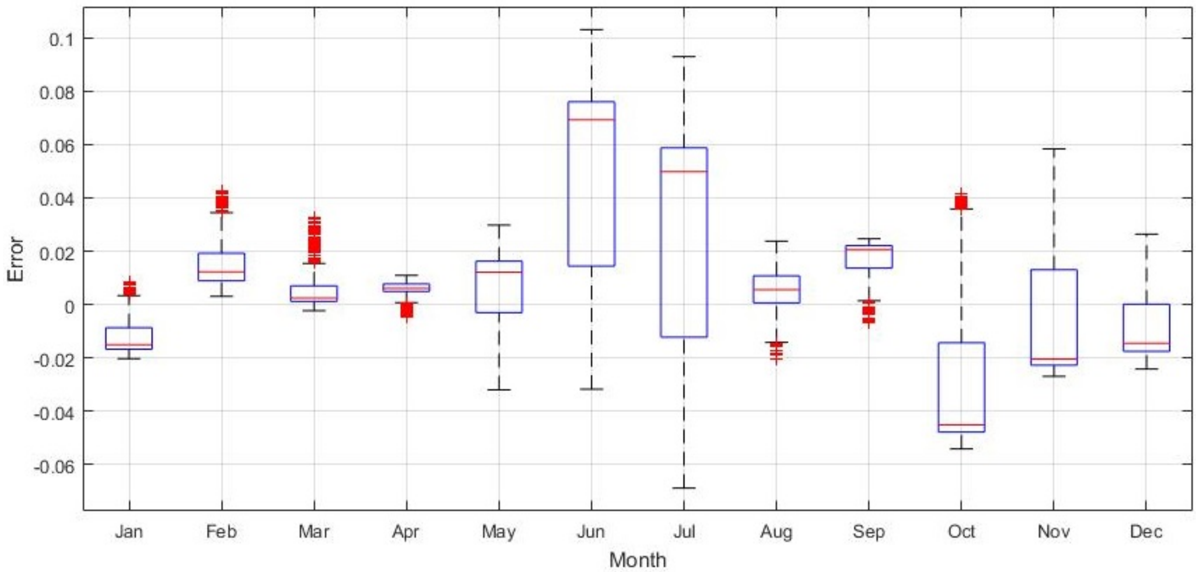

Figure 2. Residual error of the aggregated cost function for monthly simulations compared to the yearly results

The month of April provided a mean error close to zero ($5.463 \cdot 10^{-3}$), with a relatively small standard deviation ($3.407 \cdot 10^{-3}$), and was selected for the optimization processes. It is important to emphasize that this is not a generalization, but a problem-specific result, and that the same conclusion may not be valid for distinct problems.

5.3 Building Simulation Software and Optimization Algorithms Parameters

For the Domus software, some parementers were configured. A one minute step for both the simulation and sampling of the data were 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 stopping 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, except for the PSO, which has no parameters to be configured. In this study, each parameter was limited to the set of values found in Tab. 2.

Table 2. Possible values assumed for the parameters of each optimization algorithm.

Algorithm	Parameter	Values
GA	Cr	$0.2, 0.4, 0.6, 0.8$
	Mr	$0.02, 0.04, 0.06, 0.08$
DE	F	$0.4, 0.8, 1.2, 1.6$
	Cr	$0.2, 0.4, 0.6, 0.8$
COR	Ng	$3, 5, 7, 10$
	Dr	$1, 2, 3, 5$

Each algorithm parameter was divided into four possible values, resulting in a total of 16 parameter combinations for the three algorithms. However, only one optimization for each combination was run, due to the high computation cost of performing multiple simulations. The same initial population was assumed for all the algorithms in order to perform a fair comparison.

For the GA, the values for the crossover parameters were scattered through its entire interval, while the mutation only for the first 10% since it is an operation that should rarely happen (Goldberg, 1989). For the DE, both parameters were spread through all their intervals. Finally for the COR algorithm, since it does not have any upper limit for its parameters, a number of groups up to 10 and death rate up to 5 were arbitrarily chosen.

6. RESULTS

The convergence graphs of the sensitivity analysis for the three algorithms can be observed in Fig. 3. The best runs are shown in the graph of each algorithm, along with the average of the total 16. The result of the single optimization run of the PSO was also included. Table 3 displays the parameter sets for the best algorithm runs.

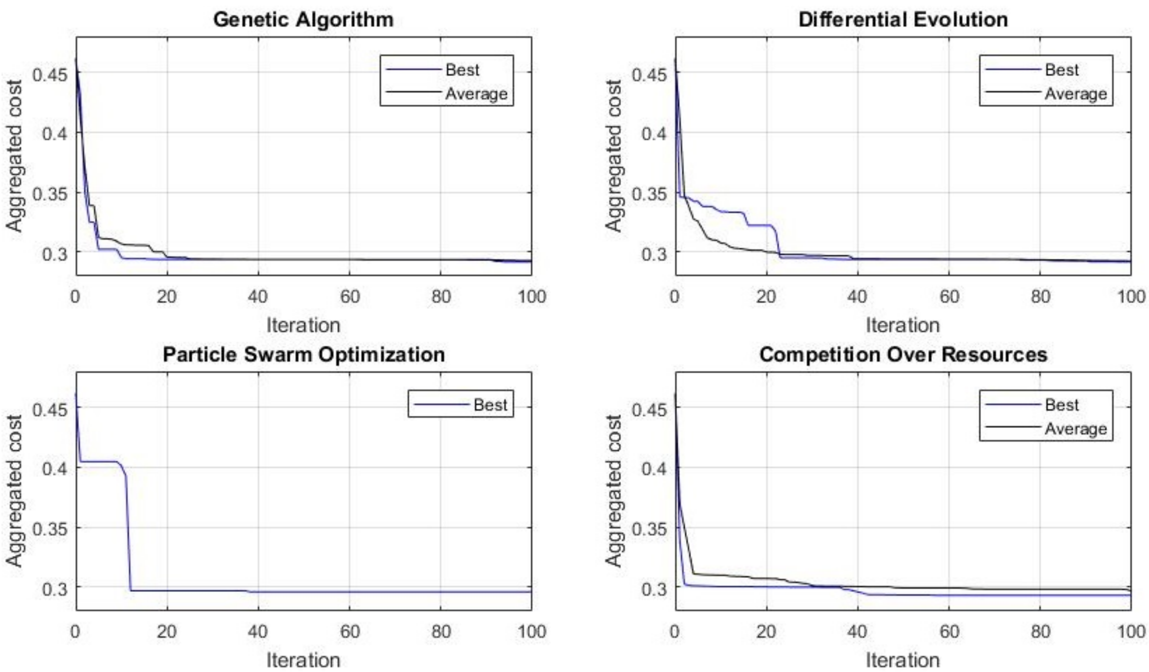

Figure 3. Convergence of the algorithms through its iterations.

In general, all four algorithms converged to a similar solutions in terms of objective function values and input parameters. Table 5 shows the values of these solutions over each one of the three objectives, while Tab. 4 shows the input that generated those solutions. Finally, Tab. 6 displays a comparison between the final four solutions under each optimization objective.

As it can be seen, the solution found by the DE out-performed, or tied in the worst case, the other three solutions in every category, even if the improvements were relatively small. The other three solutions have showed a variety of trade-offs, the one found by PSO was the worst one, providing the worst values for two of three objectives. It's also important

Table 3. Combination of parameter values for the best optimization runs.

Algorithm	Paramter	Optimal value
GA	Cr	0.8
	Mr	0.02
DE	F	0.4
	Cr	0.2
COR	Ng	3
	Dr	5

Table 4. Optimization input values considering four final solutions.

Algorithm	Orientation	Window size	AC Schedule	Walls pattern	Ceiling pattern
GA	182.23	0.99	2	25	9
DE	170.38	0.99	3	25	9
PSO	280.74	0.82	4	25	4
COR	264.31	0.99	3	25	4

Table 5. Optimization objective values considering four final solutions (one-month simulation).

Algorithm	Energy Consumption (kWh)	Thermal Comfort (PMV)	Construction Cost ($R\$$)
GA	303.35	0.88	3319.68
DE	303.31	0.88	3319.68
PSO	303.31	0.91	3600.09
COR	303.31	0.89	3462.05

Table 6. Comparison among the final four solutions over each optimization objective (one-month simulation).

Base	Comparison[1]											
	Energy Consumption (%)				Thermal Comfort (%)				Construction Cost (%)			
	GA	DE	PSO	COR	GA	DE	PSO	COR	GA	DE	PSO	COR
GA	—	−0.01	−0.01	−0.01	—	0	3.41	1.14	—	0.00	8.45	4.29
DE	0.01	—	0	0	0	—	3.41	1.14	0.00	—	8.45	4.29
PSO	0.01	0	—	0	−3.30	−3.30	—	−2.20	−7.79	−7.79	—	−3.83
COR	0.01	0	0	—	−1.12	−1.12	2.25	—	−4.11	−4.11	3.99	—

[1] Improvement of the algorithms on the base column over each other, for every objective.

to note that even though the solutions found were relatively close to each other, these differences might get magnified if an entire building is accounted for, since this work considered a building comprised of a single environment.

To validate our complexity reduction approach, the same input values for the final solutions, as previously shown in Tab. 4), where applied to a one-year simulation in order to check out of the monthly values would be close to the average for the entire year. The results of this process can be found below in Tab. 7 showing the objective values and Tab. 8 the comparison between solutions.

Table 7. Optimization objective values for the four final solutions (One-year simulation).

Algorithm	Energy Consumption (kWh)	Thermal Comfort (PMV)	Construction Cost ($R\$$)
GA	3612.19	0.90	3319.68
DE	3613.09	0.90	3319.68
PSO	3606.3	0.94	3600.08
COR	3608.16	0.92	3462.05

The results generated by the yearly simulation showed that the one-month approximation was valid enough to predict the energy consumption, as the results were relatively close to the average of the year. On the other hand, the thermal comfort objective suffered a negative impact, where it increased for the all of the four solutions. This may have happened due to the fact the climate pattern on the sole month of April wasn't enough to foresee the whole year's. The construction

Table 8. Comparison between the final four solutions over each optimization objective (One-year simulation).

Base	Comparison(1)											
	Energy Consumption (%)				Thermal Comfort (%)				Construction Cost (%)			
	GA	DE	PSO	COR	GA	DE	PSO	COR	GA	DE	PSO	COR
GA	—	0.02	−0.16	−0.11	—	0	4.40	1.10	—	0	8.45	4.29
DE	−0.02	—	−0.19	−0.14	0	—	4.40	1.10	0	—	8.45	4.29
PSO	0.16	0.19	—	0.05	−4.21	−4.21	—	−3.16	−7.79	−7.79	—	−3.83
COR	0.11	0.14	−0.05	—	−1.09	−1.09	3.26	—	−4.11	−4.11	3.99	—

(1) Improvement of the algorithms on the base column over each other, for every objective.

cost stayed the same, as it is a one-time investment, independent of temperature.

7. CONCLUSION

In this study, we presented one of many approaches to a building optimization problem, where metaheuristics were the choice due to the black-box nature of the problem, and four algorithms were chosen to find the results. A study case was presented, the problem was formulated and the optimization variables were chosen. However, it was soon apparent that the complexity of the problem was too big, and had to be reduced.

It was possible to see that the algorithms performed similarly, with the PSO falling behind. That might have been due to the fact that it had no configuration variables, which gave an advantage to the others, since their parameters could be tuned to better serve the current problem. Considering this, it would be interesting as a next step, to include a variant of the PSO that better fits this kind of problem, or even to test how algorithms with self-adjustable parameters perform. However, due to the stochastic nature of the optimization algorithms, it is necessary to perform a statistical analysis of the outcomes of the algorithms through several runs (Derrac *et al.*, 2011). This will require more computations and is thus left for future work.

The approach of simulating for a single month generated results that were deemed valid to the evaluated case. However, from a more broad perspective, that choice in itself changed the overarching optimization problem, as is not possible to affirm that the solutions encountered for the one-month simulation would be the best results for the whole year simulation.

Our next step in the overall scenario is to work on more elaborate techniques to reduce the time that it takes to perform whole-building optimizations. Now that we have a reliable and scalable way to run multiple simulations and the same time, the focus can be switched to speeding up each individual one.

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9. REFERENCES

Asadi, E., Da Silva, M.G., Antunes, C.H. and Dias, L., 2012. "Multi-objective optimization for building retrofit strategies: A model and an application". *Energy and Buildings*, Vol. 44, No. 1, pp. 81–87.

ASHRAE, 2005. *ASHRAE Handbook - Fundamentals*. American Society of Heating, Refrigerating & Air Conditionin.

Bamdad, K., Cholette, M.E., Guan, L. and Bell, J., 2017. "Ant colony algorithm for building energy optimisation problems and comparison with benchmark algorithms". *Energy and Buildings*, Vol. 154, pp. 404–414.

Bichiou, Y. and Krarti, M., 2011. "Optimization of envelope and HVAC systems selection for residential buildings". *Energy and Buildings*, Vol. 43, No. 12, pp. 3373–3382.

Blum, C. and Roli, A., 2003. "Metaheuristics in combinatorial optimization: overview and conceptual comparison". *ACM Computing Surveys*, Vol. 35, No. 3, pp. 189–213.

Crawley, D.B., Lawrie, L.K., Winkelmann, F.C., Buhl, W.F., Huang, Y.J., Pedersen, C.O., Strand, R.K., Liesen, R.J., Fisher, D.E., Witte, M.J. and Glazer, J., 2001. "EnergyPlus: Creating a new-generation building energy simulation program". *Energy and Buildings*, Vol. 33, No. 4, pp. 319–331.

Cunningham, T., 2013. "Factors Affecting The Cost of Building Work - An Overview". *Dublin Institute of Technology*, pp. 1–21.

Delgarm, N., Sajadi, B., Kowsary, F. and Delgarm, S., 2016a. "Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO)". *Applied Energy*, Vol.

170, pp. 293–303.

Delgarm, N., Sajadi, B. and Delgarm, S., 2016b. “Multi-objective optimization of building energy performance and indoor thermal comfort: A new method using artificial bee colony (ABC)”. *Energy and Buildings*, Vol. 131, pp. 42–53.

Delgarm, N., Sajadi, B., Delgarm, S. and Kowsary, F., 2016c. “A novel approach for the simulation-based optimization of the buildings energy consumption using NSGA-II: Case study in Iran”. *Energy and Buildings*, Vol. 127, pp. 552–560.

Derrac, J., García, S., Molina, D. and Herrera, F., 2011. “A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms”. *Swarm and Evolutionary Computation*, Vol. 1, No. 1, pp. 3–18.

Empresa de Pesquisa Energética, 2018. “Balanço Energético Nacional”. Technical report, Ministério de Minas e Energia, Brasília.

Fanger, P.O., 1970. *Thermal comfort. Analysis and applications in environmental engineering.* Danish Technical Press, Copenhagen, 1st edition.

Filho, A.V., 2009. *O Brasil no Contexto Energético Mundial*. NAIPPE, São Paulo, 1st edition.

Goldberg, D.E., 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley, Boston, 1st edition.

Griego, D., Krarti, M. and Hernández-Guerrero, A., 2012. “Optimization of energy efficiency and thermal comfort measures for residential buildings in Salamanca, Mexico”. *Energy and Buildings*, Vol. 54, pp. 540–549.

Hamdy, M., Nguyen, A.T. and Hensen, J.L., 2016. “A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems”. *Energy and Buildings*, Vol. 121, pp. 57–71.

ISO, 2005. “ISO 7730: Ergonomics of the thermal environment. Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria”.

Kennedy, J. and Eberhart, R., 1995. “Particle swarm optimization”. *Neural Networks, 1995. Proceedings., IEEE International Conference on*, Vol. 4, pp. 1942–1948.

Klein, S.A., 2004. “TRNSYS 16, a TRaNsient SYstem Simulation program”. Solar Energy Laboratory, University of Wisconsin-Madison. 06 Jul. 2019 <http://sel.me.wisc.edu/trnsys>.

Mendes, N., Oliveira, R.C.L.F.D. and Santos, G.H., 2003. “Domus 2.0: a Whole-Building Hygrothermal Simulation Program”. *International IBPSA Conference*, Vol. 8, pp. 863–870.

Mohseni, S., Gholami, R., Zarei, N. and Zadeh, A.R., 2014. “Competition over Resources: A New Optimization Algorithm Based on Animals Behavioral Ecology”. In *2014 International Conference on Intelligent Networking and Collaborative Systems*. pp. 311–315.

Pérez-Lombard, L., Ortiz, J. and Pout, C., 2008. “A review on buildings energy consumption information”. *Energy and Buildings*, Vol. 40, No. 3, pp. 394–398.

Peruzzi, L., Salata, F., De Lieto Vollaro, A. and De Lieto Vollaro, R., 2014. “The reliability of technological systems with high energy efficiency in residential buildings”. *Energy and Buildings*, Vol. 68, pp. 19–24.

Quaschning, V., 2005. *Understanding Renewable Energy Systems*. Earthscan, London, 1st edition.

Rode, C. and Woloszyn, M., 2007. “Whole-Building Hygrothermal Modeling in IEA Annex 41”. In *Thermal Performance of the Exterior Envelopes of Whole Buildings X*. ASHRAE, Atlanta, pp. 1–15.

Soares, N., Costa, J.J., Gaspar, A.R. and Santos, P., 2013. “Review of passive PCM latent heat thermal energy storage systems towards buildings’ energy efficiency”. *Energy and Buildings*, Vol. 59, pp. 82–103.

Storn, R. and Price, K., 1997. “Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces”. *Technical report, International Computer Science Institute*, Vol. 11, No. 4, pp. 341–359.

Zirkelbach, D., Schmidt, T., Kehrer, M. and Künzel, H.M., 2007. “WUFI® Pro - Manual”. Fraunhofer Institute. 06 Jul. 2019 <https://wufi.de>.

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