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Energy efficiency optimization of architectural projects using an Evolutionary Algorithm combined with Energy Plus

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ABSTRACT
This study formulates an optimization problem that adjusts social housing physical parameters to minimize energy consumption and thermal discomfort. Candidate solutions were generated using Genetic Algorithm via the Python computational platform and evaluated on the EnergyPlus program. The analyzed social housing unit meets minimum conditions according to Brazilian standards NBR 15575 and 15220 and the Federal Government's Casa Verde Amarela Program. Optimization variables included cardinal tweaking; thickness of materials that make up external walls, roofing, and flooring; external wall and roof absorptance; floor-to-ceiling height and window size. Unlike other studies, instead of optimizing the thermal transmittance of walls, roof, and floor, we decided to directly target their thickness and to optimize window size and the floor-to-ceiling height. Evaluated according to different physical project configurations, the results proved to be coherent, presenting adequate variable exploration in order to obtain a project that universalizes the use of simple and systemic techniques to improve energy efficiency and that can be applied to any type of housing. We also obtained solution automation, providing an optimal feasible solution that increases energy efficiency and reduces energy consumption, thus contributing to a more sustainable project.

KEY-WORDS: Genetic Algorithms. Energy Efficiency. EnergyPlus.

1 INTRODUCTION

The Commercial and Residential Building sector accounts for the largest share of electricity consumption, whose use and cost continues to grow (EPE, 2020). This reality reinforces the importance of developing energy conservation and environmental sustainability strategies already in the project design phase.

In Brazil, the sector that most suffers from energy efficiency is the Social Housing sector (SHS) (Bavaresco et al., 2021), which became popular after creation of the National Housing Bank in 1964, and the federal housing programs “Minha Casa, Minha Vida” (instituted in 2009) and “Casa Verde Amarela” (instituted in 2019).

Bavaresco et al. (2021) point to little evolution in the SHS regarding energy efficiency aspects when evaluating the period from 2009 to 2019. In response, they have proposed a protocol for designers to evaluate housing characteristics to encourage knowledge about energy efficiency in buildings to become more widespread.

Moreover, the sector lacks tools and computational simulations that include design, building envelope and location characteristics, among others, to obtain energy-efficient projects.

Building efficiency can be achieved by analyzing various parameters such as shape, construction orientation, materials adopted, choice of building envelope techniques, shading, window sizes, heating or cooling system characteristics, ventilation, afforestation, costs, energy savings and the building's life cycle, insulation performance using building elements that block heat to increase thermal comfort, more effective thermal insulation glazing systems for low sun exposure, natural ventilation, among others (LEITZKE et al., 2021).

Given their interconnectedness, empirical and manual design decisions may produce inefficient results when compared with those obtained via optimization techniques. Besides, more energy efficient projects bring more quality of life, comfort and sustainability compared to conventional projects (NGUYENA, REITERA and RIGOB, 2014).

An automated study of simple physical configurations may not imply high investments in materials and can provide thermal comfort for most of the year in residential projects, which have greater tolerance to internal temperatures and less intensive internal load.

Suitable tools for this purpose can evaluate project variables and thus reallocate project decisions to achieve better energy performance goals established by various certificates and regulations (KAPSALAKI, LEAL and SANTAMOURIS, 2012).

Following this strategy, this study presents a tool that uses an evolutionary algorithm to solve an optimization problem aimed at minimizing energy consumption and thermal discomfort in houses already in the design phase, adjusting the following physical design variables: cardinal positions, thickness of materials that make up external walls, roof and floor, external walls and roof absorptance, floor-to-ceiling height, and window size.

2 OBJECTIVES

Of the computational analysis tools available on the market to evaluate the results of constructive choices before project design, Energy Plus (EP) is one of the most used tools to analyze building energy efficiency and thermal comfort (SOUSA, 2012) and will be used in this work.

According to Didonè and Pereira (2010), evaluating building energy performance is a complex task that involves many interdependent variables and multidisciplinary concepts, which made way for a branch in the architecture and construction sector focused on initial project analysis using computer simulations.

Since an ideal project depends on numerous variables and different evaluation parameters, it is humanly impossible to obtain a good composition by performing empirical parameterizations—a repetitive, time-consuming, and unreliable process that can lead to losses (DELGARM et al., 2016).

As an attempt to replace this repetitive process, evolutionary algorithms have been used to seek better solutions to a problem that depends on parameter adjustment.

Evolutionary algorithms (EAs) are based on the ‘survival of the fittest’ ideal and seek candidate solutions to an optimization problem. They iteratively change and combine solutions to create other solutions, the fitness of which are evaluated against the objective function. The fittest solutions are selected to survive and reproduce. The process is then repeated to generate new solutions.

EAs comprise several types, such as Genetic Algorithms (GA)—a metaheuristic inspired by natural selection—, Differential Evolution (DE)—a stochastic optimization algorithm whose solutions operate through steps—, Particle Swarm Optimization—based on the concept of swarms, such as shoal of fishes and flocks of birds—, and others.

Chart 1 summarizes some studies that use Evolutionary Algorithms to solve architecture-related multiobjective functions.

Their results show that the energy efficiency analysis of building models becomes more efficient when combining more than one variant, which has become a trend in the use of evolutionary algorithms to optimize energy efficiency by adjusting various architectural physical parameters in the project design phase.

One of the limitations of using Energy Plus is in terms of configuring many simulations with variations in the components of interest, as it lacks functionalities that allow multiple scenarios to be generated via automatic component parameterization (LEITZKE et al., 2021).

Considering multiple combinations of technical construction solutions for a specific study involving the use of EP is no simple task, as it lacks an interface capable of changing the information entered into the program, causing each simulation to run individually on a study object.

Philip and Tanjuatco (2011) advanced in this direction by developing EPPY (Energy Plus Python), a Python programming language-based program that allows data communication with the Energy Plus software. As a result, one can browse, search, and modify EP files, such as the geometric model file saved as “Energy Plus Input Data File” (.idf) and the “Energy Plus Weather Format” (.epw) weather file. EPPY opened the following possibilities (PHILIP and TANJUATCO, 2011):

- Make changes to an EP .idf file with just a few lines of code, i.e., manual work within the EP software can be replaced by a few lines coded in Python;

- Make systemic changes in several .idf files.

- Generate different input files for EP, simulating construction in different cardinal positions, changing the composition of windows, lighting, efficiency, power of electronic equipment, compiling energy consumption, thermal discomfort, among other features.

LEITZKE et al. (2020) offer an example of EPPY application through the computational tool “IDFModifier,” capable of parameterizing the thermal transmittances of external walls, redefining and facilitating the parameterization of computational simulations run by the EP.

These references supported important decisions regarding the formulation and computational implementation of an evolutionary algorithm applied to an optimization problem that aims to minimize energy consumption and thermal discomfort in housing during the design phase.

Thus, we established the following study premises:

- Choice of optimization variables, such as: different cardinal positions, thickness of materials that make up external walls, roof and floor, external walls, and roof absorptance, floor-to-ceiling height and window size. Unlike the work by Leitzke et al. (2021), instead of optimizing the thermal transmittances of the walls, roof, and floor, we chose to act directly on the thickness of these materials, in addition to optimizing window size and floor-to-ceiling height.
- Use of the Energy Plus software, commonly applied in energy efficiency analysis.
- Choice of Python programming language due to the EPPY program, which allows data communication between Python and the EP.
- Use of Genetic Algorithms to solve the optimization problem, as often cited in the literature.
- Application of the proposed tool in three Brazilian cities with different bioclimatic zones: Caxias do Sul, Picos and Brasília.

Chart 1- Works on evolutionary algorithms for solving multiobjective functions

Author(s)	Overview	Optimization tool	Simulation tool	Objective
Nguyens, A-T, Reitera, S. and Rigob, P. (2014)	Points out the importance of carefully selecting multiobjective optimization algorithms to achieve better search techniques to reduce time and effort in obtaining architectural projects with better construction performance.	Bibliographic analysis of Multiobjective Analysis Methods		
Delgarm, N.; Sajadi, B. and Delgram, S. (2016).	Optimizes the following variables: building orientation, projection specifications for shading, window size, and wall material properties.	Particle Swarm	Energy Plus, MATLAB® and jEPlus	Energy consumption
Santana, Laila Oliveira (2016).	Optimizes the energy performance of residential building geometry considering room size, ceiling height, window area and roof slope.	*Octopus*: SPEA-212 and HypE	*Grasshopper, Energy Plus* and *Radiance*	Thermal comfort
Ferdyn-Grygierek, J. and Grygiurek, K. (2017)	Optimizes the following variables: windows, building orientation, exterior wall, roof, and ground floor insulation, as well as the Life Cycle Impact (LCC) of each element.	Self-adaptive genetic algorithm based on fuzzy arithmetic	TRNSYS	Thermal comfort
Bre, F.; Fachinotti, V. D. A. (2017)	Optimizes construction compositions based on orientation, window shading level, external frame solar absorptance, level of air infiltration through frames and doors, percentage of ventilation opening of frames, frame size and type, and the composition of the external and internal walls, floor and roof.	NSGA-II	*Energy Plus* and Python	Energy consumption and thermal comfort
Grygiurek, K. and Ferdyn-Grygierek, J. (2019)	Optimizes construction compositions based on window type and size, building orientation, external wall insulation, roof for unheated attic and ground floor in Polish climatic conditions.	Genetic Algorithms and Particle Swarm	*Energy Plus*, MATLAB®	Energy consumption and life cycle
Leitzke et al. (2021)	Optimizes the following variables: wall, roof and floor thermal transmittances, cardinal orientation, and wall and roof solar absorptance.	Evolutionary methods	*Energy Plus* and Python	Thermal comfort

Source: Authors

3 THE OPTIMIZATION PROBLEM TO MINIMIZE ENERGY CONSUMPTION AND THERMAL DISCOMFORT

This section aims to describe the mathematical formulation of the optimization problem that has as criteria the minimization of energy consumption (kWh/m^{2}year) and thermal discomfort (%) of a given social housing.

The formulation was initially inspired by Leitzke et al. (2021), which optimizes the following variables: thermal transmittance of the wall (W/m^2 K), thermal transmittance of the roof (W/m^2 K), thermal transmittance of the floor (W/m^2 K), absorbance of the external wall, absorbance of the coverage and cardinal orientation (°).

This work proposes to replace the optimization of thermal transmittances by wall, roof, and floor thicknesses and to insert more optimization variables, related to the height of the floor to the ceiling and the height of the windows (keeping the widths fixed).

The problem to be described is solved in a hybrid way as it reconciles the use of Energy Plus (EP) and Genetic Algorithms (via Python's “GA instance” function). The solution processes tours through the search field delimited by the constraints, and each solution obtained by the GA is evaluated by the EP software, which provides consumption and discomfort values.

To parameterize the data simulated by the EP, a library developed in the Python programming language called EPPY is used (PHILIP and TANJUATCO, 2011).

3.1 Multiobjective function

The objective function (OF) to be minimized during the process of optimizing the variables mentioned in the previous sections includes the following criteria:

$$OF = min[\ f_c + \ f_d] \tag{1}$$

where

OF – objective function to be minimized

f_c – energy consumption (kWh/(m^{2year} year))

f_d – discomfort level (per unit, pu).

Each of the optimization criteria is calculated by Energy Plus output reports.

In problems with a single objective, the optimal solution is obtained by simply maximizing (or minimizing) an objective function of decision variables subject to a series of constraints. Differently, the multiobjective analysis selects the best compromise solution between the criteria.

Equation (1) seeks the optimization of two objective functions that consists of determining a set of decision variables, which optimizes the vector function, whose elements represent the performance indices to be optimized.

In a multiobjective optimization problem, there is not only one optimal solution, but a set of possible solutions called efficient or Pareto-Optimal. And, as the importance of each of the objectives is not known, all Pareto-optimal solutions are equally important (COELLO, 2000).

There are a variety of methods to solve a multiobjective optimization problem (COELLO, 2000), such as the global criterion method, weighting method, and penalization method, among others.

An example of easy implementation is the Global Criterion Method, which combines several objective functions within a single function, obtaining a single solution as a result of the optimization.

This Global Criterion Method will be used to form a single objective function, whose set of optimal solutions is obtained via GA.

The Global Criterion Method uses the ideal value as a calculation basis to define an individual's fitness level. This method converts the multiobjective function into a single objective being expressed mathematically by the following function (COELLO, 2000):

$$FO = min[\frac{f_c - f_c^0}{fmax_c - f_c^0} + \frac{f_d - f_d^0}{fmax_d - f_d^0}] \tag{2}$$

where

f_c - energy consumption
f_d - discomfort level
f_c^0 - ideal consumption value, assumed to be zero
f_d^0 - ideal discomfort value, assumed to be zero
$fmax_c$ - worst case consumption. It is obtained after simulations in which variable values are randomly changed, selecting the highest consumption value obtained
$fmax_d$ - worst case discomfort. As the discomfort value is a percentage, 100% or 1 per unit (pu) is considered as the worst situation.

As the ideal values (f_c^0 and f_d^0) are assumed to be zero and $fmax_d$ has unit value, and the eq. (2) becomes:

$$FO = min[\frac{f_c}{fmax_c} + f_d] \quad (3)$$

3.2 Optimization variables and their limits

The thicknesses of the external walls, roof and floor will be optimized to obtain new thermal transmittance values for the external wall, roof, which meet the standards NBR 15220-2 (ABNT, 2005).

The materials whose thickness will be optimized are ceramic blocks for the external walls, EPS plates (expanded polystyrene) and concrete for the floor, according to the equation contained in the NBR 15220.

The compositions of the walls, roof and floor stored in the tab "Material" of the EP are modeled like Leitzke et al. (2021). The compositions and physical limits of the variables are presented below.

3.2.1 Composition of external walls formed by groat, ceramic block and groat

The value of the thickness of the ceramic block, e_{cer} (m), is optimized to obtain better levels of consumption and thermal discomfort. For each new thickness, e_{cer}, a new thermal resistance value of the ceramic(RT_{cer}) is obtained as NBR 15220:

$$RT_{cer} = \frac{e_{cer}}{\lambda_{cer}} \quad (4)$$

where
e_{cer} – ceramic block thickness (m)
λ_{cer} – thermal conductivity of the ceramic block (W/m K)
RT_{cer} – thermal resistance of ceramic block (m^2 K/W).

The total thermal resistance of the wall, RT_{wall} is formed by the sum of the thermal resistances of each component of the wall (NBR 15220):

$$RT_{wall} = 2 * RT_{gr} + RT_{cer} + RT_{air} \quad (5)$$

where
RT_{gr} - thermal resistance of groat (m^2 K/W)
RT_{cer}– thermal resistance of ceramic block (m^2 K/W)
RT_{air}– air thermal resistance (m^2 K/W), adopted value equal to 0.16 (m^2 K/W).

The new value of the total Thermal Transmittance of the external wall (TTP) is calculated by the inverse of the new value of RT_{wall} (NBR 15220).

3.2.2 Roof composition made up of fiber cement tile, wooden lining and EPS

The thickness value, e_{EPS} (m), of the plate block EPS are optimized to obtain better levels of consumption and thermal discomfort.

The new thermal resistance value of EPS (RT_{EPS}) is recalculated for each new EPS thickness value (NBR 15220):

$$RT_{EPS} = \frac{e_{EPS}}{\lambda_{EPS}} \tag{6}$$

where
e_{EPS} – EPS board thickness (m)
λ_{EPS} - thermal conductivity of EPS board (W/m K)
RT_{EPS} – heat resistance of EPS board (m^2 K/W).

The total thermal resistance of the roof (RT_{roof}) is formed by the sum of the thermal resistances of each component of the roof (NBR 15220):

$$RT_{roof} = RT_{EPS} + RT_{wood\ lining} + RT_{fibercementtile} + RT_{air} \tag{7}$$

where
RT_{EPS} – heat resistance of EPS board (m^2 K/W)
$RT_{fibercementtile}$– thermal resistance of fiber cement tile (m^2 K/W)
$RRT_{wood\ lining}$– thermal resistance of wood lining (m^2 K/W)
RT_{air}– air thermal resistance (m^2 K/W), adopted value equal to 0.21 m^2 K/W.

The new value of the total thermal transmittance of the roof (TTC) is recalculated by the inverse of the new value of RT_{roof} (NBR 15220).

3.2.3 Composition of the floor formed by concrete slab, groat and ceramic coating

The thickness value of concrete, e_{conc}, is optimized to obtain better levels of consumption and thermal discomfort.

The new thermal resistance value of concrete, RT_{conc}, is recalculated for each new concrete thickness value, e_{conc} (NBR 15220):

$$RT_{conc} = \frac{e_{conc}}{\lambda_{conc}} \tag{8}$$

where
e_{conc} – concrete thickness (m)
λ_{conc} - thermal conductivity of concrete (W/m K)
RT_{conc} – thermal resistance of concrete (m^2 K/W).

The total thermal resistance of the floor (RT_{floor}) is formed by the sum of thermal resistances of each component of the roof (NBR 15220):

$$RT_{floor} = RT_{conc} + RT_{gr} + RT_{cer} \tag{9}$$

where
RT_{conc} – thermal resistance of concrete (m^2 K/W)
RT_{gr}– thermal resistance of grout (m^2 K/W)
RT_{cer}– thermal resistance of ceramics (m^2 K/W).

3.2.4 Limits of Variables

Next, the physical limits used for each of the optimization variables of the problem are described.

The maximum and minimum thickness limits of the external wall ceramic block (e_{cer}) and wall absorbance (AP) are:

$$e_{cer}^{min} \leq e_{cer} \leq e_{cer}^{max} \tag{10}$$

$$AP^{min} \leq AP \leq AP^{max} \tag{11}$$

where

e_{cer} - ceramic block thickness (m)
e_{cer}^{min} - minimum thickness limit of the ceramic block (m)
e_{cer}^{max} - maximum thickness limit of the ceramic block (m)
AP - solar absorbance of external wall
AP^{min} minimum solar absorbance limit of the external wall
AP^{max} – maximum solar absorbance limit of the external wall.

The maximum and minimum limits of the plate thickness (e_{EPS}) and solar absorbance of roof (AC) are:

$$e_{EPS}^{min} \leq e_{EPS} \leq e_{EPS}^{max} \tag{12}$$

$$AC^{min} \leq AC \leq AC^{max} \tag{13}$$

where

e_{EPS} – EPS board thickness (m)
e_{EPS}^{min} - minimum EPS thickness limit (m)
e_{EPS}^{max} - maximum EPS thickness limit (m)
AC - solar absorptance of roof
AC^{min} - minimum solar absorbance of roof limit
AC^{max} - maximum solar absorbance of roof limit.

Maximum and minimum limits of floor concrete thickness (e_{conc}) are:

$$e_{conc}^{min} \leq e_{conc} \leq e_{conc}^{max} \tag{14}$$

where

e_{conc} – concrete thickness (m)
e_{conc}^{min} - minimum concrete thickness limit (m)
e_{conc}^{max} - maximum concrete thickness limit (m).

The new external wall thickness, $e_{cer}\ (m)$, roof thickness, $e_{EPS}\ (m)$, floor thickness (e_{conc}) and absorbances are updated in the tab "Material" of EP (via EPPY).

The maximum and minimum limits of cardinal orientation (Or) are:

$$Or^{min} \leq Or \leq Or^{max} \tag{15}$$

where

Or - orientation (°)
Or^{min} – minimum orientation limit
Or^{max} - maximum orientation limit.

This new orientation value is updated in the tab "Building[0].North_Axis" of EP (via EPPY).

Maximum and minimum limits for floor-to-ceiling height (h) are:

$$h^{min} \leq h \leq h^{max} \tag{16}$$

where
h - floor to ceiling height (m)
h^{min} - minimum floor-to-ceiling height limit (m)
h^{max} - maximum floor-to-ceiling height limit (m).

The new height values generated by the GA are stored in the tab "BuildingSurface:Detailed" of EnergyPlus for each room of the house (via EPPY).

Maximum and minimum limits of height (hw) from the top of the window to the ceiling are:

$$hw^{min} \leq hw_i \leq hw^{max} - 0.15 \qquad i=1, \ldots, nw \qquad (17)$$

where
hw_i - height from the top of each window, i, to the ceiling (m)
hw^{min} - minimum window height limit (m)
hw^{max} - maximum window height limit (m)
nw - number of windows of the house.

The minimum value comprises the height of the bottom part of the window (kept fixed); the maximum value is dynamic since it depends on the optimized height obtained in equation (16). It is considered 15 cm below the ceiling, to ensure that it does not coincide with the height of the ceiling.

The new height values generated by the AG are stored in the tab "FenestrationSurface:Detailed" of Energy Plus for every window of the house (via EPPY).

Thus, the complete optimization problem, composed by the equations (3) and (10 -17), is solved by Genetic Algorithms, using the function "*ga_instance"* of Python.

3.3 Genetic Algorithms

Genetic Algorithms are evolutionary algorithms that are based on natural and genetic selection mechanisms to solve optimization problems. They employ random search strategies that aim to obtain points that minimize or maximize the objective function being analyzed.

This technique requires individuals to be coded to solve the problem. In this study, the individuals are of the decimal type and Frame 2 presents what each gene represents in the code.

Frame 2 - Individual Codification

Gene 1	Gene 2	Gene 3	Gene 4	Gene 5	Gene 6	Gene 7	...	Gene $6+_{nw}$
e_{cer}	e_{EPS}	e_{conc}	AP	AC	h	hw_1	...	hw_{nw}

Source: Authors.

The first gene informs the thickness value of the external wall (e_{cer}), the second gene informs the thickness value of EPS plate (e_{EPS}. The third gene informs the concrete thickness of the floor (e_{conc}), the fourth gene informs the solar absorbance value of the wall (AP), the fifth gene informs the solar absorbance value of the roof, the sixth gene informs the height floor-to-ceiling and the last nw genes inform the heights of the upper parts of each window in the house.

After the creation of individuals, they are decoded, i.e., the optimization variables are found, updated in the EP database, and the consumption and discomfort values of the evaluation function are provided.

To find the best solutions to the problem, a reproduction mechanism is applied to each generation, based on the evolutionary process, which is based on genetic operators of mutation and crossover, among others, acting on the genetic material of the chromosome (RABELO and OCHI, 1996).

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The operators used by GA in this work and the configuration of the parameters are shown in Frame 3.

Frame 3- Configuration of GA parameters

Feature	Parameter	Configuration
Individual	Codification	Decimal
	Number of genes	6+ number of windows
Population	Size	10 Individuals
	Initial	Random
Selection	Elitism	2 Individuals
	Method	Roulette
Crossing	Type	One point
Mutation	Type	Uniform
	Rate	20%
Stop	Number of generations	100 Generations

Source: Authors.

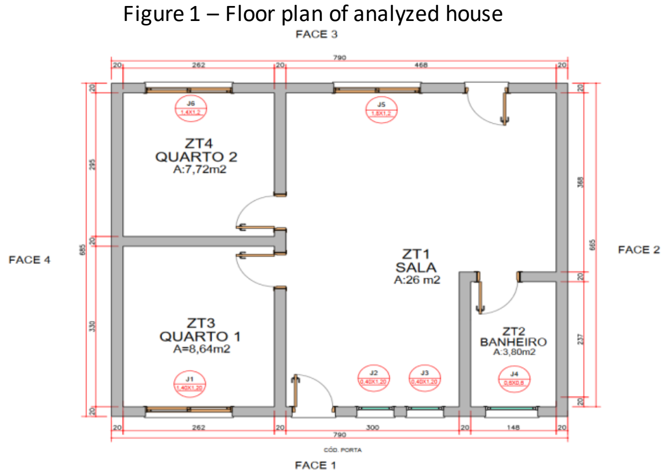
The main steps needed to solve the optimization problem at hand are described below:
Step 1 – Definition of maximum number of generations and enabling consumption and discomfort functions.
Step 2 - Definition of the housing model.
Step 3 - Preparation of data entry files of housing parameters in the EP format (.idf).
Step 4 - Choice the city where the house is located and loading of its climate data from the Bioclimatic Zone (.epw).
Step 5 - Reading the physical limits of the optimization variables.
Step 6 – Execution of GA, via function "*ga_instance"* of Python.

After updating the EP data entry of each decoded individual, the EP is performed and consumption and discomfort values are obtained, which are used to calculate the objective function (eq.3):
Step 7 -Convergence of the process after executing the number of generations specified in the Step 1**: END**.

4. RESULTS

To test the proposed optimization tool, we used the architectural model modeled in Oliveira (2012), adapted to better meet some requirements of the "Casa Verde Amarela" Program (Figure 1).

Figure 1 – Floor plan of analyzed house



Source: Adapted from Oliveira (2012).

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The house is 54.11 m² with a ceiling height of 2.6 m. It consists of two bedrooms, one bathroom and one living room with an integrated kitchen. Each room was categorized by a name and thermal zone, namely: living room/kitchen – Thermal Zone 1 (ZT 1), bathroom – Thermal Zone 2 (ZT 2), bedroom 1 – Thermal Zone 3 (ZT 3) and bedroom 2 – Thermal zone 4 (ZT 4).

To test the optimization tool in different climatic conditions, we used climate data (.epw) and monthly average soil temperatures from the cities Caxias do Sul (Bioclimatic Zone 1), Brasília (Bioclimatic Zone 4) and Picos (Bioclimatic Zone 4), chosen due to their great bioclimatic differences, thus allowing comparison between the results obtained.

In addition to the different cities, we also conducted tests to assess whether introducing the floor-to-ceiling height and window height would influence the results.

After conducting several consumption simulations, we chose the maximum energy consumption values—of 1500 kWh/(m² year) for Brasília and 3000 kWh/(m² year) for Caxias do Sul and Picos—to normalize the consumption function. We used a maximum discomfort value of 100% to normalize the discomfort function.

The investigated the following cases studied:

- Case 0, evaluate the best multiobjective function composition via the following simulations: Min Consumption (minimization of consumption only), Min Discomfort (minimization of discomfort only), and Min Consumption and discomfort (simultaneous minimization of consumption and discomfort).

- Case 1, simulation using the city of Brasilia, optimization problem composed of inequality constraints (10 to 15), keeping the floor-to-ceiling height fixed at 2.6 m.

- Case 2, simulation using the city of Brasilia, optimization problem composed of equations (10 to 15) and inclusion of floor-to-ceiling height optimization (eq. 16).

- Case 3, simulation using the city of Brasilia, optimization problem composed of equations (10 to 16) and inclusion of window height optimization (eq. 17).

- Case 4, simulation using the city of Caxias do Sul, optimization problem composed of equations (10 to 17).

- Case 5, simulation using the city of Picos, optimization problem composed of equations (10 to 17).

We analyzed the maximum and minimum thermal transmittance limits for each city according to NBR 15220 (Table 1).

Table 1 - Maximum and minimum thermal transmittance limits according to NBR 15220

	Caxias do Sul ZB1	Picos ZB7	Brasília ZB4
Wall thermal transmittance	≤ 2.5	≤ 1.85	≤ 1.85
Roof thermal transmittance	≤ 0.7	≤ 2	≤ 2

Source: Authors

Based on the maximum transmittance limits, we calculated the minimum thickness values needed to satisfy the NBR 15220 standard for each city considered. Table 2 shows all the limits used for each city.

Table 2 – Maximum and minimum limits of all optimization variables for each city

Limits	Caxias do Sul ZB1	Picos ZB7	Brasília ZB4
$e_{cer}^{min}\ (m)$	0.14	0.24	0.24
$e_{cer}^{max}(m)$	0.40	0.40	0.40
AP^{min}	0.2	0.2	0.2
AP^{max}	0.9	0.9	0.9
$e_{EPS}^{min}(m)$	0.045	0.015	0.015
$e_{EPS}^{max}(m)$	0.15	0.150	0.150
AC^{min}	0.2	0.2	0.2
AC^{max}	0.9	0.9	0.9
$e_{conc}^{min}(m)$	0.1	0.1	0.1
$e_{conc}^{max}(m)$	0.25	0.25	0.25
Or^{min}	0^0	0^0	0^0
Or^{max}	315^0	315^0	315^0
$h^{min}(m)$	2.6	2.6	2.6
$h^{max}(m)$	3.3	3.3	3.3
hw^{min}	2.1	2.1	2.1
hw^{max}	3.2	3.2	3.2

Source: Authors

Table 3 presents the results of the objective function (FO) values composed of consumption and/or discomfort; wall, roof and floor thicknesses and transmittances; absorptances and cardinal orientation. For Case 0, we used the city of Brasilia and the optimization problem tested consists of the inequality constraints presented in eq. (10 to 15), keeping the floor-to-ceiling height fixed at 2.6 m.

Table 3 - Case 0 - Evaluation of multiobjective function composition.

Case	OF	Consump. (kWh/(m² year))	Disc. (%)	TTP (W/m² K)	e_{cer} (m)	TTC (W/m² K)	e_{EPS} (m)	e_{conc} (m)	AP	AC	Or. (°)
Cons.	0.805	1007.00	57.36	1.3072	0.40	0.2416	0.150	0.25	0.6	0.2	0
Disc.	0.537	1020.19	53.76	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	45
Cons. and Disc.	1.346	1007.83	54.00	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	0

Source: Authors

According to Table 3:

- the lowest consumption value (1007.00 kWh/(m²·ano)) and the highest discomfort value (57.36%) are obtained when only consumption is minimized.

- the lowest discomfort value (53.77%) and the highest consumption value (1020.19 kWh/(m²·ano)) are obtained when only discomfort is minimized.

- simultaneous minimization creates a compromise between minimizing discomfort and consumption, with discomfort and consumption values 6.27% and 1.3% lower than the worst case, respectively. Thus, this combination will be used in subsequent simulations.

The solution that minimizes both consumption and discomfort opted for a combination (in relation to minimization of consumption only, for example) that reduced the use to only one EPS board for the roof (instead of 10 boards) and the wall and roof absorptances from 0.9 to 0.2.

Table 4 presents the results of the objective function (FO) values composed of consumption and discomfort, and wall, roof and floor thicknesses, absorptances and orientation, keeping the floor-to-ceiling height fixed at 2.6 m (Case 1) and addition of floor-to-ceiling height adjustment (Case 2).

Table 4 - Case 1 and 2 - Performance for Brasília with adjusted wall, roof, and floor thicknesses, absorptances, and orientation with and without floor-to-ceiling height control.

Case	OF	Consump. (kWh/(m² year))	Disc. (%)	TTP (W/m² K)	e_{cer} (m)	TTC (W/m² K)	e_{EPS} (m)	e_{conc} (m)	AP	AC	Or. (°)
1	1.3463	1007.83	54.00	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	0
2	1.3463	1007.83	54.00	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	0

Source: Authors

Case 2 (floor-to-ceiling height optimization) maintained the floor-to-ceiling height at 2.6 m was maintained, as in Case 1, demonstrating that this is the best value for this variable.

Table 5 presents the results of the objective function (FO) values composed of consumption and discomfort, wall, roof, and floor thicknesses, absorptances, orientation, floor-to-ceiling height (Case 2) and addition of window height (Case 3).

Table 5 – Cases 2 and 3 - Performance of Brasilia with adjustment of wall, roof and floor thicknesses, absorbances and orientation, floor-to-ceiling height, with and without window height control.

Case	OF	Consump. (kWh/(m2 year))	Disc. (%)	TTP (W/m² K)	e_{cer} (m)	TTC (W/m² K)	e_{EPS} (m)	e_{conc} (m)	AP	AC	Or. (°)
2	1.3463	1007.83	54.00	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	0
3	1.3454	1009.58	53.77	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	0

Source: Authors

Case 3 used a floor-to-ceiling height of 3.00 m.

According to Table 5, minimizing floor-to-ceiling height together with window size results in a 1.00% increase in consumption (from 1007.83 kWh/(m²·year) to 1009.58 kWh/(m²·year)) and a 0.43 % decrease in thermal discomfort. To improve the FO we adjusted the floor-to-ceiling height (4 cm increase) and the areas of windows 3 and 4. Table 6 presents the original and optimized window dimensions. We increased the areas of windows 3 and 4 to minimize thermal discomfort.

Table 6 – Case 3 – Original and optimized window dimensions - Brasília

Windows	Original Height (m)	Original Area (m²)	Optimized Height (m)	Optimized Area (m²)
Window 1	2.10	1.68	2.10	1.68
Window 2	2.10	1.68	2.10	1.68
Window 3	2.10	2.16	2.57	3.01
Window 4	2.10	0.48	2.19	0.51
Window 5	2.10	0.48	2.10	0.48

Source: Authors

According to Table 5, the objective function composition presented only a 0.07% gain in relation to the base case. In short, small adjustments were made to reward thermal comfort in detriment of increasing energy consumption.

Choosing the best solution depends on a cost analysis and on the designer's priority of choosing the solution with the lowest consumption or least discomfort.

The following analyses focus on comparing different results obtained for three cities located in very different climatic zones: Brasília, Caxias do Sul and Picos.

Table 7 presents consumption and discomfort values for the three cities considering all possible optimization variables. The floor-to-ceiling height values obtained were:

- Brasília: 3.0 m
- Caxias do Sul: 2.6 m
- Picos: 2.6 m.

Table 7 - Cases 3, 4 and 5 - Performance for Brasília, Picos and Caxias do Sul with adjustment to wall, roof and floor thicknesses, absorptances, orientation, floor-to-ceiling height and window height.

Case	OF	Consump. (kWh/(m² year))	Disc. (%)	TTP (W/m² K)	e_{cer} (m)	TTC (W/m² K)	e_{EPS} (m)	e_{conc} (m)	AP	AC	Or. (°)
Bras.	1.3454	1009.58	53.77	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	0
Cax.	1.3462	2639.00	66.95	1.3072	0.40	0.2416	0.150	0.25	0.9	0.9	0
Picos	1.4255	3762.00	55.06	1.3072	0.40	1.3089	0.015	0.25	0.2	0.2	180

Source: Authors

Table 8 presents the optimized window dimensions for housing in the cities of Brasília, Caxias do Sul and Picos, considering all possible optimization variables.

Table 8 - Cases 3, 4 e 5 – Window dimensions considering all optimization variables – Brasília, Caxias do Sul and Picos

Windows	Height (m)			Area (m²)		
	Brasília	Caxias	Picos	Brasília	Caxias	Picos
Window 1	2.10	2.10	2.10	1.68	1.68	1.68
Window 2	2.10	2.10	2.45	1.68	1.68	2.17
Window 3	2.57	2.10	2.45	3.01	2.16	2.79
Window 4	2.19	2.10	2.10	0.51	0.48	0.48
Window 5	2.10	2.10	2.10	0.48	0.48	0.48

Source: Authors

According to Table 8, the city of Picos, located in the bioclimatic zone ZB7, presents the worst consumption condition, and thus requires lower values of absorptance (0.2), coverage thickness and areas of windows 4 and 5 (Table 7).

When simulating the optimization problem with different combinations of optimization criteria, it was verified that if only the electrical consumption is optimized, very high levels of thermal comfort are obtained, or if only the thermal comfort is optimized, values very high electrical consumption. Thus, the combination of consumption and discomfort sought to equalize the benefits of both energy efficiency criteria.

As the results obtained, it was verified that as new adjustments are increased (such as floor-to-ceiling height and window dimensions) the final performance of the project increases, materialized by the value of the objective function (FO), gradually providing lower consumption or minor discomfort from simple design decisions.

When evaluating the impact of the efficiency level for different bioclimatic zones, the results can be validated, because for more extreme climatic conditions (Picos), the developed computational tool opted for smaller dimensions of roof thickness; lower values of solar absorbance (0.2), lower values of floor-to-ceiling height (2.6 m) and smaller window dimensions, as expected.

5. CONCLUSION

This paper formulated an optimization problem capable of adjusting physical parameters for social housing. Reduction of energy consumption and thermal discomfort, our evaluation criteria, were treated as a global criterion problem allowing us to present a single solution that offered the best compromise between the two optimization criteria.

Cardinal position, thickness of materials that make up external walls, roof and floor, external walls, and roof absorptance, floor-to-ceiling height, and window size were used as optimization variables.

Unlike other studies, we decided to directly adjust the thickness of the materials instead of optimizing their thermal transmittances (as in LEITZKE et al., 2021) to obtain feasible thickness values, the physical limits of which were calculated to satisfy the thermal transmittance limits per climatic zone (Tables 3 and 4). Floor-to-ceiling height and window size optimization was included as another instrument to increase the project’s energy efficiency.

Energy efficiency was evaluated using the Energy Plus software, of widespread use in this type of analysis. The Python programming language was chosen due to the EPPY application (both open free), which allows data communication between Python and Energy Plus.

Since our main interest was formulating the optimization problem and not solving it, we chose the Genetic Algorithm (GA) as a solution technique simply because it is the most cited in the literature, but another technique such as Differential Evolution could have been used with similar results.

Our results show that the computational tool developed can help to universalize the use of simple energy efficiency techniques systemically (be applied to any type of housing) and automatically (without failures in obtaining solutions performed manually), providing a feasible optimal solution (in addition to the Pareto-Optimal solutions, also included at the end of the last generation) and facilitating decision-making in the early stages of a building project to increase its energy efficiency and thus environmental sustainability.

BIBLIOGRAPHIC REFERENCES

ASSOCIAÇÃO BRASILEIRA DE NORMAS TÉCNICAS. NBR 15220: Desempenho térmico de edificações. Rio de Janeiro, 2005.

EMPRESA DE PESQUISA ENERGÉTICA (EPE). AÇÕES PARA PROMOÇÃO DA EFICIÊNCIA ENERGÉTICA NAS EDIFICAÇÕES BRASILEIRAS: NO CAMINHO DA TRANSIÇÃO ENERGÉTICA. Nota Técnica, 2020.

BAVARESCO, M. V.; CUCHIVAGHE, H. Y. O.; SCHINAZI, A.; GHISI, E. Aspectos impactantes no desempenho energético de habitações de interesse social brasileiras: revisão de literatura. Ambiente Construído, v. 21, n. 1, 2021, p. 263-292. doi.org/10.1590/s1678-86212021000100505.

BRE, F.; FACHINOTTI, V. D. A. Computational multi-objective optimization method to improve energy efficiency and thermal comfort in dwellings. Energy and Buildings, v. 154, 2017, p. 283-294. doi.org/10.1016/j.enbuild.2017.08.002.

COELLO, C.A.C. An updated survey of GA-based multiobjective optimization techniques. ACM Computing Surveys, Vol 32, no 2, 2000, p. 109-143. doi.org/10.1145/358923.358929.

DELGRAM, N.; SAJADI, B.; DELGRAM, S. Multi-objective optimization of building energy performance and indoor thermal comfort: A new method using artificial bee colony (ABC). Energy and Buildings, v. 131, 2016, p. 42-53. doi:10.1016/j.enbuild.2016.09.003.

DIDONÈ, E. L.; PEREIRA, F. O. R. Simulação computacional integrada para a consideração da luz natural na avaliação do desempenho energético de edificações, Ambient. constr. 10 (4), 2010. doi.org/10.1590/S1678-86212010000400010.

ENERGYPLUS, Available in: https://energyplus.net/downloads.

FERDYN-GRYGIEREK, J.; GRYGIUREK, K. Optimization of window size design for detached house using TRNSYS simulations and Genetic Algorithm. Architecture, Civil Engineering, Environment, vol.10, no.4, 2017, p. 133-140. doi.org/10.21307/acee-2017-057.

GRYGIUREK, K.; FERDYN-GRYGIEREK, J. Multi-variable optimization models for building envelope design EnergyPlus simulation and metaheuristic algorithms. Architecture Civil Engineering Environment, no. 2/2019. doi:10.21307/ACEE-2019-0.

KAPSALAKI, M.; LEAL, V.; SANTAMOURIS, M. A methodology for economic efficient design of Net Zero Energy Buildings. Energy and Buildings Volume 55, 2012, p. 765-778, https://doi.org/10.1016/j.enbuild.2012.10.022.

LEITZKE, R. K.; CUNHA, E. G.; MACIELI, T. S.; DEMBINSKI, F. M. D.; PRESTES, I. B. Algoritmo para análise evolutiva multiobjetivo em simulações termo energéticas. Gestão e Tecnologia de Projetos, São Carlos, v.16, n.1, 2021, p.24-42. doi.org/10.116/gtp.v16i1.164048.

LEITZE, R. K.; CUNHA, E. G.; SCHRAMM, F. K.; CORREA, C. M. B.; FERRUGEM, A. P. Idfmodifier: Aplicação para parametrização das propriedades de configuração do EnergyPlus, XVII Encontro Nacional de Tecnologia do Ambiente Construído, Por Alegre, 4 a 6 de novembro de 2020.

NGUYENA, A.T.; REITERA, S.; RIGOB, P. A review on simulation-based optimization methods applied to building performance analysis. Applied Energy 113, 2014, p. 1043–1058. https://doi.org/10.1016/j.apenergy.2013.08.061.

OLIVEIRA, L. S. Avaliação dos limites das propriedades térmicas dos fechamentos opacos da NBR 15220-3, para habitações de interesse social, da Zona Bioclimática 2.168f. Dissertação (Mestrado em Arquitetura) – Faculdade de Arquitetura e Urbanismo, Universidade Federal de Pelotas. 2012.

PHILIP, S.; TANJUATCO, L. Eppy: scripting language for E+. EnergyPlus (version 0.46). Available in: https://pypi.org/project/eppy/, v.0.5.63.

RABELO, P. G.; OCHI, L. S. Um Novo Algoritmo Genético Híbrido para o Problema do Caixeiro Viajante com Grupamento. Anais do Simpósio Brasileiro de Redes Neurais, Vol. 1, 1996, p. 83–90.

SOUZA, J. Energy simulation software for buildings: review and comparison. Engineering, Computer Science, Porto, Portugal, 2012.

YUAN, X.; KARBASFOROUUSAHHA; M. A., SYAH, R. B. Y.; KHAJEHZADEH, M.; KEAWSAWASVONG, S.;MONCEF, L. N. An Effective Metaheuristic Approach for Building Energy Optimization Problems Buildings, 2023, 13(1), 80; doi.org/10.3390/buildings13010080.