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OPTIMIZATION OF AN ENERGY EFFICIENT OFFICE BUILDING IN SUBTROPICAL BRAZIL

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ABSTRACT
Energy policies have been developed to reduce buildings' impacts on climate change. As they require quantifying energy use, simulation tools can help designers in the decision process. There are several variables to be considered in early stage building design. By coupling building performance simulation with optimization methods, the designer can analyze multiple solutions and avoid excessive calculations. This paper applied a multi-objective genetic algorithm to find optimum solutions for a case study medium-rise office building in São Paulo – Brazil using passive design strategies to minimize initial construction cost and life-cycle energy cost. The method coupled EnergyPlus simulation software with the jEPlus+EA interface to run the optimization. 213 cases were simulated with five design variables: orientation, window-to-wall ratio, wall type, roof type and glazing type. The results were presented through a Pareto optimum front, with seven non-dominated solutions, grouped into two distinct clusters. An initial construction cost reduction of 6.7% was observed in one cluster's optimal solution, when compared to the base case. In the other cluster, another optimal solution presented a decrease of 5.8% in the life-cycle energy cost from the base model. The design parameters recommended for a medium-rise office building in São Paulo from this multi-objective optimization include small window-to-wall ratio, insulated flat roofs and laminated glazing with low solar heat gain coefficient. The proposed method can be further developed for more complex building shapes and include thermal comfort and environmental impacts criteria.
Keywords: Building simulation, genetic algorithm, early stage design, passive strategies.

1. INTRODUCTION

The world's energy demand has increased significantly in the past decades due to population growth and industrial development, resulting in higher carbon dioxide emissions and global warming. The building sector alone accounts for over 40% of the world's total energy consumption, mainly from fossil fuels (EIA, 2017). The efforts for mitigation of the environmental impact of this consumption has led energy policies towards energy-efficient building design (PÉREZ-LOMBARD; ORTIZ; POUT, 2008; BORGSTEIN; LAMBERTS; HENSEN, 2016). As these regulations move towards high-performance buildings and require quantifying energy use, computational simulation has been widely used to assist designers in the decision process.

Whole building energy simulation programs like EnergyPlus, eQUEST and TRNSYS have been frequently used by designers to assess building performance in early design stages (PICCO; LOLLINI; MARENGO, 2014; ØSTERGÅRD; JENSEN; MAAGAARD, 2016). Although building performance simulation (BPS) tools are convenient for considering separate systems (mechanical, lighting, equipment) and the building's envelope as co-existing parts (NEGENDAHL, 2015), there are still some setbacks. Most BPS tools were developed for HVAC engineers and the description method of the available information sometimes are inconsistent with the architect's conceptual design process (YU et al., 2015). At this stage there are several variables to be considered, such as orientation, window-to-wall-ratio, material thermal properties and cost, so that exploring each possible solution for a simple building design can be an exhausting, time-consuming process. In this context, coupling building simulation tools with an optimization procedure to analyze multiple design solutions can minimize excessive amount of calculations (EVINS, 2013).

One of the most popular optimization methods for building energy analysis is the genetic algorithm (GA), a procedure that uses an analogy of the biological evolution of living organisms (MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014; NGUYEN; REITER; RIGO, 2014). It is a heuristic search that modifies function values through predefined reproduction operators in a stochastic manner (HOBDAY; SMITH, 2000), developed by John Holland and presented in his book 'Adaptation in Natural and Artificial Systems' (HOLLAND, 1992). Various studies have used GAs in the design process using some user-friendly software interfaces, making optimization design more feasible both for architects and construction sector professionals.

Wang, Zmeureanu and Rivard (2005) presented a multi-objective optimization model using life-cycle analysis to find optimal design solutions for economic and environmental criteria. Manzan and Pinto (2009) used a GA approach to optimize shading devices in an office building with ESP-r code simulations, resulting in a reduction of energy consumption up to 17% for different shading and glazing type configurations. Negendahl and Nielsen (2015) presented a holistic building design optimization for office buildings considering multiple criteria, like energy use, capital cost, daylighting and thermal comfort. According to the authors, machine automation is difficult to combine with quality-defined problems. A great methodological problem in the field is to relate performance criteria directly with design actions. This would require energy modelers and designers to work in an integrated environment starting at the early stage.

A research study was conducted by Yu et al. (2015), where a multi-objective GA was combined with an artificial neural network (ANN) to find optimum residential building designs using energy consumption and indoor thermal comfort criteria. Still for residential buildings, Bre et al. (2016) used a single objective function GA to determine the most influential variables for a case study house. Another study utilized a graphical user interface (GUI) to analyze different architectural parameters for a room model using cooling and heating criteria (DELGARM et al., 2016). The optimization method applied was efficient in determining optimal solutions with conflicting objective functions. Following the literature review, it is clear the building performance simulation combined with optimization methods is a widely accepted and robust approach in sustainable and energy-efficient building design, especially in the conceptual stage.

2. OBJECTIVE

This paper focuses on the application of a multi-objective genetic algorithm, to find the Pareto front solutions of optimum building design alternatives. A case study of an early stage office building design that uses passive strategies to minimize two conflicting objective functions, the initial construction cost and the life-cycle energy cost is presented.

3. METHOD

The method combines the building performance simulation using EnergyPlus software (US DEPARTMENT OF ENERGY, 2016) and the graphical user interface (GUI) jEPlus+EA (ZHANG; KOROLIJA, 2018) to run the genetic algorithm and extract results.

3.1 Multi-objective genetic algorithm

A genetic algorithm begins by randomly selecting a population of possible solutions for the considered problem. Then the population evolves from one generation to the next using the objective function and selection, crossover and mutation operators. Each solution is represented by a string of bits (or chromosome), where each bit is called gene, and the values of each gene are the alleles (YU et al., 2015).

A multi-objective genetic algorithm is based on Pareto-dominance. As the objective functions are usually conflicting, the algorithm presents a set of feasible solutions which have a non-dominated relationship, located on the Pareto front. To implement the BPS optimization for this case study, the jEPlus+EA software was used to solve the multi-objective problem. It is an open source tool that provides a convenient way to perform optimization for parametric building design through simulations using EnergyPlus (ZHANG, 2012).

3.2 Building model description

For this case study a model was designed using SketchUp 3D software (TRIMBLE INC., 2018) and saved as an EnergyPlus Input File (IDF) through the Euclid plugin. The base case consists of a three-story, rectangular-shaped office building, with 600 m² of total floor area and 3 m floor to ceiling height, with 25% of window-to-wall-ratio (WWR), with a 30-year life expectancy (Figure 1). Floors are composed of porcelain tiles over concrete slab and internal ceilings are made of gypsum boards. The windows have 5 cm aluminum frame and vertical dividers every 1.5 m of the glazing.

Internal loads are kept constant through all simulations and take the default values from regulation NBR 16401-1 (ABNT, 2008). The occupancy area is 6.0 m²/person with a metabolic rate of 130 W/person in moderately active office work, and the electric equipment load is considered as medium office use of 10.76 W/m². The lighting power density is 9.7 W/m², as required for a Level "A" efficient building from the Regulation for Energy Efficiency Labeling of Commercial Buildings (RTQ-C) (ELETROBRAS, 2014).

The HVAC system is a Packaged Terminal Air Conditioner (PTAC) working from 6am to 10pm, Monday to Saturday. The system's coefficient of performance (COP) for cooling is 3.4, the cooling setpoint is 24 ºC and heating setpoint is 20 ºC. The cooling and heating capacity and the supply air flow rate of the PTAC were auto sized by simulations. Cooling is provided by a direct expansion (DX) coil and a condensing unit with single speed compressor, and heating is provided by an electric coil.

The building was simulated for the city of São Paulo, Brazil, in 23°32' South latitude and 46°38' West longitude. It is located on a humid subtropical climate region (Cfa), according to the Köppen-Geiger classification (PEEL; FINLAYSON; MCMAHON, 2007), with 74.3% of annual average relative humidity, a 12.3 °C average minimum temperature in the winter and a 28.8 °C average maximum temperature in the summer (INMET, 2018). Figure 2 shows the monthly average temperature and relative humidity for São Paulo.

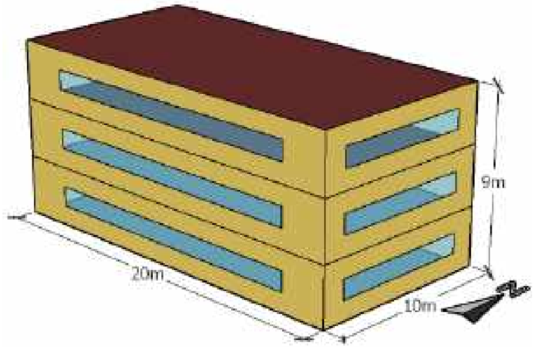


Figure 1: Sketch of the office building base case

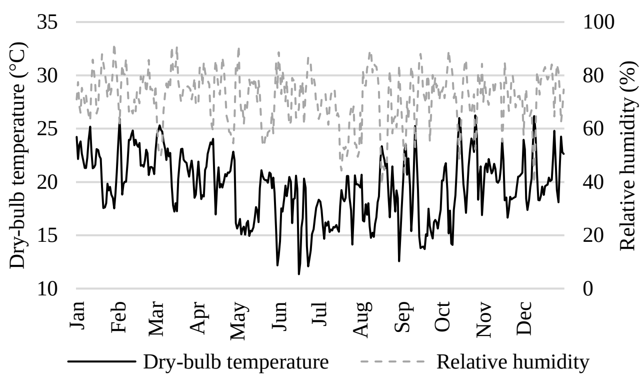


Figure 2: Average temperature and relative humidity in São Paulo

3.3 Optimization parameters

As the purpose of this study is to assist designers in the early stage of an architectural project, the model focus on initial construction cost of the building envelope and life-cycle energy cost. Variations of the HVAC system, occupancy, lighting and equipment density were not analyzed.

3.3.1 Variables and constraints

The optimization model is composed of variables, constraints and objective functions. Table 1 shows the defined variables and their corresponding constraints, while the properties of the wall, roof and glazing types can be found in Table 2. The building orientation is defined in EnergyPlus in degrees with clockwise direction being positive as shown in Figure 3. The building materials were defined as typical construction components from RTQ-C (ELETROBRAS, 2014). For simulation purposes, the wall and roof types were defined as equivalent layers in EnergyPlus according to Weber et al. (2017).

Table 1: Constraints of the variables defined for the GA optimization

Variables	Unit	Range
Orientation	Deg.	0, 15, 30, 45, 60, 75, 90, 105, 120, 135, 150, 165
Window-to-wall ratio	%	25, 50, 75
Wall type	-	W1, W2, W3, W4, W5, W6
Roof type	-	R1, R2, R3, R4, R5, R6
Glazing type	-	G1, G2, G3, G4

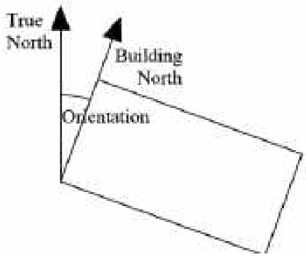
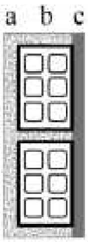
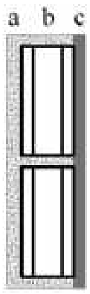
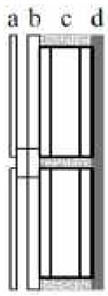
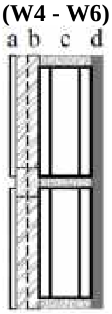
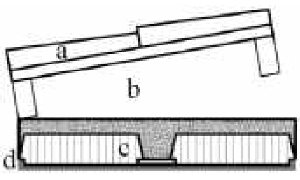
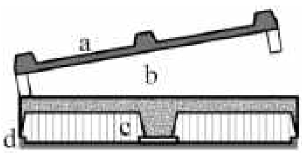
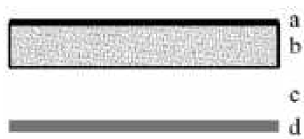
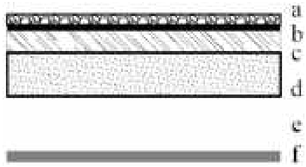


Figure 3: Orientation definition

Table 2: Composition, thermal properties and initial cost of the building envelope parameters used in the simulations

Wall type 1 (W1) Layers: a. External plaster (2.5 cm) b. Ceramic brick (9.0 cm) c. Gypsum board (2.0 cm) U_1 = 2.00 W/m²-K $\$_1$ = 12.40 USD/m² 	**Wall type 2 (W2)** Layers: a. External plaster (2.5 cm) b. Concrete block (9.0 cm) c. Gypsum board (2.0 cm) U_2 = 2.24 W/m²-K $\$_2$ = 13.95 USD/m² 	**Wall type 3 (W3)** Layers: a. Porcelain tile (1.0 cm) b. Air gap (7.0 cm) c. Concrete block (9.0 cm) d. Gypsum board (2.0 cm) U_3 = 1.65 W/m²-K $\$_3$ = 28.40 USD/m² 	**Wall types 4 / 5 / 6 (W4 - W6)** Layers: a. Porcelain tile (1.0 cm) b. EPS insulation (2.0 – 4.0 – 6.0 cm) c. Concrete block (9.0 cm) d. Gypsum board (2.0 cm) U_4 = 1.09 W/m²-K U_5 = 0.72 W/m²-K U_6 = 0.54 W/m²-K $\$_4$ = 32.50 USD/m² $\$_5$ = 34.70 USD/m² $\$_6$ = 36.90 USD/m² 
Roof type 1 (R1) Layers: a. Ceramic tile (1.0 cm) b. Air gap (15.0 cm) c. Pre-cast concrete and ceramic slab (8.0 cm) d. Internal plaster (2.0 cm) U_1 = 2.00 W/m²-K $\$_1$ = 28.40 USD/m² 	**Roof type 2 (R2)** Layers: a. Metallic/PU panel (4.2 cm) b. Air gap (15.0 cm) c. Pre-cast concrete and ceramic slab (8.0 cm) d. Internal plaster (2.0 cm) U_2 = 0.55 W/m²-K $\$_2$ = 59.80 USD/m² 	**Roof type 3 (R3)** Layers: a. Waterproof membrane (4 mm) b. Concrete slab (8.0 cm) c. Air gap (10.0 cm) d. Gypsum board (2.0 cm) U_3 = 2.02 W/m²-K $\$_3$ = 26.20 USD/m² 	**Roof types 4 / 5 / 6 (R4 - R6)** Layers: a. Pebble layer (2.0 cm) b. Waterproof membrane (4 mm) c. EPS insulation (2 - 4 - 6 cm) d. Concrete slab (8.0 cm) e. Air gap (10.0 cm) f. Gypsum board (2.0 cm) U_4 = 0.79 W/m²-K U_5 = 0.58 W/m²-K U_6 = 0.45 W/m²-K $\$_4$ = 37.30 USD/m² $\$_5$ = 39.50 USD/m² $\$_6$ = 41.70 USD/m²

			
Glazing type 1 (G1) Single tempered clear glass (6 mm) U_1 = 5.80 W/m²-K $SHGC_1$ = 0.82 $ = 210 USD/m²	**Glazing type 2 (G2)** Laminated clear glass (6 mm + PVB + 6 mm) U_2 = 5.60 W/m²-K $SHGC_2$= 0.38 $ = 280 USD/m²	**Glazing type 3 (G3)** Double insulated clear glass (6 mm + 10 mm air gap + 6 mm) U_3 = 2.70 W/m²-K $SHGC_3$ = 0.70 $ = 400 USD/m²	**Glazing type 4 (G4)** Double insulated reflective glass (6 mm + 10 mm air gap + 6 mm) U_4 = 2.70 W/m²-K $SHGC_4$ = 0.46 $ = 480 USD/m²

U: thermal transmittance
SHGC: solar heat gain coefficient

3.3.2 Objective functions

Two objective functions were defined: the minimization of initial construction cost (IC) of the building's envelope and the minimization of life cycle energy cost (LCE). LCE is part of the life-cycle analysis (LCA), which involves an assessment from owning, operating, maintaining and ultimately disposing of a project NIST Handbook 135 (FULLER; PETERSEN, 1995). However, the LCE used in his study considers only the electricity cost from the energy demand of the building, while operating, repair and maintenance costs are neglected. This approach refers to the early design stage, where usually architects do not have enough information to estimate the real-life building costs.

With X representing a variable vector, the general expressions to calculate IC [$/m²] and LCE [$/m²] are shown in Equations 1 and 2 below:

$$IC(X) = GF(X) + IF(X) + WT(X) + RT(X) + GT(X) \qquad \text{Equation 1}$$

$$LCE(X) = EC(X) \times PV \qquad \text{Equation 2}$$

Where:
GF ground floor cost [$/m²]
IF internal floors cost [$/m²]
WT wall type cost [$/m²]
RT roof type cost [$/m²]
GT glazing type cost [$/m²]
EC first year electricity cost for the city of São Paulo [$/m²]
PV present value

Both IC and LCE data are extracted as results from the Economic Calculations of EnergyPlus. IC is part of the component costs and LCE combines the electricity rate and life-cycle cost computations. For each year of study, the present value (PV) is calculated on EnergyPlus using Equation 3.

$$PV_{yr} = \frac{1}{(1 + DR)} \qquad \text{Equation 3}$$

Where:
DR discount rate

The PV uses the discount (or interest) rate (DR) to determine the current equivalent value of a set of future cash flows, considering a forecast inflation rate. For energy costs, EnergyPlus multiplies the PV of each year by the price escalation of that year. For this study the DR used was the forecast interest rate in Brazil for the year of 2019, with a value of 0.65 from the Central Bank of Brazil (BRASIL, 2019). The price escalation is updated in EnergyPlus from the NIST Handbook 135 (FULLER; PETERSEN, 1995). Since the main source of energy used in the model building is electricity, the energy rate was obtained from the São

Paulo Electric Company (Enel). The rate for commercial buildings with over 200 kWh consumption per month is 0.16 USD/kWh, including a total of 30% taxes.

3.3.3 Genetic algorithm

The jEPlus+EA software adopts the non-dominated-and-crowding sorting genetic algorithm II (NSGA-II), developed by Srinivas and Deb (1994). This algorithm ensures convergence and spreading of the solution front and can maintain the population diversity. It is recognized as one of the most efficient multi-objective evolutionary algorithms (YU et al., 2015).

For the GA implementation, the following parameters were selected, as recommended by Chen, Yang and Zhang (2017): population size = 10, number of generations = 50; crossover probability = 0.9; mutation probability = 0.1; the selection operator is the binary tournament selection. After the optimization run, the results were extracted from jEPlus+EA and stored in Excel files for evaluation. As mentioned before, the GA is based on Pareto-dominance, i.e., for each solution in the Pareto front, one objective cannot be minimized without increasing the other objective. This is why they represent the best solutions found in a multi-objective optimization. The results for this study are presented in the next section.

4. RESULTS

The multi-objective optimization was run in a single scenario with Windows 10 operating system on a laptop computer (2.40 GHz Intel i7 processor, 8 GB RAM). The run took 45 minutes and the results were exported as CSV files for analysis in Excel software. A total of 213 solutions were simulated, and through the GA method, seven cases represent the non-dominated solutions, as presented in Figure 4. The dominated solutions are shown as light grey circles, the blue diamonds represent the initial population, the red circles are the fiftieth (final) generation, and the black circles represent the non-dominated solutions on the Pareto front.

As the initial population was randomly selected, the results were widely distributed. From there to the final generation (red circles), there is a clear distribution difference, with the results concentrated on the bottom end of the Pareto front (here represented by the dashed curve). It can be noticed that the seven optimal solutions in the Pareto solutions appear clustered into two distinct groups. Solutions 1 through 4 (S1-S4) are clustered on the upper end of the front, while solutions 5 through 7 (S5-S7) are located on the bottom end of the curve. The upper cluster contains the individuals with the lowest values for the initial construction cost (IC), ranging from 94.9 $/m² to 99.3 $/m², but life-cycle energy cost (LCE) values ranging from 206.8 $/m² to 214.0 $/m². The bottom cluster holds the individuals with the lowest LCE (from 199.0 to 199.9 $/m²) but higher IC values (from 114.4 to 127.1 $/m²).

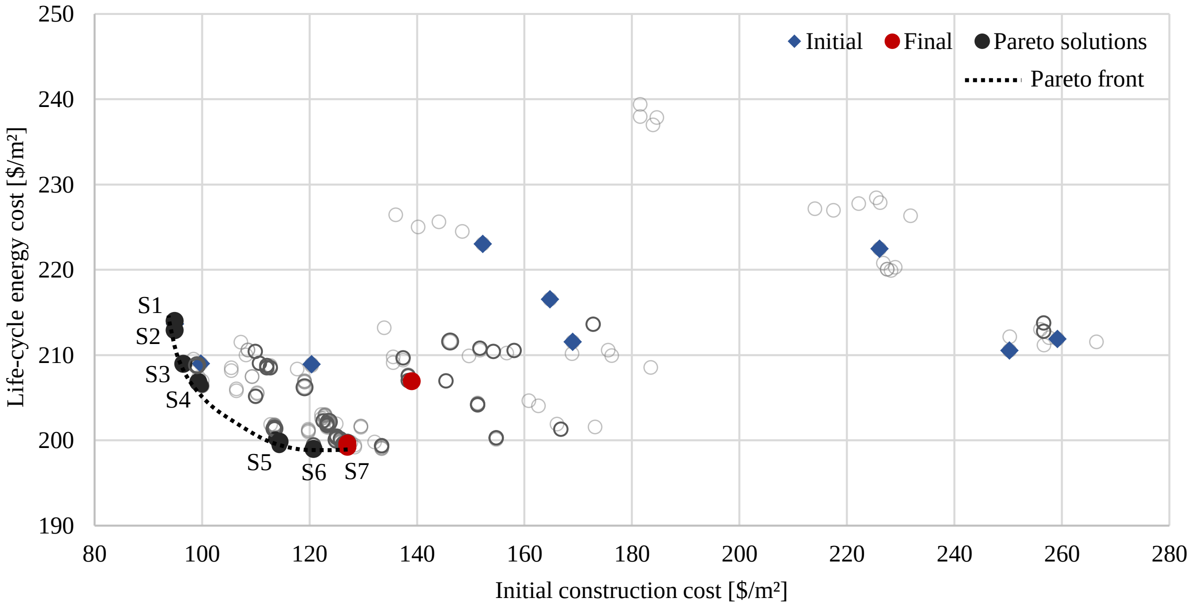


Figure 4: Multi-objective optimization chart. Evolution of the 20 generations towards the optimal solutions with initial construction cost (IC) and life-cycle energy cost (LCE) criteria

From Figure 4 the seven individuals that appear on the Pareto optimal front were further analyzed to understand the design parameters associated with them, as presented in Table 3. The results in the table were sorted from the smallest IC values to the largest. The first remark from the table is that all optimum results have a window-to-wall ratio (WWR) of 25%. This clearly indicates that large glazed facades are not recommended for subtropical climate regions like São Paulo, as solar heat gains from the glass increase cooling loads and consequently the electricity consumption.

On the window aspect, only the glazing types G1 and G2 appear on the best solutions, probably because of the cost per square meter of the element. There is a significant price increase in double insulated glazing compared to monolithic or laminated glasses (400 $/m² and 480 $/m² compared to 200 $/m² and 280 $/m²), respectively. A sensitivity analysis can be later conducted to determine if energy efficient glazing (with lower SHGC) would be selected in an optimization process if it was less expensive than current market prices.

Regarding the opaque elements, the predominant wall type solution was W2 in both clusters (four out of seven), followed by two solutions with and W1 (the same as the base case) and only one solution with W5. Like the glazing elements, in this optimization study, the cost of the material had greater impact than its thermal properties. Even so, this indicates that simple traditional wall elements in Brazil (ceramic or concrete blocks with plaster) can be used in constructions with an energy and cost-efficient approach. On the other hand, the roof type was more diverse, and solutions with all roof types (R1-R5) were identified, although R3 appears in two solutions in the upper cluster (S1 and S2) and R5 is present in S5 and S7 from the bottom cluster. This indicates that the roof plays a more important role in medium-rise buildings' thermal performance. The low U-factor of the roof due to insulation ensures lower solar heat gains and decreases significantly the cooling loads and electricity consumption. In this case study, a flat concrete roof with a 4 cm EPS insulation is a more suitable solution if the long-term energy consumption cost is observed, as it has similar thermal performance than a metallic/PU panel with a pre-cast concrete and ceramic slab but is considerably cheaper.

As for the orientation, the optimum solutions have diversified values, with the north angle ranging from 0° to 135°. However, values 0° and 15° appear two times each, indicating that longer facades of the building facing north and south are more suitable for medium-rise office buildings, like the one in this study. The solutions S1 and S4 northwest and southeast (105º) or north-northwest and south-southeast (135º / 150º). The design solution S1, for example, have the longer facades facing east and west, and presented the higher life-cycle energy cost. These results show that different orientations can be combined with other design variables to achieve cost-energy efficiency. Also, further analysis on the orientation impact on the building energy consumption and thermal comfort is desired.

Table 3: Parameters considered for the optimal solutions from the GA optimization

Solution	**Orient.**	**WWR [%]**	**Wall type**	**Roof type**	**Glazing type**	**Heating [kWh/m²-yr]**	**Cooling [kWh/m²-yr]**	**IC [$/m²]**	**LCE [$/m²]**
Base case	0	25	W1	R1	G1	2.4	32.6	101.8	211.2
S1	75	25	W1	R3	G1	3.1	33.2	94.9	214.0
S2	15	25	W1	R3	G1	3.0	32.8	94.9	212.9
S3	0	25	W2	R1	G1	2.4	31.7	96.6	209.0
S4	135	25	W2	R4	G1	1.7	31.4	99.3	206.8
S5	90	25	W2	R5	G2	1.9	28.1	114.4	199.9
S6	15	25	W2	R2	G2	1.8	27.8	120.8	199.0
S7	0	25	W5	R5	G2	0.8	28.9	127.1	199.3

Comparing the optimum solutions from the Pareto front with the base case results, in the upper cluster, there is a 6.7% reduction in the initial construction cost on S1 and S2 (94.9 $/m² compared to 101.8 $/m²). However, the life-cycle energy cost is slightly increased by 1.3% on S1 (from 211.2 $/m² to 214.0 $/m²). On the other hand, in the bottom cluster, there is a 5.8% reduction in the LCE from the base case on S6 (from 211.2 $/m² to 199.0 $/m²), even though the IC is increased by 18.6% (120.8 $/m² compared to 101.8 $/m²). In this case, the annual energy consumption for cooling is reduced from 32.6 to 27.8 kWh/m²-yr (14.7% less), which is an important energy saving if the 30-year life expectancy of the building is considered.

In this stage, once the Pareto optimum solutions set is obtained, the decision-making process lies with the professionals involved in the design of the building. Designers and engineers may select the best design by including other objectives. For example, if there is a limited initial construction budget, the solutions from upper cluster on Table 3 can be selected. However, if the client is willing to spend more on the construction for an energy-efficient building, a solution from the bottom cluster may be used.

5. CONCLUSIONS

This paper used a multi-objective genetic algorithm to find optimal solutions for an early stage office building design in a subtropical climate region, using passive strategies to minimize the initial construction cost and the life-cycle energy cost. The jEPlus+EA interface was used to run the genetic algorithm and extract results from the simulations using EnergyPlus software. Based on the analyzed results, some conclusions are presented.

From a single scenario run, 213 solutions were simulated, and seven individuals compose the non-dominated solutions on the Pareto optimal front. They were grouped into two distinct clusters, where the first one holds the results with lower initial construction cost and higher life-cycle energy cost. The second cluster have higher IC and lower LCE. Results from the upper cluster showed a decrease in IC of 6.7% in one solution and a 1.3% increase in LCE when compared to the base case. In the bottom cluster, even though IC presented an increase up to 18.6% in one solution, LCE was reduced by 5.8% from the base case. Based on these criteria, designers and engineers can select the most suitable design option.

This case study was set for São Paulo, in a subtropical climate region. From the optimal solutions, there are some design recommendations for medium-rise office buildings. Different orientations can be used, so designers can have more freedom when locating the building on the site. A small window-to-wall ratio is more adequate for reducing solar heat gains. The roof type should have low thermal transmittance, and insulated flat roofs are energy-efficient and cheaper than sloped roofs with a non-ventilated attic. Monolithic and laminated glasses are preferred from the economical point of view. Even though insulated glazing can have lower SHGC, their market prices do not justify their use, but a sensitivity analysis can be conducted to determine the cost-efficiency relation.

The proposed method used in this paper considered only the envelope parameters as decision variables and construction cost and life-cycle energy cost as objective functions, as usually in the early design stage architects have little information regarding the building actual operating costs. A more comprehensive life-cycle analysis can include operating, repair and maintenance costs, so these aspects are suggested for future studies. This research is expected to further develop the method for more complex building shapes, with other design strategies. Analyzing the occupancy, lighting and equipment profiles, as well as the HVAC system is encouraged. Other important criteria like thermal comfort, natural ventilation and environmental impacts can also be studied in future works.

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