UNIVERSIDADE ESTADUAL DE CAMPINAS
Faculdade de Engenharia Civil, Arquitetura e Urbanismo

FELIPE DA SILVA DUARTE LOPES

USO DE ALGORITMOS GENÉTICOS PARA OTIMIZAÇÃO DO DESEMPENHO TERMOENERGÉTICO EM EDIFICAÇÕES NAS ETAPAS INICIAIS DE PROJETO

USE OF GENETIC ALGORITHMS FOR OPTIMIZATION OF THERMAL ENERGY PERFORMANCE IN BUILDINGS IN EARLY STAGE DESIGN

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Orientadora: Profa. Dra. Lucila Chebel Labaki

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À minha querida vovó Socorro, seu amor incondicional invade minha alma de alegria e gratidão...

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Resumo

A demanda de energia em edificações vem aumentando consideravelmente nos últimos anos, e no Brasil os edifícios já são responsáveis pela metade do consumo total de eletricidade no país. Em relação ao meio ambiente, regulamentos energéticos em edifícios têm sido desenvolvidos para reduzir o impacto nas mudanças climáticas. Como estas normativas requerem a quantificação do consumo energético, ferramentas de simulação podem ajudar arquitetos na tomada de decisão nas fases iniciais de projeto de edifícios de alto desempenho, visando a melhoria dos aspectos ambientais, energéticos e econômicos. Existem diversas variáveis a serem consideradas no projeto arquitetônico, e nesse contexto, métodos de otimização podem gerar muitas alternativas para solucionar um problema, obtendo-se as soluções mais adequadas a partir de critérios conflitantes, como custos do consumo energético durante o ciclo de vida da edificação e horas de desconforto térmico. Os algoritmos genéticos, por exemplo, são métodos de otimização baseado na seleção natural dos organismos vivos que otimiza funções de avaliação a partir de operadores de diversidade. Esta pesquisa teve como objetivo avaliar a aplicação de um método com algoritmos genéticos para encontrar soluções ótimas nas etapas iniciais de projeto a partir de critérios de eficiência energética, custo do ciclo de vida e conforto térmico. O trabalho tem como intenção a proposição de um procedimento de otimização para sugerir uma melhoria do atual Regulamento Técnico da Qualidade para o Nível de Eficiência Energética de Edificações Comerciais, de Serviços e Públicas (RTQ-C). A metodologia da tese se baseia em uma pesquisa exploratória aplicada a estudos de casos. Foi realizada uma revisão sistemática da literatura sobre algoritmos genéticos em estudos de eficiência e conforto, dando suporte aos estudos de simulação de desempenho com o software EnergyPlus. O estudo de validação aplicou um algoritmo genético multiobjetivo para um edifício de escritórios de médio porte na cidade de São Paulo, utilizando estratégias passivas para minimizar o custo inicial da construção e o custo energético no ciclo de vida. 213 casos foram simulados e foi observada uma redução de custo da construção de 6,7% e do custo energético em 5,8% quando comparadas com os resultados do caso base. No segundo caso, o procedimento de otimização acoplou o método non-dominated and crowding distance sorting genetic algorithm (NSGA-II) com o EnergyPlus para reduzir o custo do ciclo de vida e horas de desconforto térmico em outra edificação de escritórios para três cidades em diferentes regiões bioclimáticas brasileiras. As variáveis de projeto foram divididas em geometria, envelope e sistema de ar-condicionado, e a otimização foi realizada no programa jEPlus+EA. Os resultados demonstraram um potencial de redução de 11% no custo do ciclo de vida e de até 37% nas horas de desconforto. Os resultados do trabalho sugerem que o uso dos algoritmos genéticos tem grande potencial em contribuir com as normativas de eficiência energéticas brasileiras, gerando projetos arquitetônicos mais econômicos, energeticamente eficientes e com alta qualidade ambiental em diferentes regiões bioclimáticas do país.

Palavras-chave: Simulação de desempenho de edificações; Algoritmos genéticos; Eficiência energética; Conforto térmico; Etapas iniciais de projeto.

Abstract

Energy demand in buildings has increased considerably in recent years, and Brazilian buildings already account for half of the country's total electricity consumption. Concerning the environment, building energy regulations have been developed to reduce the impact on climate change. As these standards require quantifying energy use, simulation tools can assist architects in decision-making in the early design stages of high-performance buildings to improve environmental, energy and economic aspects. There are several variables to consider in architectural design, and in this context, optimization methods can generate many alternatives to solve a problem, obtaining the most appropriate solutions based on conflicting criteria, such as energy consumption cost during the building's life-cycle and thermal discomfort hours. Genetic algorithms, for example, are optimization methods based on the natural selection of living organisms that optimize evaluation functions from diversity operators. This research aimed to evaluate the application of a method with genetic algorithms to find optimal solutions in the early design stages based on energy efficiency, life cycle cost and thermal comfort criteria. The work intends to propose an optimization procedure as an improvement of the current Regulation for Energy Efficiency Labeling of Commercial, Services and Public Buildings (RTQ-C). The thesis methodology is based on an exploratory research applied to case studies. A systematic literature review was developed on genetic algorithms in efficiency and comfort studies, supporting building performance simulation studies with EnergyPlus software. The validation study applied a multi-objective genetic algorithm for a medium-size office building in the city of São Paulo, using passive strategies to minimize the initial construction cost and the life cycle energy cost. 213 cases were simulated and a reduction of 6.7% in construction cost and 5.8% in energy cost were observed when compared to the results of the base case. In the second case, the optimization procedure coupled a non-dominated and crowding distance sorting genetic algorithm (NSGA-II) method with EnergyPlus to reduce the life cycle cost and hours of thermal discomfort in another office building for three cities in different Brazilian bioclimatic regions. The design variables were divided into geometry, envelope and air conditioning system and the optimization was run in jEPlus+EA engine. The results demonstrated a potential reduction of 11% in life cycle cost and up to 37% in discomfort hours. The results of the work suggest that the use of genetic algorithms has great potential to contribute to the Brazilian energy efficiency standards, generating more economical, energy efficient and high environmental quality architectural projects in different bioclimatic regions of the country.

Keywords: Building performance simulation; Genetic algorithms; Energy efficiency; Thermal comfort; Early stage design.

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List of Abbreviations

ABNT	Associação Brasileira de Normas Técnicas
AG	Algoritmos Genéticos
ANN	Artificial Neural Network
ASHRAE	American Society of Heating Refrigerating and Air-Conditioning Engineers
BESO	Building Energy Simulation and Optimization
BESTEST	Building Energy Simulation Test
BPS	Building Performance Simulation
CAPES	Coordenação de Aperfeiçoamento de Pessoal de Nível Superior
CDD	Cooling Degree Days
COP	Coefficient of Performance
DH	Discomfort Hours
DOE	Department of Energy
GA	Genetic Algorithms
GUI	Graphical User Interface
HDD	Heating Degree Days
HVAC	Heating, Ventilation and Air-conditioning
INMET	Instituto Nacional de Meteorologia
INMETRO	Instituto Nacional de Metrologia, Qualidade e Tecnologia
LCA	Life-Cycle Analysis
LCC	Life-Cycle Cost
LCE	Life-Cycle Energy
LCEI	Life-Cycle Environmental Impact
MOGA	Multi-objective Genetic Algorithm
NREL	National Renewable Energy Laboratory
NSGA-II	Non-dominated and crowding distance sorting genetic algorithm
NZEB	Net Zero Energy Building
PBE	Programa Brasileiro de Etiquetagem

PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
PROCEL	Programa Nacional de Conservação de Energia Elétrica
PV	Present Value
RTQ-C	Requisitos Técnicos da Qualidade para o Nível de Eficiência Energética de Edifícios Comerciais, de Serviços e Públicos
RTQ-R	Requisitos Técnicos da Qualidade para o Nível de Eficiência Energética de Edifícios Residenciais
SHGC	Solar Heat Gain Coefficient
SRL	Systematic Review of the Literature
WWR	Window-to-Wall Ratio

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Chapter 1

Introduction

Since the energy crisis of the 1970s, there has been an increasing concern with sustainability and building performance, as a way to protect the environmental heritage and guarantee the quality of life for future generations [1,2]. The increase in energy consumption in buildings over the last decades (Figure 1.1) demonstrates the importance of the architectural process combined with thermal-energy performance analysis of spaces, aiming to minimize the associated environmental impacts [3].

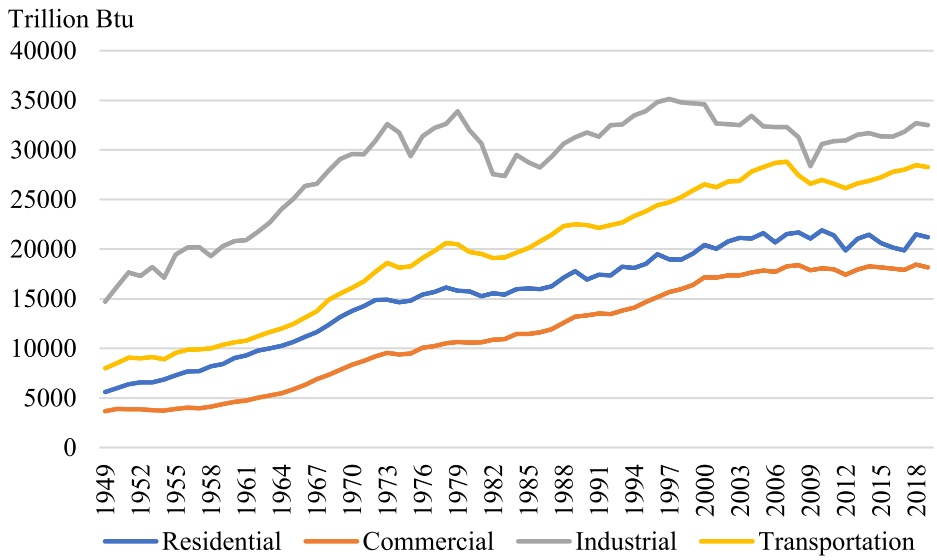

Figure 1.1: Total consumption by end-use sector

(Source: EIA [4]*)*

In Brazil, for example, buildings are responsible for 50.5% of the country's electricity consumption (Figure 1.2), and 33% of this percentage comes from commercial buildings [5]. This high demand was one of the main factors for the development of environmental certification programs and energy efficiency labels [6,7]. Programs such as LEED, BREEAM and AQUA (HQE), and the Brazilian PROCEL Edifica have been used to improve the energy performance and environmental quality of [7–9]. Despite this, many office buildings in Brazil do not have design considerations compatible with local climatic characteristics.

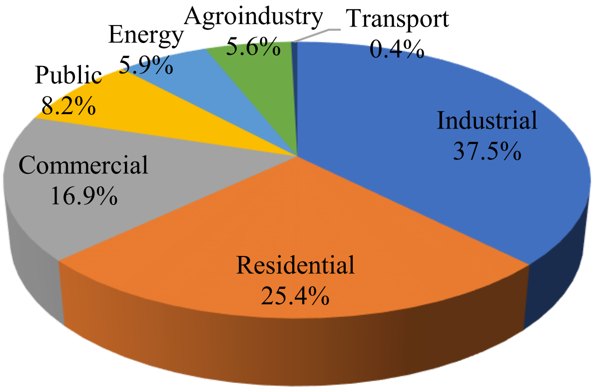

Figure 1.2: Brazilian electricity consumption share by sector

(Source: Brazil [5]*)*

The use of control variables and strategies is not always verified and many architectural projects do not follow the suggested bioclimatic principles [10], where the use of "imported" models from cold-climate countries, such as large glazed facades, is common. This practice results in increased heat gains from solar radiation, consequently increasing the energy demand for artificial air conditioning systems [11,12]. Thus, environmental conditioning measures must be established to ensure comfort and reduce buildings' energy demand. As a way of quantifying this performance, computer simulation tools present better results in terms of environmental comfort, lighting and energy consumption, especially in early stage building design [13,14].

Computer simulation is a powerful analysis tool, used in different areas, from games, economic development, to architectural design. However, it is important to note that any simulation is an approximate representation of reality, which does not solve problems or provide answers, and it is sometimes difficult to guarantee the quality of the simulated results [15]. Still, predicting and analyzing the future behavior of buildings is more efficient and economical than solving problems in construction already in use.

The simulation process involves several disciplines such as physics, mathematics, material, environmental and behavioral sciences for building performance analysis [15]. From the various software available for building thermal-energy simulation, EnergyPlus (EP) is the most widespread because its gratuity and reliability [16], as it is constantly updated by the United States Department of Energy [17]. For complex commercial buildings, simulation tools consider separate building systems (lighting, equipment, mechanical) and the envelope as coexisting elements. In addition, there is a growing trend towards net zero energy buildings (nZEB), developed with strategies that minimize energy consumption, usually connected to the grid and generating energy through renewable sources [8,18,19].

Based on the complexity of the architectural design development, and on the many variables involved in the decision-making process, alternative design methods have been developed since the 1960s as problem solving processes, like generative systems, capable of creating a wide variety of potential solutions [20]. In this context, computational optimization methods can be used to generate several alternatives for solving a problem, enabling the achievement of a good project.

Among such methods, evolutionary algorithms are mechanisms based on the theory presented by Charles Darwin, where biological evolution has been incorporated into computer science [21], with a basic cycle with different presentations' model or specific combinations of variation, mutation, selection, and replacement methods (Figure 1.3). The genetic algorithms (GA) [22] implemented Darwin's evolutionary theory mechanisms into computer simulations [23]. It is a heuristic search that modifies values in a coded function by applying pre-defined recombination operators in a stochastic manner [24].

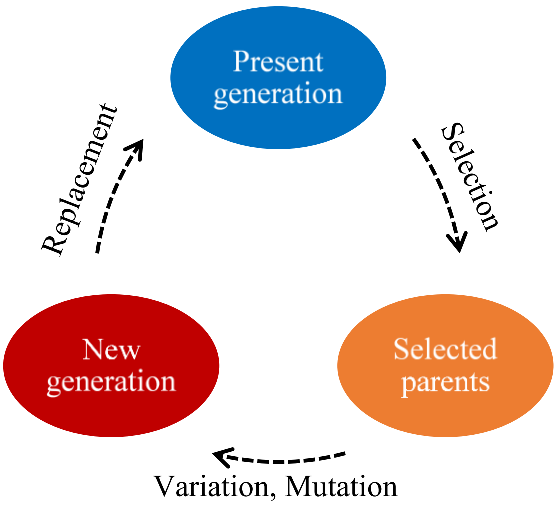

Figure 1.3: Basic cycle of evolutionary algorithms

(Adapted from Dianati et al. [21]*)*

In the architectural environment, designers usually are not familiar with programming languages or optimization methods concepts, and the use of such tools can bring more problems than solutions. On the other hand, more friendly computational resources and interfaces have allowed the application of optimization methods in the design process in the last few years. Since national policies and environmental certification programs require energy efficiency strategies, developing effective procedures in high performance commercial building design becomes increasingly necessary.

From the uncertainties of traditional design methods in performance evaluation, optimization methods can generate optimal solutions with relative simplicity in thermal-energy simulation of commercial buildings [25]. Genetic algorithms analyze significant data simultaneously, reducing results computation time [26]. Thus, the development of optimization processes through GA is a viable solution to assist in decision making in early stage design.

In commercial buildings design, there are optimal solutions for conflicting objectives, such as thermal energy performance and cost analysis, which present both technical and economic viability to be applied in early stage design. So, applying an optimization method with genetic algorithms in the Brazilian national energy efficiency regulation context allows obtaining optimum design solutions from a multicriteria assessment, with conflicting objectives, like energy efficiency, cost analysis and thermal performance.

From the previously exposed, this research aimed at evaluating the application of a method with genetic algorithms to find optimal solutions in the early design stages of commercial buildings based on energy efficiency, life-cycle cost, and thermal comfort criteria. To better develop the work, some specific objectives were established.

- Analyze bioclimatic strategies to be applied in artificially conditioned office building models, aiming at minimizing energy consumption, initial constructions costs and thermal comfort parameters.

- Establish a comparison between the simulated results with genetic algorithms and the application of the Brazilian energy efficiency regulation (RTQ-C).

- Propose an optimization procedure with a specific genetic algorithm method through a computer tool suited for architects for different Brazilian bioclimatic regions.

This thesis is divided into seven main chapters, as further described in Chapter 2. Following the University of Campinas regulation, the main chapters have a journal paper structure, for a better understanding of the content. The chapters were or will be submitted to peer-reviewed, recognized papers for dissemination of the knowledge developed in this research to the academic community.

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Chapter 2

Material and methods

This chapter presents the work structure and methodology. The thesis is based on an exploratory research applied to case studies. A literature review supports the research and conducts the application studies mainstream. Table 2.1 shows the thesis structure, which is divided into three main stages.

Table 2.1: Thesis structure

INTRODUCTION AND OBJECTIVES	
STAGE I Literature Review	**CHAPTER 3** Genetic algorithms in building design optimization for energy efficiency and thermal comfort: a review
STAGE II Validation Study	**CHAPTER 4** Optimization of an energy efficient office building in subtropical Brazil
STAGE III Optimization Procedure	**CHAPTER 5** Multi-objective optimization using NSGA-II to minimize life-cycle cost and thermal discomfort in early stage building design
DISCUSSION, CONCLUSION AND REFERENCES	

The introduction contemplated the general context of the research theme, presenting the work problem and motivations which have led for the doctorate development. After the introduction and objectives, the first stage corresponds to the literature review, where Chapter 3 presents a Systematic Review of the Literature was conducted on relevant studies on genetic algorithms for energy efficiency and thermal comfort research. In this chapter the main definition and characteristics of genetic algorithms is discussed. A Systematic Mapping Study is applied by defining the review questions, selecting adherent studies, collecting data and interpreting results. 115 papers on the theme are further analyzed to identify the timeline of studies, the main themes, which methods are used and what are the main contributions of the studies to the present research.

The second stage is the validation study, where a genetic algorithm method is applied 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. In Chapter 4, EnergyPlus simulation software is coupled with the jEPlus+EA interface to run the optimization. Over 200 cases were simulated with five design variables and the results were presented through a Pareto optimum front.

The third stage comprises Chapter 5, which presents a case study of a multi-objective genetic algorithm (MOGA) to achieve optimal design alternatives for an office building in three Brazilian climatic regions, aiming to minimize two conflicting objective functions: the life-cycle cost, and indoor thermal discomfort hours, as a contribution to the current energy efficiency regulation. The variables defined in the procedure were divided into three categories, i.e. building design, building envelope and HVAC system. The solutions were compared with RTQ-C regulation and indicated the potential for higher energy efficiency and thermal comfort in different climatic regions of the country.

In Chapter 6 the content of all previous chapter is discussed, with a summary of the optimization procedure proposed in the research. Chapter 7 brings the conclusion of this doctorate research, with the study limitations and suggestions for future work. The references are presented separately in each chapter to facilitate the reader’s understanding of the work.

Chapter 3

Genetic algorithms in building design optimization for energy efficiency and thermal comfort: a review

3.1 Introduction

The world population growth in the past century has led to a rapid expansion of residential and commercial buildings on urban areas. Buildings already account for over 40% of the world's total energy consumption, mainly from fossil fuels sources [1]. This large consumption has impacted on higher levels of pollution, greenhouse gas emissions and climate change, which ultimately raised concern on environmental aspects and development of energy regulations and certifications [2,3].

As these regulations move towards high-performance buildings and require better understanding energy use, computational simulation has been widely used to help designers and other construction sector professionals make decisions [4]. For complex buildings simulations are further encouraged, for considering separate systems (mechanical, lighting, equipment) and the building's envelope as co-existing parts [5]. As space design solutions can lead to conflicting objectives, optimization computational methods have many advantages in zero energy buildings (ZEB), usually designed with strategies to minimize energy consumption and adopting renewable energy sources [6,7].

One of the most popular optimization method for building energy analysis is the genetic algorithm (GA), a procedure that uses an analogy of the biological evolution of living organisms [8,9]. GA was presented by John Holland's 'Adaptation in Natural and Artificial Systems' [10]. It is an heuristic search that modifies function values through predefined reproduction operators in a stochastic manner [11].

Genetic algorithms have been extensively applied in engineering problems, as discussed in the next section. However, when it comes to architectural design, there are some obstacles in using optimization methods, as usually architects are not familiar with complex algorithms or simulation programs. After the Second World War, technological, economic, and social transformations impacted the way processes and activities were being developed, including architecture. The Design Methods movement made clear that the design process did not let evident the adopted procedures in problems' solutions [12].

The architectural design process can basically be compared with two procedures (Figure 3.1). In the black box, the process internal structure is unknown, only the inputs and outputs are known. In the glass box, the thought is clearly presented, and the objectives, variables and criteria are previously defined, following a logic structure [13]. These approaches involve multiple agents, with possible conflicting values. Thus, alternative design methods were developed since the 1960's as a problem-based process, like the generative systems, capable of creating a wide variety of potential solutions [14].

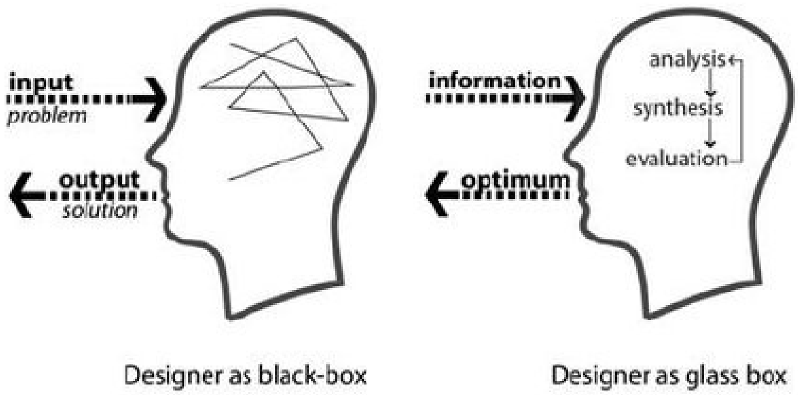

Figure 3.1: Main conceptual models of design
(Adapted from Jones [13], pp. 46–56)

Since then, the use of evolutionary algorithms, like GA have been employed to solve wicked problems (those of difficult solutions, without a well-defined formulation and that allow more than one possible explanation). Although GA was originally created to study the adaptation phenomenon occurring in nature, Holland [10] presented a theoretical scenario to simulate the natural adaptation mechanisms through computational implementation.

The main elements of the evolutionary theory used for GA were reproduction with genetic heritage, random variation in a population of individuals and natural selection to compose future generations. The main components of GA proposed by Holland were individuals, populations, fitness function, selection mechanisms, diversity operators (mutation and recombination) and the number of generations [15], as illustrated in Figure 3.2.

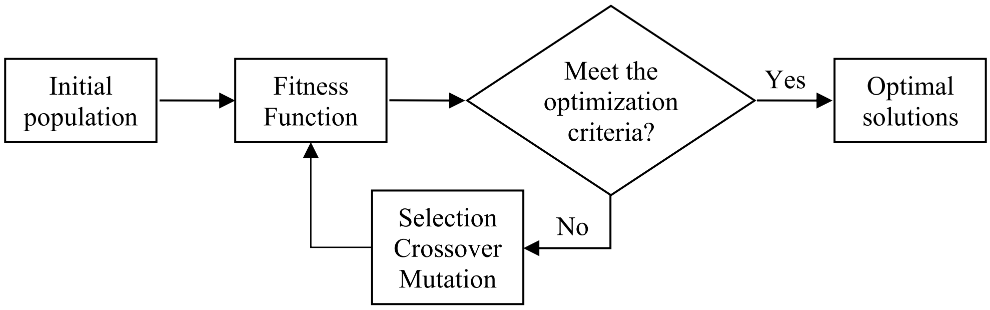

Figure 3.2: Genetic algorithm optimization procedure

In building design, each component is associated with the features of an architectural or engineering project. The individuals and populations they compose are represented by the cases or building models to be analyzed. The fitness functions correspond to the multi-criteria objectives through which the optimization procedure is submitted, such as reducing energy consumption and thermal discomfort values in a determined simulation problem. The selection mechanisms and diversity operators are then configured to perform changes and recombination between the building design variables and their constraints, in order to generate a new population. Finally, the number of generations can be fixed or set to end when there is no statistical possibilities of a more suitable set of individuals for that specific problem [11].

The possible solutions in a multi-criteria optimization such as genetic algorithms are often presented as a set of Pareto optimal solutions [16]. These solutions form a front in the objective space called as Pareto front [17]. In a case of two objective functions the Pareto front is a curve in a two-dimensional space, as shown in Figure 3.3. Every point on the Pareto front is a non-dominated solution, i.e., you cannot improve one objective without hampering the other.

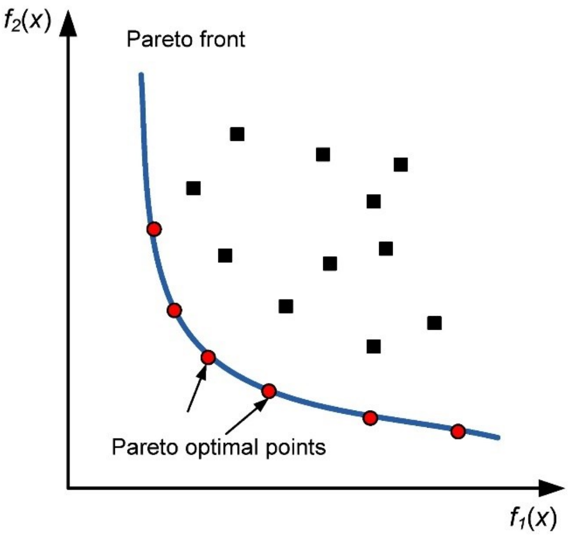

Figure 3.3: Example of a Pareto front for a problem with two objective functions

(Adapted from Huang et al. [17])

In an optimization problem, with multiple variables and objective functions, there may be infinite solutions and innumerous Pareto optimal solutions. In recent years, a diverse number of GA methods have been applied in engineering problems, with the most popular being the multi-objective genetic algorithm (MOGA) and the non-dominated sorted genetic algorithm (NSGA-II) [17]. This last one will be further explained in the case studies chapters.

In this context, the objective of this chapter is to present a brief review of genetic algorithms and their application in building design optimization for energy efficiency and thermal comfort criteria. The study builds on existing literature from the past decade to present numerical findings and determine if significant trends could be mapped to assist architects and engineers in optimizing design practices towards sustainable development.

3.2 Previous reviews

In recent years, many studies have used genetic algorithms in engineering problems with different optimization platforms and simulation programs, as supported by several literature reviews. Evins [4] covered 74 works that focused on the application of computational optimization in sustainable building design problems. The author analyzed papers related to heuristic optimization methods, i.e., direct search, evolutionary algorithms, and other bio-inspired algorithms. From this review, a clear trend was presented: genetic algorithm was the most common optimization method, used in more than half of the works. In 60% of the cases, energy use was the main objective and 40% of the papers dealt with the building envelope.

Nguyen, Reiter and Rigo [8] conducted a review study focusing on the three major phases of simulation-based optimization, i.e., preprocessing, running optimization and post-processing stages. The authors also presented an overview of twenty optimization programs applied to building performance simulation and like the previous review, they found out that genetic algorithm is the most common method applied to BPS. Although about 60% of the analyzed studies used a single-objective approach, the authors stated that "…in real-world building design problems designers often have to deal with conflict design criteria simultaneously, such as minimum energy consumption vs maximum thermal comfort, minimum energy consumption vs minimum construction cost, etc.".

Among these review studies, only a few deals with building design optimization from a perspective of architects. Shi et al. [18] is an example of this type of work. The authors analyzed 116 papers on energy efficient design optimization with an emphasis on the architectural practice. This study contributed greatly to the present research as architects often find it difficult to use building energy efficient design optimization technique, as this professional is usually not trained with optimization algorithms and complex programs. However, several efforts have been made to address this issue. Several friendly graphical user interface (GUI) programs – like GenOpt [19] and jEPlus+EA [20] – have been developed to help designers and architects using optimization methods in the design practice, especially regarding the building envelope, with energy consumption and environmental comfort criteria [18].

Cui et al. [21] presented a review on multi-objective optimization problems, focusing on energy saving and pollutants emissions reduction. The authors discussed some difficulties to be solved, like the challenge to generate a set of well converged, uniformly distributed, and diverse non-dominated optimal solutions. Also, they stated that “in real-time application where the action should be taken dynamically within seconds, the considerable computational time is a disadvantage”. They concluded that an appropriate optimization algorithm trades-off method for optimizing simultaneously costs, energy efficiency, environmental emissions, technical and social effects of a building design.

Finally Tian et al. [22] conducted a survey and a review on optimization for passive building design in early stages. The authors discussed that long calculation time, lack of adequate advertisement, and lack of a standard method or procedure are the top three potential hindrances of building energy simulation and optimization (BESO). This study classified the main BESO procedures, their application to building form design, opaque envelopes, fenestrations, shadings, natural ventilation, and thermal mass materials, and discussed if standard BESO procedures satisfy the needs of designers. All these review studies served as a basis for this research to better understand how multi-objective optimization can help architects in achieving feasible design solution when several variables need to be considered in solving energy efficiency and thermal comfort criteria.

3.3 Methodology: Systematic Review of the Literature

A Systematic Review of the Literature (SRL) is a high-level summary of existing evidence focused on answering a precise question. It must pose a clearly formulated question and use a systematic and explicit method to identify, select, and critically appraise relevant research [23]. The use of a pre-defined protocol to identify relevant literature reduces author bias and allows identifying and discussing of best evidence, contradictions and gaps in the literature [24]. According to the Cochrane Handbook [23], a clearly defined, focused review is divided into these main steps: defining the review question, searching and selecting studies, collecting and analyzing data, identifying and reporting bias, and presenting and interpreting results. Aiming at elaborating an overview of the exposed theme, the following questions are proposed in this study.

1. What is the timeline of studies with genetic algorithms in energy efficiency and thermal comfort studies?
2. What are the main themes?
3. Which methods are used?
4. What is the main contribution of the studies to this present research?

To answer these questions and based on the narrative background, keywords were selected on the second stage of the SRL. The search began on ScienceDirect and Scopus research databases, with publications from 2005 to 2018 on journal and conference papers. The search string was: “energy consumption” OR “energy demand” AND “thermal comfort” AND “genetic algorithm” AND “optim*”. The search on both databases resulted on a total of 1186 documents. The metadata (title, authors, journal or conference, year of publication and abstract) were stored in an electronic sheet. To identify relevant documents, a series of filters were applied to select adherent papers (Figure 3.4).

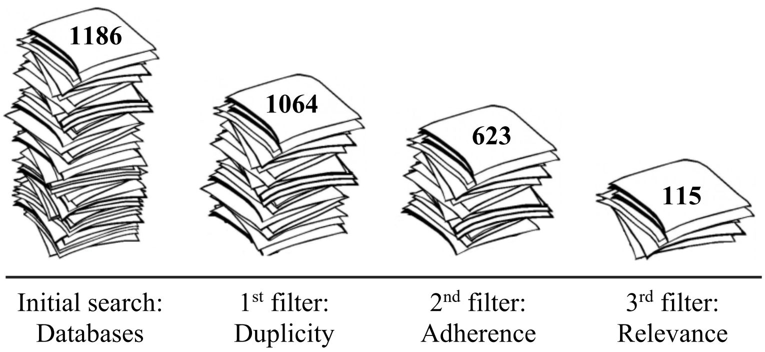

Figure 3.4: Systematic review filters

The first filter removed duplicated documents from both databases, eliminating 122 papers, remaining 1064 papers. The second filter consisted in analyzing the results adherence from reading the documents titles. Titles that clearly did not indicate relation with the research were eliminated. For example, papers exclusively related to building’s mechanical systems did not contribute to this research aim. After the second filter, 623 documents remained. On the third filter, the documents abstracts were analyzed to indicate relevance to the theme, from which 115 papers remained and are presented on this study. The third filter removed documents where the strings "genetic algorithm" or "optimization" were not found either on the title, abstract, highlights or keywords.

3.4 Data analysis

From the Systematic Review, 115 papers were selected after the filters were applied. Even though not all papers are directly discussed in this work, they are kept within the references, as they are part of the review analysis. This section provides the results from the SRL to answer the questions proposed in the methodology.

3.4.1 Year and source of publications

The search period of the review was from 2005 to 2018. Figure 3.5 shows the number of publications by year. A significant increase in studies can be seen starting in 2015 and continuing until the present time. There is a clear trend in the topic of optimization methods in building performance simulations in the last four years. Among the analyzed papers, 95 are journal papers (83%) and 20 are conference papers (17%).

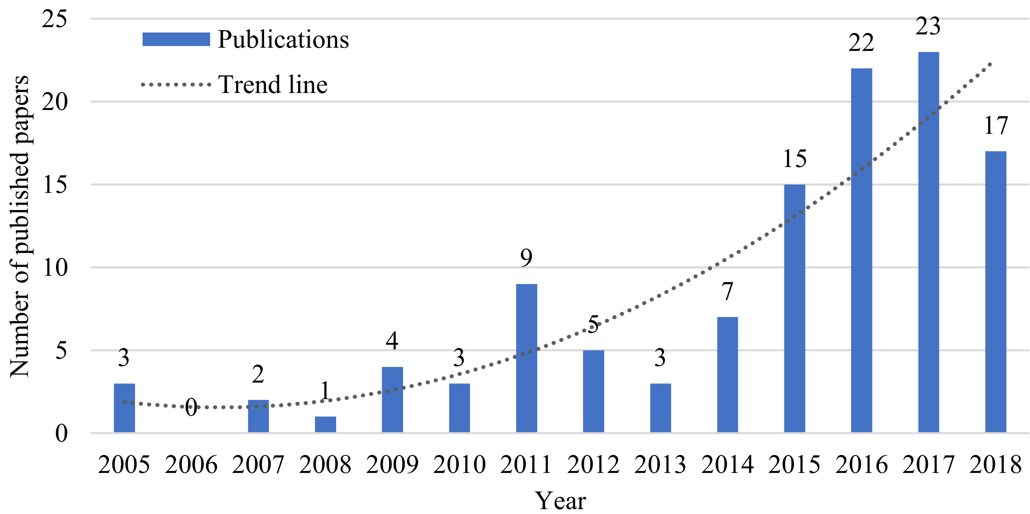

Figure 3.5: Increasing trend of number of publications by year

From the journal papers, that vast majority were published in Energy and Buildings (25), followed by Building and Environment (8) and Applied Energy (6), confirming the journals preferences for optimization studies, as shown in Figure 3.6. In the figure, only journals with two or more studies are presented, as all other journals returned as results only one paper each.

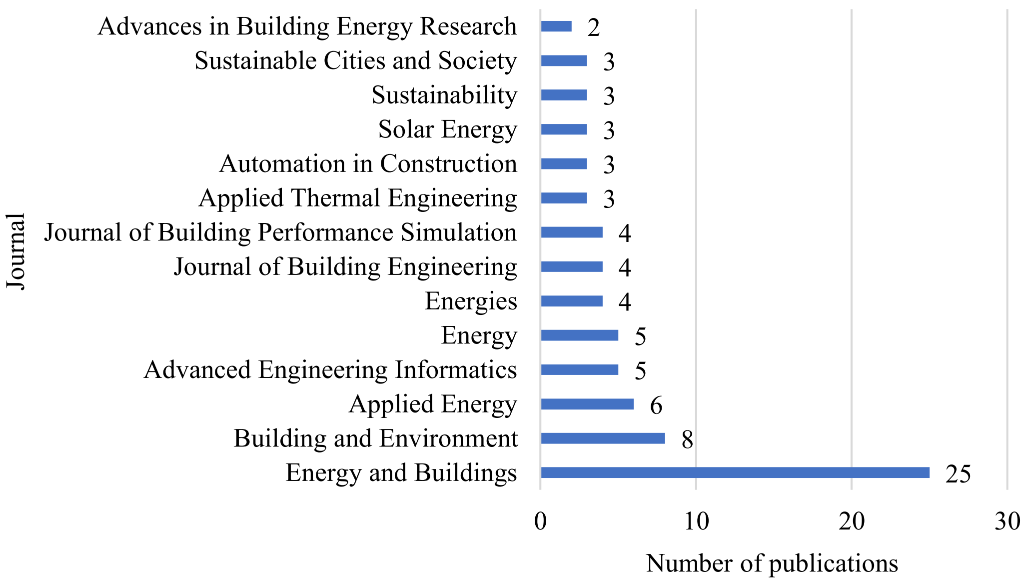

Figure 3.6: Number of publications by journal

3.4.2 *Building types and design*

A graphical overview of the main information of the studies regarding building types and design is presented. Residential and commercial buildings represent most of the case studies (Figure 3.7a). As for category of building design, the envelope and geometry are the most design variables in the optimization procedures (Figure 3.7b). It can be noted that some studies covered more than one category, so the total number of works is not the same in every graph.

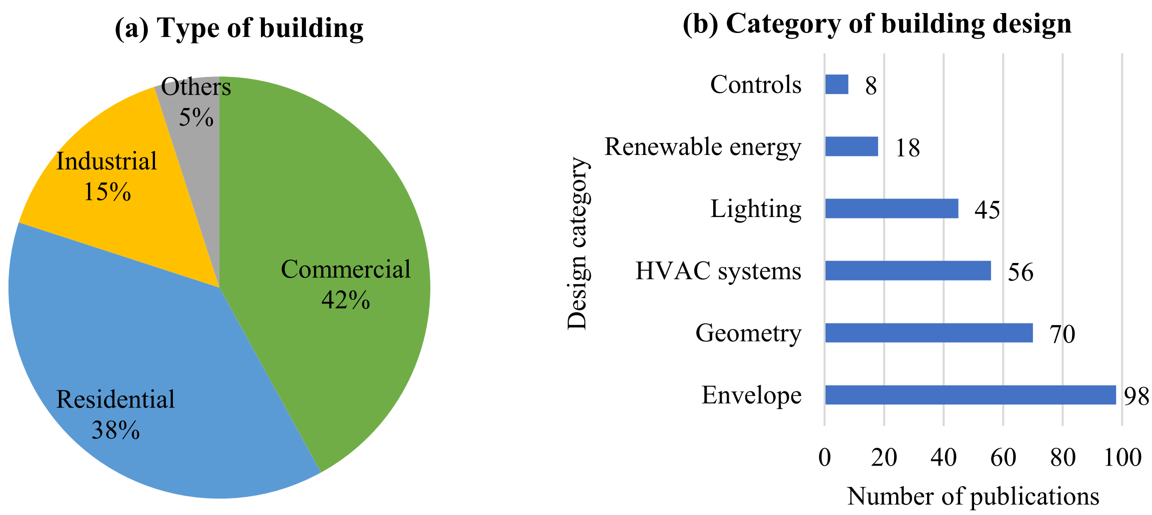

Figure 3.7: Graphical summary of building type and design

3.4.3 Simulation and optimization tools

Figure 3.8a brings the graphical summary of the main used simulation software and optimization tools in the studies. EnergyPlus is the most used simulation tool, mainly because of its diverse capabilities, cost-free, constant updates, tutorials, and online forums available for users. The software was developed by the US Department of Energy and is composed by modules that evaluate a building's performance in thermal, energetical, economic, environmental aspects, among others. For validation of the software, the National Renewable Energy Laboratory (NREL) BESTEST is applied through a normative for discrepancy detection in Building Performance Simulation (BPS) software [25,26].

To run an optimization procedure, BPS tools are coupled with other software. Figure 3.8b shows that MATLAB [27] is the most common programming software used for this purpose. The review also presented some Graphical User Interfaces (GUI) that are more user-friendly for architects, such as GenOpt [19] and jEPlus+EA [20]. jEPlus+EA has a NSGA-II method already defined in its configuration and was developed to couple EnergyPlus simulations directly with this genetic algorithm method.

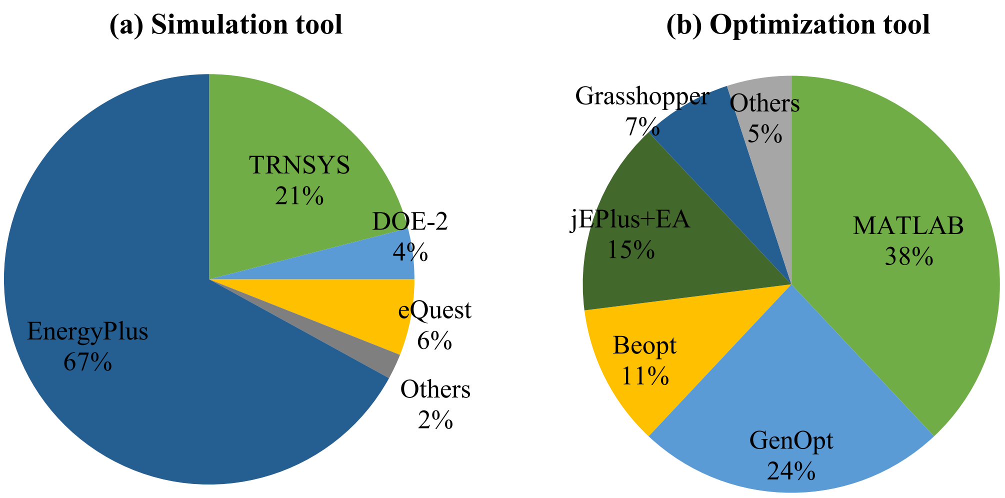

Figure 3.8: Graphical summary of simulation and optimization tools

3.5 Discussion

This section brings a discussion about the results presented. A summary is provided regarding the main themes and methods used. Next, the main contributions of the studies are analyzed. Finally, future research directions are postulated in the conclusions.

3.5.1 Summary of findings

The SRL here presented focused on works related to energy efficiency and thermal comfort criteria. However, other themes appeared in the analyzed papers, so these four major categories served as basis for paper division in this analysis: Energy Efficiency, Thermal Comfort, Life-cycle Assessment, and Lighting. Tables 3.1 through 3.4 bring an overview of each theme with the main features of some of the papers, e.g., the region of study, objectives, application and main results. It must be said that not all 115 papers are cited directly in this work. However, they are kept within the references as they were used in the data analysis section on the text. This section provides the obtained results from papers [28-59].

Table 3.1: Overview of papers characteristics on energy efficiency

Paper	Region	GA objectives	Application and results
[28]	Asia	Energy use Building shape	Relate different building shapes and designs according to their expected energy use in a high-rise office building. The GA moved towards building compactness.
[29]	N. America	Energy use	Optimize the energy consumption of a manufacturing facility regarding building design and production scheduling. GA can be used to improve a facility productivity.
[30]	Asia	Energy use	Design goal of energy saving during the scheme phase. An experimental software is created.
[31]	N. America	Energy use	Apply a GA in building geometry, envelope and occupancy using jEPlus+EA. Energy savings potential from 63 to 76%.
[32]	Europe	Energy use Envelope cost	Use of GA in residential building design. Results were compared to European energy regulation.
[33]	Asia	Cooling energy Lighting electricity	Use of a NSGA-II to explore the effect of architectural parameters on building energy consumption. Optimum cases lead to 23.8–42.2% decrease in the annual consumption.
[34]	Asia	Energy use	Comparison of different optimization methods for building energy efficient design optimization. The algorithm efficiency depends on the facing problem.
[35]	Europe	Energy use	Optimize the design of the mix of renewable energy systems for the integration of building energy demand. Thermal solar systems, photovoltaic panels and efficient heat pumps are investigated.
[36]	S. America	Energy use Degree-hours	Use of NSGA-II to optimize residential design with envelope and geometry variables. Improvement up to 95% in thermal comfort and up to 82% in energy performance.
[37]	Europe	Energy use Construction cost	MOGA coded in MATLAB to consider different energy efficiency measures. Best solutions presented a payback time from 2 to 4 years.
[38]	Asia	Energy use	Optimize apartment units for geometry aspects. Results indicated energy saving potential up to 26%.
[39]	Europe	Energy use Life-cycle cost	Methodology for simulation-based multi-criteria optimization of NZEBs for envelope parameters. A set of Pareto fronts solutions are presented.
[40]	Asia	Energy use Thermal discomfort	Integrates sensitivity analysis and design optimization for zero/low energy buildings. Envelope and energy system design must be considered when integrated solar power generation is adopted.

Table 3.2: Overview of papers characteristics on thermal comfort

Paper	Region	GA objectives	Application and results
[41]	Asia	PMV Temperature	Use of CFD* for optimal design method considering their distribution. The investigation allowed the optimal design conditions to be applied efficiently with a small volume of computations.
[42]	Europe	Thermal and visual discomfort	NSGA-II applied in GenOpt with EnergyPlus to find best solutions for summer and winter in residences. Results support the design team in achieving a pool of variants with good values of all the considered objective functions.
[43]	Asia	Energy use Thermal comfort	Apply a MOGA procedure combined with ANN to optimize residential buildings design. Energy consumption reduced 50% but indoor comfort is improved only 1.5%.
[44]	Europe	Primary energy Discomfort hours	Optimization of building envelope with a GA implemented in MATLAB. Insulation in walls of Mediterranean climate should be from 13 to 18 cm.
[45]	Asia	Energy use User comfort	Improved optimization function to achieve maximum user comfort in smart homes. Results showed energy reduction up to 31% and user comfort improved up to 10%.

*CFD (Computational fluid dynamics)

Table 3.3: Overview of papers characteristics on life-cycle assessment

Paper	Region	GA objectives	Application and results
[46]	N. America	LCC* LCEI	Framework implements genetic algorithms to solve single and multi-objective optimization problems. Results show that the optimization program can find the optimal solutions from a large design space.
[47]	Europe	LCEI** Energy use Thermal comfort	NSGA-II is coupled to TRNSYS to develop an optimization tool. MultiOpt can be used to compare different combinations of options and constraints, thus constituting a basis for operational decision-making.
[48]	N. America	LCC Energy use	GA is used to find optimal solutions with design parameters in early stage design. The result emphasizes that different design options have an impact on the energy consumption of the buildings.
[49]	-	LCC	BIM*** and GA is used to reach best design options during the initial stages of residential project.
[50]	N. America	LCEI Energy use	Envelope design is optimized in office building using eQuest. Results show best design for a case study.
[51]	Europe	LCC Primary energy	NSGA-II is used to find optimal solutions for a NZEB case of residential building coupling TRNSYS with MATLAB.
[52]	N. America	LCC LCEI	LCA is used in early stage building design with GA to analyze climate and energy-related impact in optimal solutions.

*LCC (Life-cycle cost) **LCEI (Life-cycle environmental impact) ***BIM (Building Information Modeling)

Table 3.4: Overview of papers characteristics on lighting

Paper	Region	GA objectives	Application and results
[53]	N. America	Illuminance Glare	GA tool explores facade designs for better visual comfort. Results demonstrated the range of possible design solutions that a user can obtain using a set of non-dominated solutions.

Paper	Region	GA objectives	Application and results
[54]	N. America	Lighting Productivity	GA is used to optimize potential lighting choices in a workspace to improve productivity. Results can help mitigate additional building costs associated with sustainable design practices.
[55]	N. America	Daylight autonomy	Ceiling parameters and variables are explored in a GA approach to optimize daylight performance.
[56]	Oceania	Daylight autonomy Energy use	Optimization of external shadings in an office space is presented. Results reveal enhancement of comfort levels and energy efficiency.
[57]	Asia	Daylight factor	Conventional shading design is compared with a GA approach to achieve optimal results. Optimization method using Galapagos provides various design alternatives.
[58]	Europe	Useful Daylight Energy use	Optimization of a fixed shading device in an office room. Results show a reduction up to 26% in energy consumption.
[59]	Asia	Useful Daylight Energy use	GA is used to optimize office building design for best daylight performance. A set of useful daylight metrics are provided.

3.5.2 Contributions to the present research

This section provides a deeper analysis from the papers presented in Tables 3.1 through 3.4. Each one of the four themes defined for the purpose of this research is presented below.

3.5.2.1 Energy efficiency

Energy concern in buildings was the main research objective for this SRL. Energy efficiency topic appears not only in this theme, but on all others, either as an optimization objective function, or as performance indicator. When using EnergyPlus as simulation tool, the studies set as output data heating, cooling, lighting, and equipment energy demands. Liu et al. [29] main issue was to minimize cooling and heating loads of the HVAC system of a welding manufacturing facility by using different materials and orientations of the windows in the building. Ascione et al. [35] integrated renewable energy solutions to supply a building's heating and cooling, as well as hot water and electric equipment demands. Other papers followed that application, applying GA with EnergyPlus [31–34,37,40,60], supporting the use of the software as BPS tool.

Energy efficiency studies using genetic algorithms can also be applied in countries' energy policies. Bre and Fachinotti [36] for example proposed a GA method to improve efficiency in Argentinian dwellings with both natural or hybrid ventilation systems. They found out that the envelope has a great impact in energy savings potential, with reduction up to 82% and thermal comfort improvement up to 95%.

3.5.2.2 Thermal comfort

Following the energy efficiency studies, thermal comfort is another topic of importance in the analyzed papers. Most papers evaluate thermal discomfort using PMV index for conditioned buildings [61]. The index presents the thermal sensation on a seven-point scale, produced by a combination of physical parameters (air temperature, radiant temperature, relative humidity, and air velocity) and personal variables (activity and clothing). For mixed-mode buildings that incorporate natural ventilation, the adaptive method [62] can also be used. The approach considers thermal comfort as a function of outdoor temperature, using two acceptability limits (80% and 90%).

Yu et al. [43] for example, combined an artificial neural network with an improved genetic algorithm to find optimal building design in China with energy consumption and thermal comfort criteria. The authors applied a NSGA-II approach on several envelope and geometry variables in a residential building. From the results a series of adjustments are proposed for the optimal project, such as changes in orientation, WWR, different thermal inertia for walls and roofs and U-factor for the glazing.

Sghiouri et al. [63] also used a NSGA-II method for residential buildings in Morocco, varying only shading devices configurations to improve thermal comfort. The authors coupled jEPlus+EA with TRNSYS to minimize the discomfort degree-hours through the adaptive comfort model for the model in three different cities. Results indicated up to 4.1% of energy reduction and improvement in thermal comfort.

3.5.2.3 Life-cycle assessment

As the genetic algorithm method is used for multi-criteria optimization, other aspects rather than thermal-energetic performance were found in the SRL. The economic impact of the building sector is beyond question, so architectural projects must consider construction costs from the early design stages. In this context Life-cycle analysis (LCA), assesses from owning, operating, maintaining and ultimately disposing of a project [64]. The studies presented in Table 3.3 are examples of this approach.

Wang, Rivard, and Zmeureanu [46] proposed a framework using GA for green building design optimization. They applied the framework on a case study in Canada to minimize life-cycle cost (LCC) and life-cycle environmental impacts (LCEI). LCC is the sum of initial construction cost and operating cost during the life cycle of the building. LCEI is “based on the exergy of all natural sources consumed by a building and the exergy required by necessary operations if the wastes produced in the life-cycle phases of a building are removed or recovered to avoid their releases to the environment". Exergy refers to a concept from thermodynamics that represents the maximum theoretical work that can be done by a system with respect to the reference environment [46].

Azari et al. [50] focused on LCEI and coupled an Artificial Neural Network (ANN) with GA to minimize the environmental impacts of a low-rise office building in the United States, optimizing parameters of the building envelope (insulation material, wall R-value, WWR, and glazing type). The authors found a set of optimal solutions that mitigated the environmental impact and greenhouse gasses emissions.

From an architectural point of view, in the early deign stages, considering envelope and main systems cost, as well as energy costs throughout the whole life cycle of the building, can help designers find better suited solutions for a real project. However, an LCEI approach requires further knowledge on environmental impacts of each building element, which involves a multi-disciplinary design team.

3.5.2.4 Lighting

Although lighting and acoustics are discipline of environmental comfort, these topics were not included in the initial search strings of the SRL. Nonetheless, various papers were found after the search, mainly because they appear together with energy efficiency and/or thermal comfort studies. No paper was found regarding acoustic comfort, but since it is not the purpose of this research, it was not further discussed.

Visual comfort and daylight properties were the main themes that appeared in the lighting-related papers. Gagne and Andersen [53] for example, considered ten design parameters, including materials and geometry of apertures and shading devices to optimize a façade design based on illuminance and glare objectives. The authors ran three scenarios for different building shapes and obtained various non-dominated solutions with the desired illuminance values and low glare that causes visual discomfort.

Manzan and Clarich [58] used a modeFRONTIER algorithm coupled with DAYSIM and ESP-r simulations to estimate artificial light consumption based on daylighting distribution, and heating and cooling loads to optimize shading devices and internal blinds for an office building.

Results demonstrated up to 26% reduction of primary energy consumption with similar results for double and triple glazing. The authors stated that "multi-objective optimization can be a powerful tool in building energy design, which helps designer identify different solutions among which to select the ones which best fit in the building design" [58].

3.6 Conclusion

This study presented a brief review of genetic algorithms and their application in building design optimization for energy efficiency and thermal comfort criteria. A Systematic Review of the Literature was applied and found relevant papers that were further categorized and discussed. Based on the analyzed results, some conclusions are presented.

The review search returned 1186 documents that were carefully filtered to find relevant papers for this study, from which 115 papers remained and were analyzed. Bibliometric data showed an increase in the number of papers from the last four years of the search period (2005 to 2018), indicating a clear trend in interest growth in the field. EnergyPlus simulation software and MATLAB programming engine are the most used tools to couple building performance simulation with optimization methods like genetic algorithms. From an architectural point of view, graphical user interfaces such as jEPlus+EA can assist designers on the use of GA in a simplified yet efficient manner.

The papers were divided into four main themes, which were further discussed. Energy efficiency and thermal comfort represent the main objectives in sustainable building design, as they are critical concerns nowadays, following a global energy crisis and climate change scenario. The review also returned papers with a life-cycle assessment and lighting use in buildings. LCA should be included in early design stages, as economic issues are of most interest in the construction sector. Some papers are kept within the references, as their bibliometric data were analyzed, although not discussed [65–140].

From this study, some directions for future works can be drawn. Future research may couple genetic algorithms with building performance simulation in early stage design considering multi-criteria optimization objectives, e.g., energy, thermal and economic aspects, to find optimal solutions regarding a building's envelope, geometry, mechanical systems, and construction costs. This approach can also be implemented in national energy efficiency regulations and environmental certifications to further contribute to the development of a more efficient building stock.

3.7 References

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Chapter 4

Optimization of an energy efficient office building in subtropical Brazil

4.1 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 [1]. The efforts for mitigation of the environmental impact of this consumption has led energy policies towards energy-efficient building design [2,3]. 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 and TRNSYS have been frequently used by designers to assess building performance in early design stages [4,5] Although building performance simulation (BPS) tools are convenient for considering separate systems (mechanical, lighting, equipment) and the building's envelope as co-existing parts [6], 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 [7].

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 BPS tools with an optimization procedure to analyze multiple design solutions can minimize excessive amount of calculations [8].

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 [9,10]. It is a heuristic search that modifies function values through predefined reproduction operators in a stochastic manner [11], developed by John Holland and presented in his book ‘Adaptation in Natural and Artificial Systems’[12]. Various studies have used GAs in the design process using some user-friendly software interfaces, making optimization design more feasible for architects and construction sector professionals.

Wang, Zmeureanu and Rivard [13] presented a multi-objective optimization model using life-cycle analysis to find optimal design solutions for economic and environmental criteria. Manzan and Pinto [14] 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 [15] 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 with design actions. This would require energy modelers and designers to work in an integrated environment starting at the early design stage.

A research study was conducted by Yu et al. [7], 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. [16] 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 [17]. 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. This section 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.

4.2 Method

The method combines the building performance simulation using EnergyPlus software [18] and the graphical user interface (GUI) jEPlus+EA [19] to run the genetic algorithm and extract results.

4.2.1 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 [7].

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 relation, located on the Pareto front. To implement the BPS optimization for this case study, the jEPlus+EA software (Figure 4.1) 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 [20].

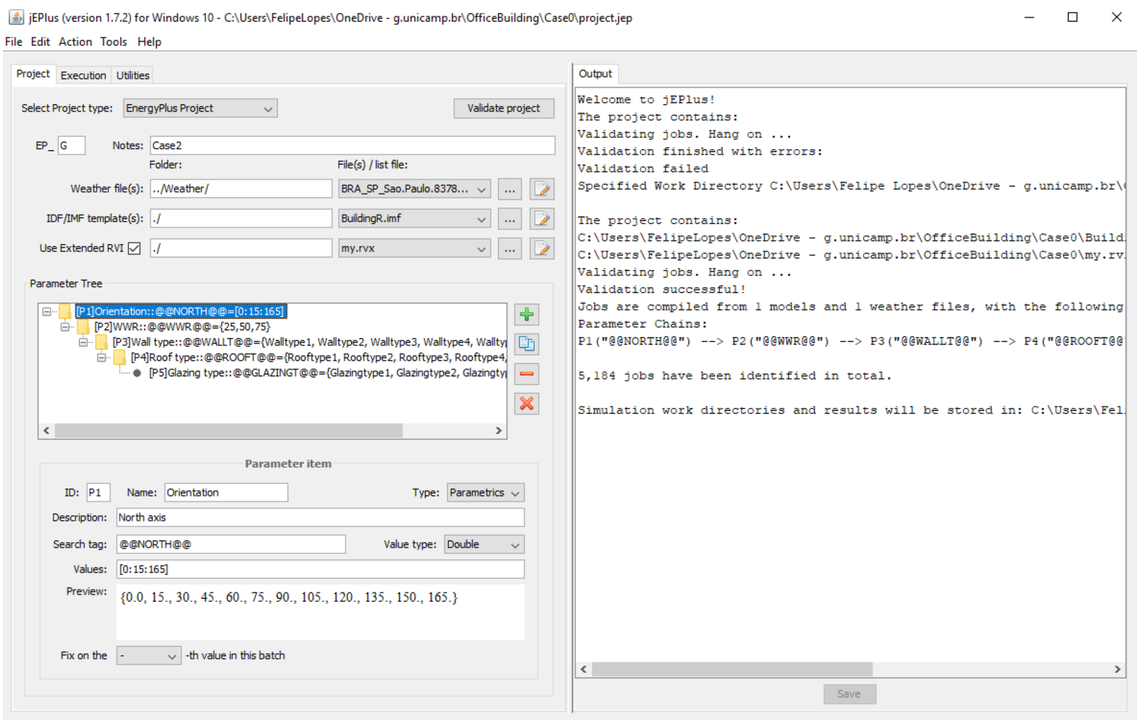


Figure 4.1: jEPlus interface with an example of the optimization project

4.2.2 Building model description

For this case study a model was designed using SketchUp 3D software [21] 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 WWR, with a 30-year life expectancy (Figure 4.2). 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.

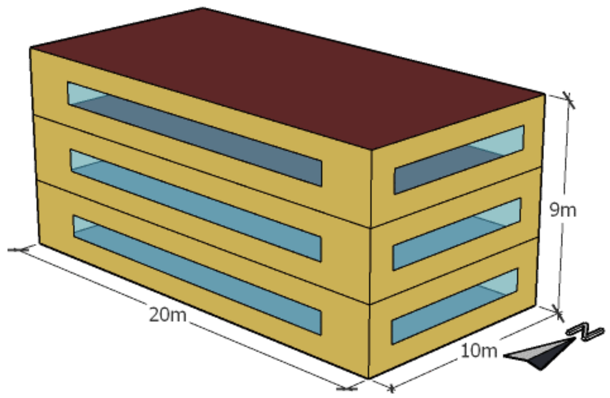


Figure 4.2: Sketch of the office building base case

Internal loads are kept constant through all simulations and take the default values from regulation NBR 16401-1 [22]. 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) [23].

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 [24], 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 [25]. Figure 4.3 shows the monthly average temperature and relative humidity for São Paulo. At this stage of the work the urban environment for the building was not considered in simulations.

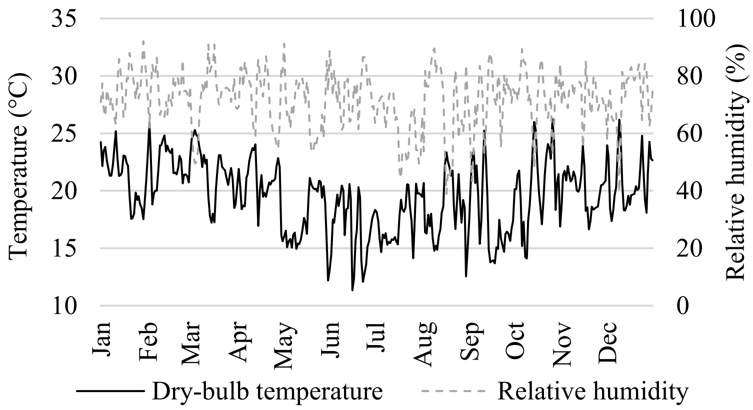


Figure 4.3: Average temperature and relative humidity in São Paulo

4.2.3 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.

4.2.3.1 Variables and constraints

The optimization model is composed of variables, constraints, and objective functions. Table 4.1 shows the defined variables and their corresponding constraints, while the properties of the wall, roof and glazing types can be found in Table 4.2. The building orientation is defined in EnergyPlus in degrees with clockwise direction being positive as shown in Figure 4.4. The building materials were defined as typical construction components from RTQ-C [23]. For simulations, the wall and roof types were defined as equivalent layers in EnergyPlus [26].

Table 4.1: 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

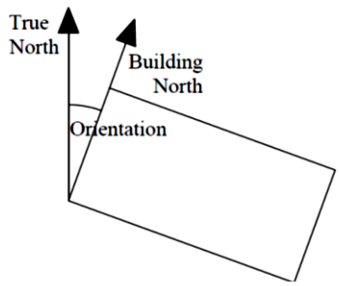
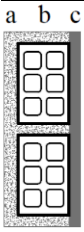


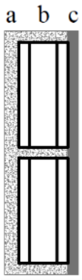
Figure 4.4: Orientation definition

Table 4.2: Composition, thermal properties and initial cost of the building envelope parameters used in the simulations

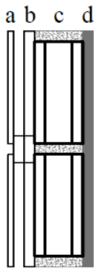
WALL TYPES[1]



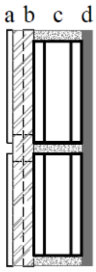
Wall type 1 (W1)
Layers:
a. External plaster (2.5cm)
b. Ceramic brick (9cm)
c. Gypsum board (2cm)
U_1 = 2.00 W/m^2-K
$\$_1$ = 12.40 USD/m^2



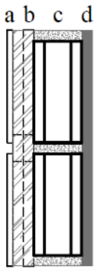
Wall type 2 (W2)
Layers:
a. External plaster (2.5cm)
b. Concrete block (9cm)
c. Gypsum board (2cm)
U_2 = 2.24 W/m^2-K
$\$_2$ = 13.95 USD/m^2



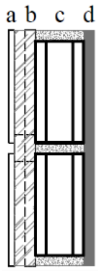
Wall type 3 (W3)
Layers:
a. Porcelain tile (1cm)
b. Air gap (7cm)
c. Concrete block (9cm)
d. Gypsum board (2cm)
U_3 = 1.65 W/m^2-K
$\$_3$ = 28.40 USD/m^2



Wall type 4 (W4)
Layers:
a. Porcelain tile (1cm)
b. EPS insulation (2cm)
c. Concrete block (9cm)
d. Gypsum board (2cm)
U_4 = 1.09 W/m^2-K
$\$_4$ = 32.50 USD/m^2

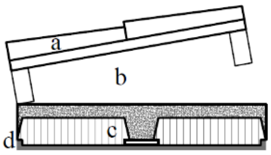


Wall type 5 (W5)
Layers:
a. Porcelain tile (1cm)
b. EPS insulation (4cm)
c. Concrete block (9cm)
d. Gypsum board (2cm)
U_5 = 0.72 W/m^2-K
$\$_5$ = 34.70 USD/m^2

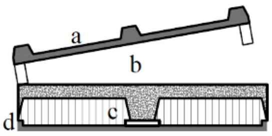


Wall type 6 (W6)
Layers:
a. Porcelain tile (1cm)
b. EPS insulation (6cm)
c. Concrete block (9cm)
d. Gypsum board (2cm)
U_6 = 0.54 W/m^2-K
$\$_6$ = 36.90 USD/m^2

ROOF TYPES[1]

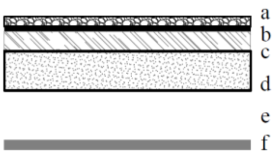


Roof type 1 (R1)
Layers:
a. Ceramic tile (1cm)
b. Air gap (15cm)
c. Pre-cast slab (8cm)
d. Internal plaster (2cm)
U_1 = 2.00 W/m^2-K
$\$_1$ = 28.40 USD/m^2

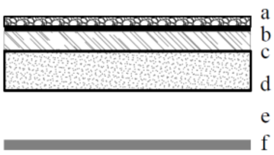


Roof type 2 (R2)
Layers:
a. Sandwich panel (4.2cm)
b. Air gap (15cm)
c. Pre-cast slab (8cm)
d. Internal plaster (2cm)
U_2 = 0.55 W/m^2-K
$\$_2$ = 59.80 USD/m^2

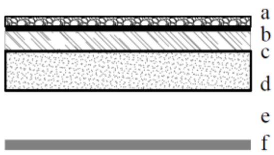
Roof type 3 (R3)
Layers:
a. Membrane (4mm)
b. Concrete slab (8cm)
c. Air gap (10cm)
d. Gypsum board (2cm)
U_3 = 2.02 W/m^2-K
$\$_3$ = 26.20 USD/m^2



Roof type 4 (R4)
Layers:
a. Pebble layer (2cm)
b. Membrane (4mm)
c. EPS insulation (2cm)
d. Concrete slab (8cm)
e. Air gap (10cm)
f. Gypsum board (2cm)
U_4 = 0.79 W/m^2-K
$\$_4$ = 37.30 USD/m^2



Roof type 5 (R5)
Layers:
a. Pebble layer (2cm)
b. Membrane (4mm)
c. EPS insulation (4cm)
d. Concrete slab (8cm)
e. Air gap (10cm)
f. Gypsum board (2cm)
U_5 = 0.58 W/m^2-K
$\$_5$ = 39.50 USD/m^2



Roof type 6 (R6)
Layers:
a. Pebble layer (2cm)
b. Membrane (4mm)
c. EPS insulation (6cm)
d. Concrete slab (8cm)
e. Air gap (10cm)
f. Gypsum board (2cm)
U_6 = 0.45 W/m^2-K
$\$_6$ = 41.70 USD/m^2

GLAZING TYPES

Glazing type 1 (G1)
Single clear glass (6mm)
U_1 = 5.80 W/m^2-K
$SHGC_1$ = 0.82
\$ = 210 USD/m^2

Glazing type 2 (G2)
Laminated clear glass
(6mm + PVB + 6mm)
U_2 = 5.60 W/m^2-K
$SHGC_2$= 0.38
\$ = 280 USD/m^2

Glazing type 3 (G3)
Double insulated clear glass
(6mm + 10mm air + 6mm)
U_3 = 2.70 W/m^2-K
$SHGC_3$ = 0.70
\$ = 400 USD/m^2

Glazing type 4 (G4)
Double insulated reflective glass
(6mm + 10 mm air + 6mm)
U_4 = 2.70 W/m^2-K
$SHGC_4$ = 0.46
\$ = 480 USD/m^2

[1] Solar absorptance is constant for all opaque elements (α = 0.5)
U: thermal transmittance
SHGC: solar heat gain coefficient

4.2.3.2 Objective functions

Two objective functions were defined: the minimization of the envelope initial construction cost (IC) of the building and the minimization of life cycle energy cost (LCE). The HVAC system initial cost was not considered in this stage of the work. 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 [27]. 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 expression to calculate IC [$/m²] is shown in Equation 4.1 and the expression for LCE [$/m²] is shown in Equation 4.2 bellow.

$$IC(X) = GF(X) + IF(X) + WT(X) + RT(X) + GT(X)$$ *Equation 4.1*

$$LCE(X) = EC(X) \times PV$$ *Equation 4.2*

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 4.3, considering the 30-year life expectancy.

$$PV = \frac{1}{(1 + DR)}$$ *Equation 4.3*

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 [28]. The price escalation is updated in EnergyPlus from the NIST Handbook 135 [27]. Since the only source of energy used in the model building is electricity, the energy rate was obtained from the São Paulo Electric Company. The rate for commercial buildings with over 200 kWh consumption per month is 0.16 USD/kWh, taxes included. For this stage of the work, only energy rate was considered, while demand rate was neglected

4.2.3.3 Genetic algorithm

The jEPlus+EA software adopts the non-dominated-and-crowding sorting genetic algorithm II (NSGA-II), developed by Srinivas and Deb [29]. 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 [7]. For the GA implementation, the following parameters were selected, as recommended by Chen et al. [30]: 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 Microsoft 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. Therefore, they represent the best solutions found in a multi-objective optimization. The results for this study are presented in the next section.

4.3 Results

The multi-objective optimization was run one time 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 4.5. The dominated solutions are shown as light grey circles, the blue diamonds represent the initial population, the red circles are the final generation which appear on the Pareto front (non-dominated solutions), and the base case is shown as the yellow square. As the initial population was randomly selected, the results were widely distributed. From there to the final generation, there is a clear distribution difference, with the results concentrated on the bottom end of the Pareto front (here represented by the dashed curve).

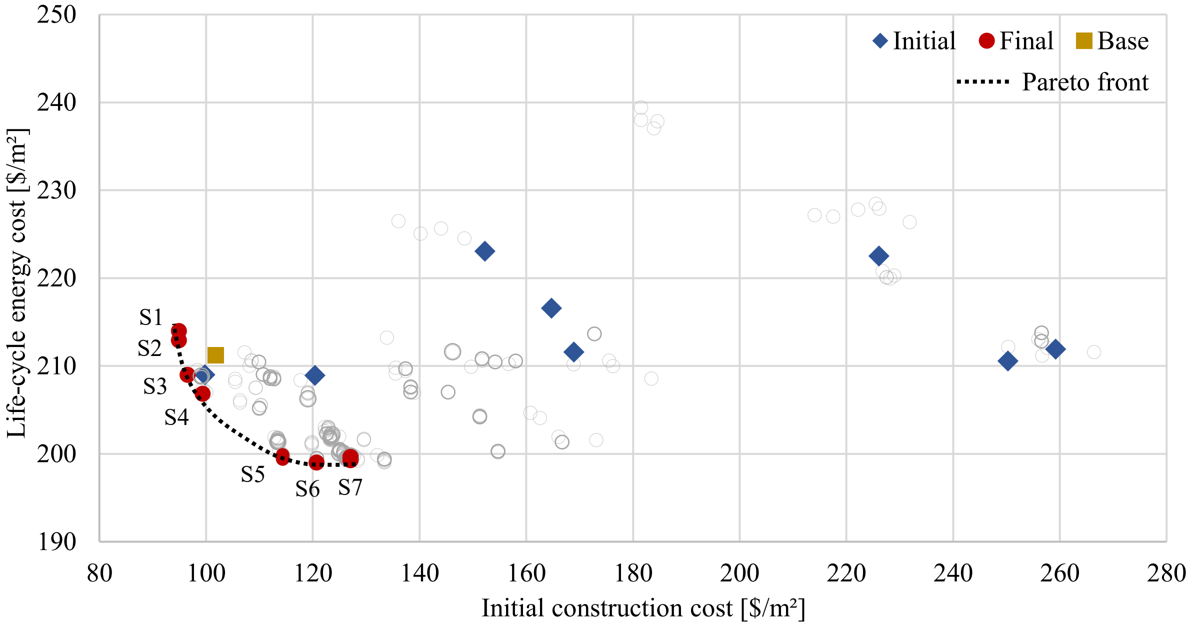


Figure 4.5: Multi-objective optimization chart. Evolution of the 50 generations towards the optimal solutions with initial construction cost (IC) and life-cycle energy cost (LCE) criteria

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).

The base case appears close to the upper cluster results, even though there is some reduction in both IC and LCE from the base model. The bottom cluster results, however, present a significant reduction in LCE when compared to the base case, but IC is somewhat higher. This is where the decision-making process lies, as once the results are known, designers can choose between a solution with lower construction cost or lowers life-cycle energy cost, if energy efficiency is the target goal in the design process.

From Figure 4.5 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 4.3. 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 climate regions in which

São Paulo is located, as solar heat gains from the glass increase cooling loads and consequently the electricity consumption.

Table 4.3: 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

On the window aspect, only the glazing types G1 and G2 appear on the best solutions, mostly 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. Figure 4.6 brings a detailed breakdown of the envelope construction costs for the best solutions (S1-S7). The glazing has the greatest impact on the initial construction cost, responsible for almost half of the envelope and floors cost composition. A more efficient glass, such as G2 (with a SHGC of 0.38) impacts the IC in 25%. 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 were less expensive than current market prices.

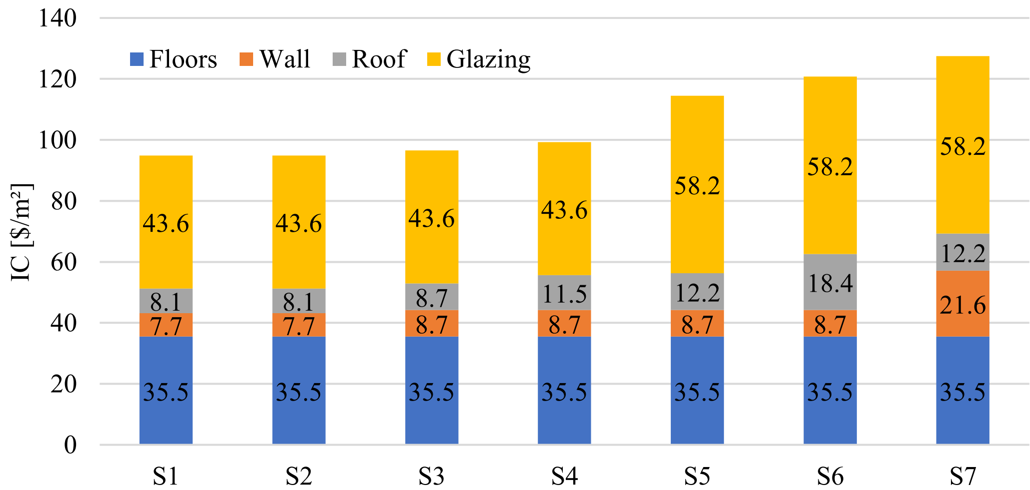


Figure 4.6: Initial construction cost breakdown for the optimal solutions

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 significantly decreases 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 observed in Figure 4.6.

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 both 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.

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 4.3 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.

4.4 Conclusion

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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Chapter 5

Multi-objective optimization using NSGA-II to minimize life-cycle cost and thermal discomfort in early stage building design

5.1 Introduction

Due to climate change and high energy demand from the construction sector in the past few decades, energy policies tend to be more strict and selective, moving towards high-performance and zero energy buildings [1,2]. In this aspect, sustainable design and building performance simulation (BPS) tools are directly related. However, using only BPS tools in the design process does not ensure an efficient solution, since several design variables such as shape, orientation, and materials could lead to conflicting objectives related to economic and thermal performance [3]. Exploring separately each design solution is an important learning process, but it can be an exhausting, time-consuming process.

Whole building energy simulation programs such as EnergyPlus [4] have been coupled with optimization methods to solve single or multi-objective problems and analyze multiple alternatives in the design stage, minimizing building performance uncertainties and offering a high probability to find optimal solutions [5]. Genetic algorithm (GA) is a widespread and popular optimization method that has been applied in various engineering problems, using the evolutionary concept of natural selection, to find optimal solutions for a given problem.

5.1.1 Genetic algorithm in building optimization

The genetic algorithm is an optimization procedure developed by John Holland in the 1970s that uses an analogy of the biological evolution of living organisms [6]. It is a heuristic search that aims to improve the objective function through predefined reproduction operators in a stochastic manner [7]. The basic difference between GA and other heuristic methods is that it works on a population of possible solutions, instead of a single solution. Also, GA uses a probabilistic method, instead of a deterministic approach to determine parameter values in each successive iteration [8].

The GA approach begins with a randomly selected population of possible solutions. The algorithm then selects the "fittest" individuals according to the objective functions and uses their "genetic" information to create a new generation, through 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. The main components in GA optimization are the building design variables, physical or financial constraints, and objective functions. In recent years, many studies have used genetic algorithms in engineering problems with different optimization platforms and simulation programs, as extensively reported in literature reviews [5,9–11]. Some studies regarding the use of GA in building energy-efficient design can be mentioned.

Wang et al. [12] applied a multi-objective genetic algorithm (MOGA) to find Pareto design solutions using a life-cycle analysis methodology. Bichiou and Krarti [13] compared GA with two other optimization algorithms to find optimum residential building design aiming to reduce life-cycle costs in five US locations. Carlucci et al. [14] optimized thermal and visual comfort for a single house in Italy using the envelope and glazing transmittance, and control strategies for shading devices as design parameters. Yu et al. [15] combined an artificial neural network with an improved genetic algorithm to find optimal building design in China with energy consumption and thermal comfort criteria. Delgarm et al. [16] coupled MATLAB with EnergyPlus to run single and multi-objective GA with passive design strategies in different Iranian climate regions.

Yang et al. [17] found optimal solutions for an office building in Taiwan with a tradeoff design between construction cost, energy performance, and window operation, achieving a 47.1% cost reduction from the initial design. Awada and Srour [18] proposed an optimization tool using GA to increase indoor environmental quality (IEQ) for users through an office building retrofit design. In most recent studies, Jalali et al. [19] used a parametric design tool to find optimal office building shapes in Iran to satisfy thermal loads and useful daylight criteria. Ascione et al. [20] applied a multi-objective GA to minimize energy consumption, global cost and discomfort hours for a residential building in different Italian climate regions.

Many of these studies use MATLAB [21] or GenOpt [22] as the optimization tool, even though these programs have some limitations. GenOpt does not have any multi-objective algorithm, and MATLAB toolboxes were not specifically designed for building simulation optimization [9]. Most of these tools are somewhat unfriendly for architects. This is a significant challenge, as these programs require skills that most architects are not familiar with. Depending on the level of collaboration between architects and engineers for the use of BPS and optimization tools, the building design and performance could be affected.

To achieve design optimization, it is necessary to switch between modeling and optimization environment, which can be inconvenient and susceptible to mistakes [10]. Usually, architects have a further, more holistic look into the design process, while engineers are often better suited in understanding individual building functions and quantifying their performances. Then, successfully implementing BPS and optimization tools in the early design stage requires an integrated process, which does not represent the traditional arrangement where the engineer is an acting assistant for the architect [23]. To overcome some of these obstacles, graphical user interface (GUI) software like MOBO and jEPlus+EA are promising optimization tools that can be used in the early design stage of energy-efficient buildings by professionals with basic programming knowledge.

These tools can be useful since energy policies are moving towards high-performance buildings. However, in some developing countries, like Brazil, energy regulations tend to consider new and existing constructions as efficient, even though they consume more energy than similar buildings with high-energy performance in countries with similar climates [24,25]. Thus, using optimization tools can assist architects and engineers in achieving optimal design solutions with multi-objective functions or performance criteria, such as energy consumption, construction costs, and thermal comfort.

5.1.2 Energy efficiency regulation for buildings in Brazil

The role of the building sector in the energy consumption, carbon dioxide emissions and global warming is acknowledged, as buildings account for over 40% of the world's total energy use, mainly from fossil fuels [26]. Following a global concern after the energy crisis from the 1970s, the Brazilian national electricity conservation program (PROCEL) was founded in 1985, encouraging energy savings in different areas. In Brazil, buildings already account for 51% of the electricity demand, from which half is consumed by the commercial and public sectors [27].

In 2009 PROCEL released the Regulation for Energy Efficiency Labeling of Commercial Buildings (RTQ-C), that classifies buildings at five levels: from "A" (most efficient) to "E" (least efficient) [28], based on two methods (prescriptive and simulation). The prescriptive method is based on the results of simulations of building prototypes for each Brazilian bioclimatic zone, where multi-linear regression was used to calculate the energy performance of the building envelope (considering building geometry, window-to-wall ratio, glazing solar factor, and shading devices). It also considers the lighting power density according to ASHRAE 90.1 [29], and the air-conditioning system according to the equipment efficiency level [30].

The simulation method compares the proposed building with a reference model. The reference building must be modeled according to the RTQ-C requirements for the intended efficiency level, and simulations for both proposed and reference buildings should be carried out using the same program and weather data. The proposed building energy consumption should be equal to or lower than that of the reference building in order to comply with the code specifications of efficiency level. Figure 5.1 shows examples of the RTQ-C energy efficiency labels for both design and construction phases.

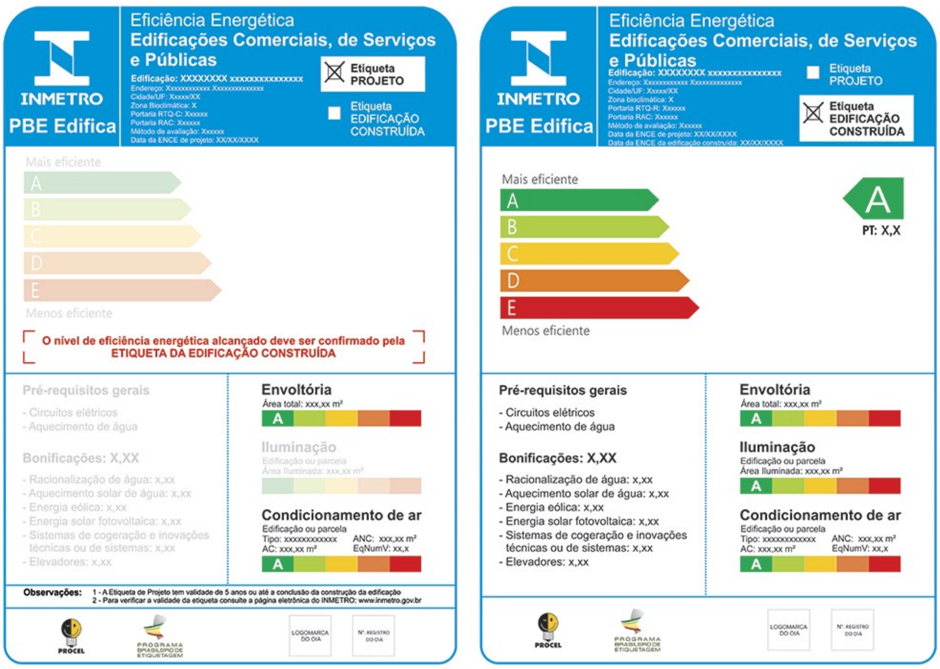


Figure 5.1: RTQ-C labels for design and construction phases

(Source: Eletrobras [31]*)*

Some studies assessed the methods used by RTQ-C and pointed out limitations of the prescriptive method regarding the building shape, envelope thermal properties and window-to-wall-ratio (WWR) [32–34]. The regulation is under revision and a new method is being developed using an artificial neural network to evaluate energy efficiency in commercial buildings [35]. This indicates that optimization methods and machine learning are important techniques that can be incorporated into energy policies. Furthermore, sustainable design goes beyond energy efficiency. In office buildings, thermal comfort analysis is of particular interest, as people tend to spend a third of their time in this environment [36]. The past decade was marked by an extensive research interest on the subject due to the impact of comfort on well-being, health, and productivity [37].

Ensuring indoor environmental quality and minimizing energy demand are critical for sustainable building design. A report from the Brazilian Electric Company for end-use consumption pointed out that in commercial buildings 47% of the electricity is consumed by the HVAC systems [38]. Passive design alternatives can greatly contribute to minimizing energy consumption in this building sector. Although it is not mandatory, RTQ-C receives increased attention from the private and public sectors. A regulation from 2014 requires all new or retrofitted federal buildings over 500 m² to achieve Level A in RTQ-C [39].

To support the adoption of RTQ-C's simulation method in assessing energy efficiency and thermal comfort of Brazilian buildings, and to address other criteria such as life-cycle cost, this paper is a contribution to improving Brazilian building energy codes. The chapter presents a case study of a multi-objective genetic algorithm (MOGA) procedure to achieve optimal design alternatives for an office building in three cities from different Brazilian climatic regions, aiming to minimize two conflicting objective functions, i.e., the life-cycle cost, and indoor thermal discomfort hours.

5.2 Methodology

5.2.1 Base case building

A typical medium-rise office building typology was defined based on information from real buildings [40]. The base case model has a three-story rectangular geometry in East-West direction, with 2,700 m² of net total floor area and 3 m floor-to-ceiling height, as shown in Figure 5.2. The WWR is 40% on all façades, and windows have 5 cm aluminum frames and vertical dividers every 1.5 m of the glazing. Horizontal overhangs (0.75 m depth) serve as shading devices on all windows. The building was modeled using SketchUp 3D software [41] and saved as an EnergyPlus Input File (IDF) through the Euclid plugin [42].

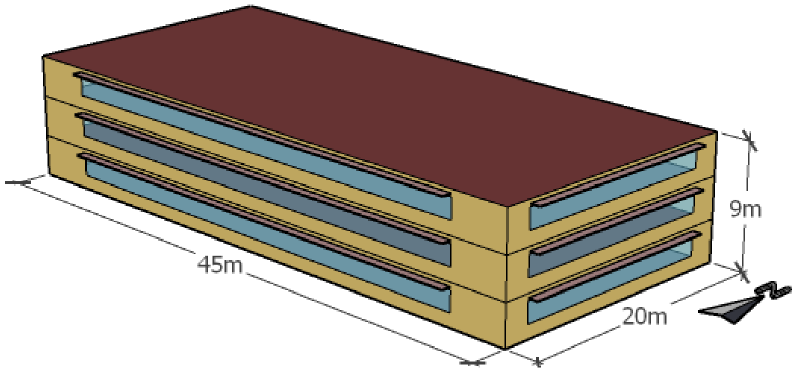


Figure 5.2: SketchUp model of the base case office building

Internal loads were kept constant through all simulations and took the default values from regulation NBR 16401-1 [43]. The occupancy area is 8.0 m²/person in moderate active office work, with a metabolic rate of 130 W/person. The building working days are from Monday to Saturday, from 07:00 to 22:00, with a variable occupancy profile, as shown in Figure 5.3a. During weekdays, 100% of the people work from 08:00 to 18:00, with a lunchbreak at 13:00. On Saturdays, the workforce is reduced at 80% from 08:00 to 12:00. On the rest of the day from 18:00 to 22:00 on weekdays and from 14:00 to 22:00 on Saturdays, there is an occupancy varying from 10% to 20% for occasional workers and maintenance staff.

The lighting power density is 9.7 W/m² (Figure 5.3b) as required for a Level A efficient building from the RTQ-C regulation [31]. During the mornings, 50% of artificial lighting is used only in the building's core, as daylight supplies lighting levels on the rest of the building. As for the electric equipment, an 8.61 W/m² load is considered for medium office use (Figure 5.3c). Equipment use follows the occupancy profile, with 100% of the load being used during weekdays from 08:00 to 13:00 and from 14:00 to 18:00. On Saturdays, equipment density is 80% from 08:00 to 13:00.

A variable refrigerant flow (VRF) system was used for cooling and heating of interior spaces. It is composed of fan coils located in each indoor unit that serves the thermal zones to satisfy the space cooling/heating loads, and of variable speed compressors in the outdoor units, with and air-cooled condenser. In EnergyPlus, the Template VRF option was used as the HVAC system, working all year long, from 06:00 to 22:00. Total cooling and heating capacity were set as auto size, the thermostat set point was kept constant at 24 ºC for cooling, and 20 ºC for heating. The system Coefficient of Performance (COP) at design conditions was 4.65 for cooling and 5.11 for heating, according to the manufacturer [44].

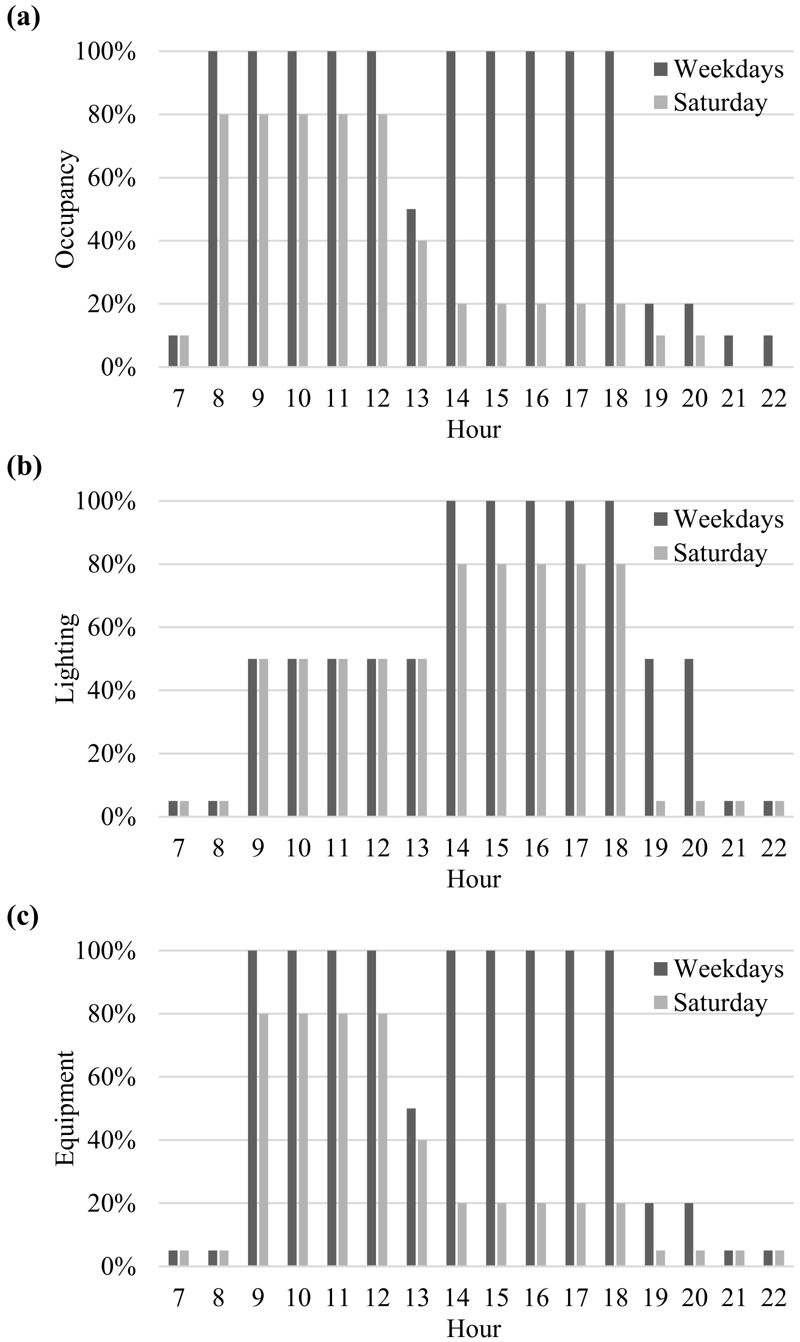


Figure 5.3: Occupancy, lighting and equipment profiles in the office building

5.2.2 Analyzed cities in different Brazilian bioclimatic zones

The Brazilian regulation for energy performance in buildings NBR 15220-3 divides the country into eight bioclimatic zones (Figure 5.4), based on Givoni's bioclimatic chart and Mahoney tables to provide passive design recommendations [45]. The regulation was developed for low-income residential buildings. However, RTQ-C adopts this zoning as a basis for its energy efficiency compliance in commercial and public buildings.

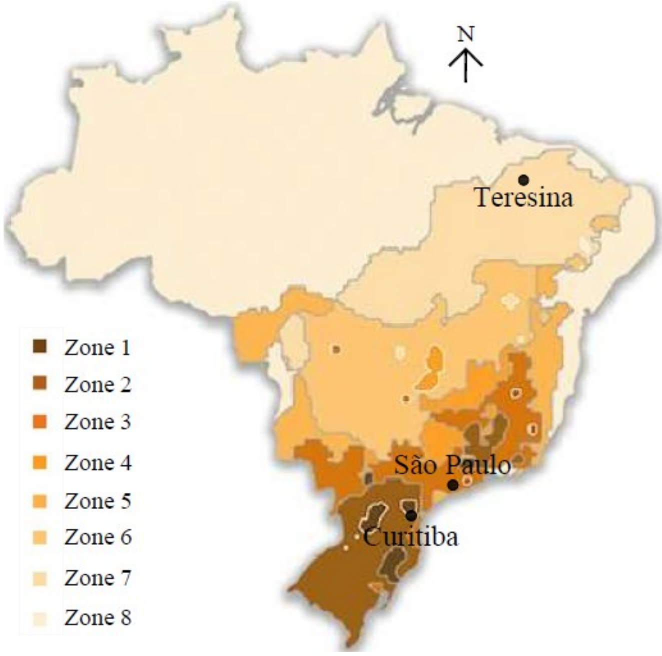


Figure 5.4: Brazilian bioclimatic zones and location of the cities selected for the study

Even though the country is divided into eight zones, for the purpose of this study, the base case building was simulated for three cities in different bioclimatic zones: Curitiba (Zone 1), São Paulo (Zone 3) and Teresina (Zone 7). As the objective of the work is to achieve optimal design solutions for a hypothetical building, once the results can be achieved for these three cities, the optimization procedure can be extrapolated for other bioclimatic zones in Brazil. Table 5.1 shows the cities' geographical location, climate classification according to Köppen-Geiger [46], cooling degree days (CDD) for a base temperature of 10 ºC, and heating degree days (HDD) for a base temperature of 18 ºC, and Figure 5.5 shows their average daily dry-bulb temperature and relative humidity [47].

Curitiba is in Southern Brazil, in a temperate oceanic climate region. Average maximum temperature is 26 ºC, and average minimum is 7.4 ºC. During summer air temperatures range between 16 ºC and 27 ºC, usually with rainstorms (January and February). Winters are usually drier periods, with clear-sky conditions and average daily temperatures ranging between 8 ºC and 20 ºC (June and July) [48]. However, the city has a rather uniform relative humidity throughout the year, with and average RH of 81%. São Paulo is the largest city in Brazil, located in the Southeastern region, in a subtropical region with mild temperatures: warm humid summers, cool dry winters. Annual average temperature in 19.1 ºC with minimum and maximum temperatures ranging from 10.7 ºC and 31.1 ºC. Annual relative humidity is 74.3%, with a rainy season from December to March and a dry season from June to August [49].

Teresina, Northeast region of Brazil, is a city of tropical climate, with wet summers and dry winters, receiving strong solar radiation levels during all year, for its proximity to the equator. In hot seasons, the average maximum temperature in Teresina is 35.9 °C (October and November), while in mild weather seasons, minimum temperatures are recorded close to 20 °C (February and March). The city has a rainy season from January to May and a dry season from July to November. The average annual air relative humidity is 70%, reaching over 90% in the rainy season, and below 20% in the driest months [50].

Table 5.1: Characteristics of the reference cities selected for the study

Zone	City	Climate	Latitude	Longitude	Elevation	CDD	HDD
Z1	Curitiba	Oceanic with cold winter (Cfb)	25°25’ S	49°16’ W	934 m	3026	627
Z3	São Paulo	Humid subtropical (Cfa)	23°32’ S	46°38’ W	760 m	3993	212
Z7	Teresina	Savanna (Aw)	05°05’ S	42°48’ W	72 m	7072	0

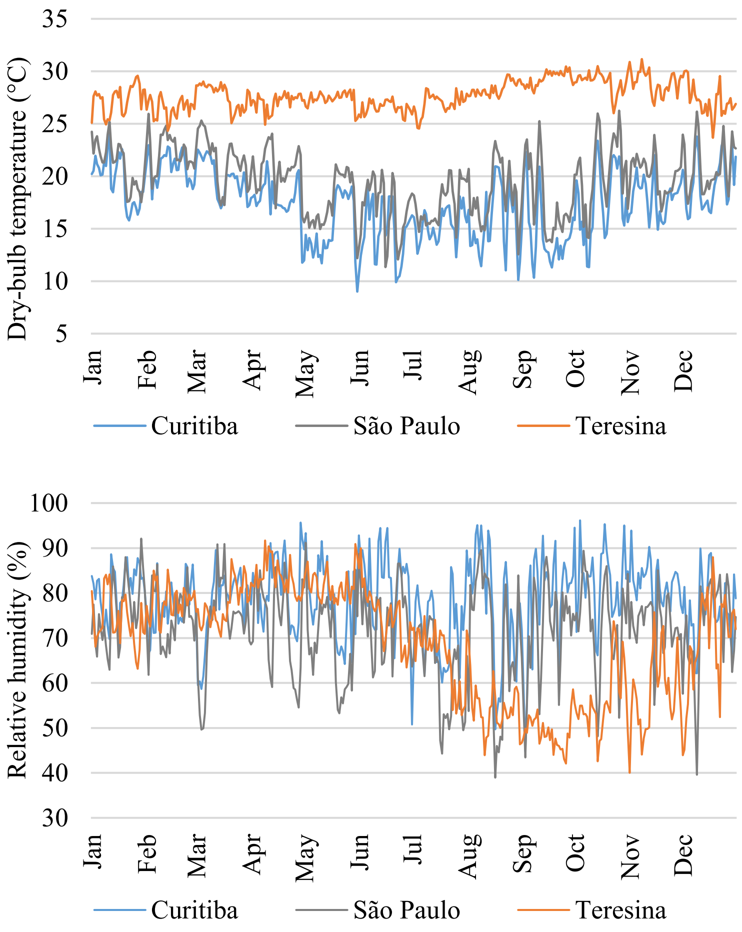


Figure 5.5: Average daily dry-bulb temperature and relative humidity in Curitiba (Z1), São Paulo (Z3) and Teresina (Z7)

Thermal comfort of the building's occupants was assessed by the predicted mean vote index (PMV), a method indicated for artificially conditioned buildings, as reported by [51–53]. PMV predicts the mean value of votes for a large group of people, based on metabolic rate, clothing insulation, air and radiant temperature, air humidity and convective heat transfer, on a 7-point thermal sensation scale, where +3 is hot, +2 is warm, +1 is slightly warm, 0 is neutral, −1 is slightly cool, −2 is cool, and −3 is cold [54]. A PMV value between -0.5 and +0.5 indicates that 90% of people in a room is thermally comfortable.

The clothing insulation was defined by season for each city defined in this study. For Curitiba and São Paulo, the clo was 0.96 in the warmer months (from November to April), and 1.14 in the colder months (from May to October). In Teresina, the clo was 0.61 in the warmer months, and 0.96 in the colder months [55]. In the optimization procedure, minimizing PMV absolute values can be confusing, as results range from negative to positive, so the number of hours where the neutral sensation was not achieved during the hours of occupancy is clearer.

5.2.3 Building envelope design

The starting point of the search for optimized solutions through the GA algorithm was the building envelope composition that complies with the current Brazilian regulation (RTQ-C) for each city for a Level "A" design (Table 5.2). The floors are the same for all cases, made of concrete slab and porcelain tiles (10 cm thick and U-value = 3.73 W/m²-K), as well as the suspended ceilings, composed of 1 cm gypsum boards [31].

Table 5.2: Base case building envelope for each zone in compliance with RTQ-C Level "A" design

Element	**Zone**	**Type***	**Thickness**	**U-value (W/m²-K)**
External wall	Z1	W5	16 cm	0.72
	Z3 and Z7	W1	13.5 cm	2.00
Roof	Z1	R5	25 cm	0.45
	Z3 and Z7	R2	20 cm	0.55
Glazing	All zones	G2	12 mm	5.60

*Element type also used in the optimization procedure (see Table 5.4)

5.3 Optimization procedure

The jEPlus+EA tool was used to couple a genetic algorithm method with EnergyPlus software. The optimization components were divided into three categories to minimize two objective functions. In this section, the optimization procedure is further described.

5.3.1 jEPlus+EA

jEPlus+EA [56] is an open source GUI software developed for managing complex parametric simulations that uses a non-dominated and crowding distance sorting genetic algorithm (NSGA-II) as the optimization method and EnergyPlus as simulation engine. NSGA-II [57], selects the initial population based on the design space and constraints, and uses the non-domination criteria of the population to sort the process.

The individuals are selected using a binary tournament with a crowded-comparison operator, where a large average crowding distance indicates a high degree of diversity. After going through crossover and mutation, the parents and their children are combined for the next generation. NSGA-II ensures both convergence and spreading of the solution front, without using an external population, maintaining the population diversity with little computation time [15]. Nowadays, the method is recognized as one of the most efficient MOGA [16].

In the jEPlus+EA interface (Figure 5.6), the user begins the optimization project by defining the design variables and their constraints, then uploading the EnergyPlus input files (IDF), and climate file (EPW). For the initial population, the software randomly selects a value for each variable, which are evaluated by the defined objective functions. Once all input parameters are selected, the optimization procedure is run, and the results are retrieved directly from the EnergyPlus output files. The multi-objective optimization results consist of a set of Pareto non-dominated solutions [36].

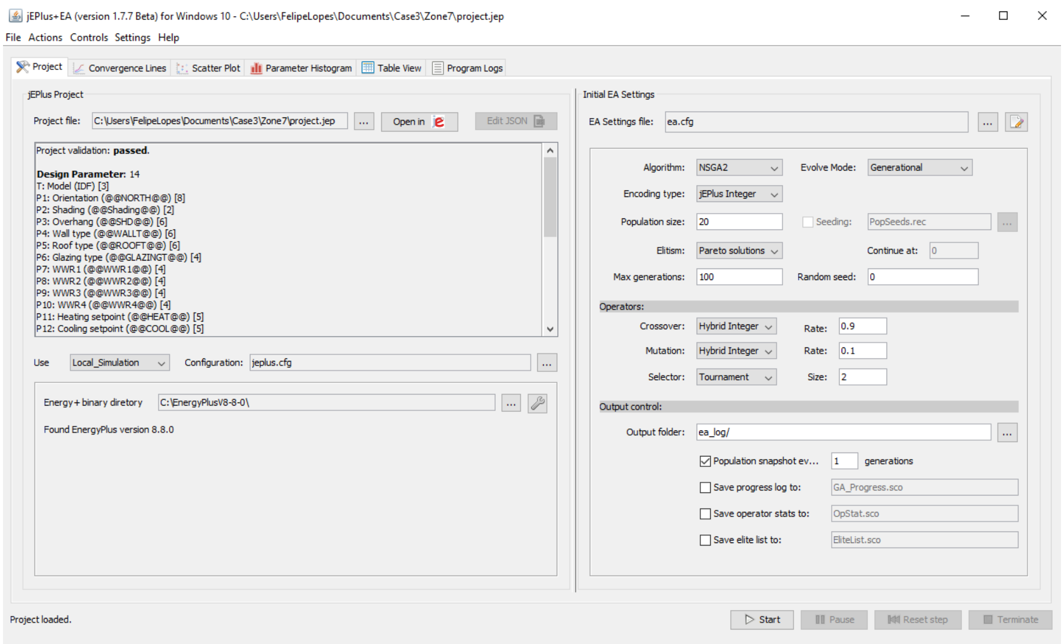


Figure 5.6: jEPlus+EA interface with the NSGA-II parameters

5.3.2 Optimization components

The components of the NSGA-II optimization method are the variables, constraints, and objective functions. The base case is a rectangular-shaped building, so two other shapes with the same floor area were chosen as design alternatives, a square-shaped and an L-shaped building (Figure 5.7). All variables and their constraints are presented in Table 5.3, divided into three categories: building shape and orientation, building envelope and HVAC system. Regarding the envelope, the characteristics of each design alternative (e.g., wall type W1, and roof type R1) are shown in Table 5.4.

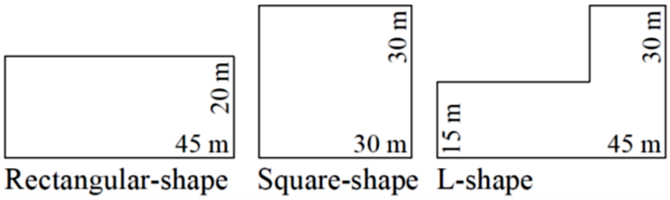


Figure 5.7: Building geometries defined as design variables

Table 5.3: Constraints of the variables defined for the MOGA procedure

Category	Variables	Unit	Constraints
Building design	Shape	-	Rectangular, Square, L-shape
	Orientation	Deg.	0, 45, 90, 135, 180, 225, 270, 315
Building envelope	WWR (North)	%	20, 40, 60, 80
	WWR (South)	%	20, 40, 60, 80
	WWR (East)	%	20, 40, 60, 80
	WWR (West)	%	20, 40, 60, 80
	Shading	-	None, Horizontal overhangs
	Overhang depth	m	0.25, 0.50, 0.75, 1.00, 1.25, 1.50
	Wall type	-	W1, W2, W3, W4, W5, W6
	Roof type	-	R1, R2, R3, R4, R5, R6
	Glazing type	-	G1, G2, G3, G4
HVAC system	Heating setpoint	°C	18, 19, 20, 21, 22
	Cooling setpoint	°C	22, 23, 24, 25, 26
	Cooling COP	-	4.65, 4.70, 4.84

Table 5.4: Properties of the building envelope parameters used in the simulations

Element	Description	Thickness (cm)	U-value (W/m²-K)	Cost ($/m²)		
				Z1	Z3	Z7
Wall type[1]						
W1	Plaster / clay brick / gypsum board	13.5	2.00	25.3	25.5	21.8
W2	Plaster / concrete block / gypsum board	13.5	2.24	28.5	28.0	25.6
W3	Tile / air gap / concrete block / gypsum board	19	1.65	47.1	51.4	56.4

Element	Description	Thickness (cm)	U-value (W/m²-K)	Cost ($/m²)		
				Z1	Z3	Z7
W4	Tile / EPS insulation (2-4-6 cm) / concrete block /	14	1.09	55.0	59.3	64.3
W5	gypsum board	16	0.72	59.0	63.2	68.3
W6		18	0.54	62.9	67.2	72.2
Roof type[1]						
R1	Ceramic tile / air gap / precast slab / plaster	26	2.00	56.3	57.9	48.2
R2	Metallic tile with PU insulation / air gap / precast slab / plaster	20	0.55	85.1	84.2	80.1
R3	Membrane / concrete slab / air gap / gypsum board	20	2.02	53.9	59.3	57.7
R4	Pebble / waterproof membrane / EPS insulation	23	0.79	62.1	67.4	65.9
R5	(2-4-6 cm) / concrete slab / air gap / gypsum	25	0.58	66.0	71.4	69.8
R6	board	27	0.45	69.9	75.3	73.8
Glazing type						
G1	Single tempered clear glass	6 mm	5.80 (S[2] 0.82)		210	
G2	Laminated clear glass (with PVB film)	12 mm	5.60 (S[2] 0.38)		280	
G3	Double insulated clear glass (6 mm + 10 mm air gap + 6 mm)	22 mm	2.70 (S[2] 0.70)		400	
G4	Double insulated reflective glass (6 mm reflective + 10 mm air gap + 6 mm clear)	22 mm	2.70 (S[2] 0.46)		480	

[1] the solar absorptance is constant for all opaque elements ($\alpha = 0.5$).
[2] S: solar heat gain coefficient (SHGC)

The two objective functions were the life-cycle cost (including initial construction, HVAC system and energy cost) and thermal discomfort hours based on PMV index. Life-cycle cost (LCC) is part of the life-cycle analysis (LCA), which assesses from owning, operating, maintaining and ultimately disposing of a project [58]. For this study, the LCC considered the initial construction and HVAC system cost, plus the life-cycle energy cost (LCE), while repair and maintenance costs were neglected. This approach refers to the early design stage, where usually architects do not have enough information to estimate the real-life building costs. The construction cost was obtained from SINAPI index, a tool from the Brazilian government to define civil construction costs for each state in the country [59]. HVAC system cost was obtained directly from a manufacturer, and the price was kept constant for all cities [44].

5.3.3 Objective functions

X represents a variable vector (Equation 5.1), where $x_1, x_2, \ldots x_n$ are values assigned for each variable from Table 5.3. Two objective functions were minimized by the multi-objective genetic algorithm. The life-cycle cost: *LCC(X)*, in $ per floor area (Equation 5.2), is a sum of the initial construction cost *IC(X)*, HVAC system cost *SC(X)* and the life-cycle energy cost *LCE(X)*, and adjusted by the present value (*PV*). The discomfort hours during the occupancy period *DH(X)*, in % (Equation 5.3) is the sum of hours (h) of all thermal zones where the mean value of the predicted mean vote (PMV) during the occupancy hours falls out of the acceptable comfort range (i.e., below -0.5 or over +0.5).

$$X = [x_1, x_2, \dots, x_n] \qquad \textit{Equation 5.1}$$

$$LCC(X) = IC(X) + SC(X) + LCE(X) \times PV \qquad \textit{Equation 5.2}$$

$$DH(X) = \sum_{\mathrm{h}} PMV_h \text{, for } PMV_h\text{<-0.5 or } PMV_h\text{>0.5} \qquad \textit{Equation 5.3}$$

IC, *SC* and *LCE* data were extracted from EnergyPlus economic calculations. *IC* and *SC* are part of the component costs and *LCE* combines the electricity rate and life-cycle cost computations. For each year from the life cycle, the present value (*PV*) is calculated by EnergyPlus (Equation 5.4). *PV* uses the discount rate (*DR*) to determine the current equivalent value of future cash flows, considering a forecast inflation rate. For energy costs, EnergyPlus multiplies the *PV* of each year by that year’s price escalation.

$$PV = \frac{1}{(1 + DR)} \qquad \textit{Equation 5.4}$$

This study considered 30 years of building economic life, and *DR* is the forecast interest rate in Brazil for 2019, of 0.65 [60]. The price escalation is updated in EnergyPlus from the NIST Handbook 135 [58]. The analyzed buildings use only electricity as energy source, and the demand and energy rates for high-voltage medium commercial buildings were obtained from the electric companies of each reference city (Table 5.5).

Table 5.5: Electricity rates with taxes included for commercial buildings in each analyzed city

Zone	**City**	**Demand rate (USD/kW)**	**Energy rate (USD/kWh)**
Z1	Curitiba	5.58	0.14
Z3	São Paulo	4.79	0.12
Z7	Teresina	6.02	0.13

5.3.4 NSGA-II parameters

To set of parameters were defined in this study to compare results spread and convergence. The convergence is said to be achieved when future generations do not improve on the objective functions targets [61]. In this work, convergence is reached when the same minimum solution is found for ten generations in a row.

The first parameters (Case A) were defined in jEPlus+EA 1.7.7 [56], as described in Chapter 4, with a population size of 10 individuals and 50 generations. The second NSGA-II parameters (Case B) were defined as recommended by Chen et al. [62]: population size of 20 individuals, 100 maximum number of generations, crossover rate of 0.9, mutation rate of 0.1, and binary tournament selection operator. After the optimization run, the results were extracted from jEPlus+EA and stored in CSV files for analysis and comparison from the two parameters configurations.

5.4 Results and discussion

For each bioclimatic zone, the optimization procedure was carried out three times with a random initial population, due to the randomness of the multi-objective genetic algorithm. Each run took around 1 hour (Case A) and 2.5 hours (Case B) with a Windows 10 operating system on a desktop computer (3.40 GHz Intel i7 processor, 16 GB RAM). Results for spread and convergence, Pareto solutions and a comparison with the Brazilian regulation follow.

5.4.1 Spread and convergence

A comparison between Case A and Case B is presented in Figure 5.8. In the graph, the solutions from the last ten generations are shown. As initial population from both cases were randomly selected by jEPlus+EA, the spread of the results is as variable as the cases. However, it can be noticed that the solutions converge towards the possible minimum for the two objective functions, i.e., life-cycle Cost (LCC) and discomfort hours (DH).

For Case A, the same results were found only in the last six generations in a row, while in Case B, in the last ten generations, similar results were found. This indicates that the Pareto front changes when population size and number of generations are increased. As reported by Chen et al. [62], for an optimization procedure of medium-size buildings with not as many parameters (less than 20), three simulation runs are sufficient for ensuring spread and convergence. This can be seen in Figure 5.8. There is no significant distance from the results of the final ten generations of Case A and Case B, indicating optimum solutions were found with a population of 10 individuals and 50 generations. Case B was used to guarantee the effectiveness of the NSGA-II method. Since results with a population of 20 individuals and 100 generations are more robust and present more reliable data, only the solutions from Case B were further analyzed in the procedure.

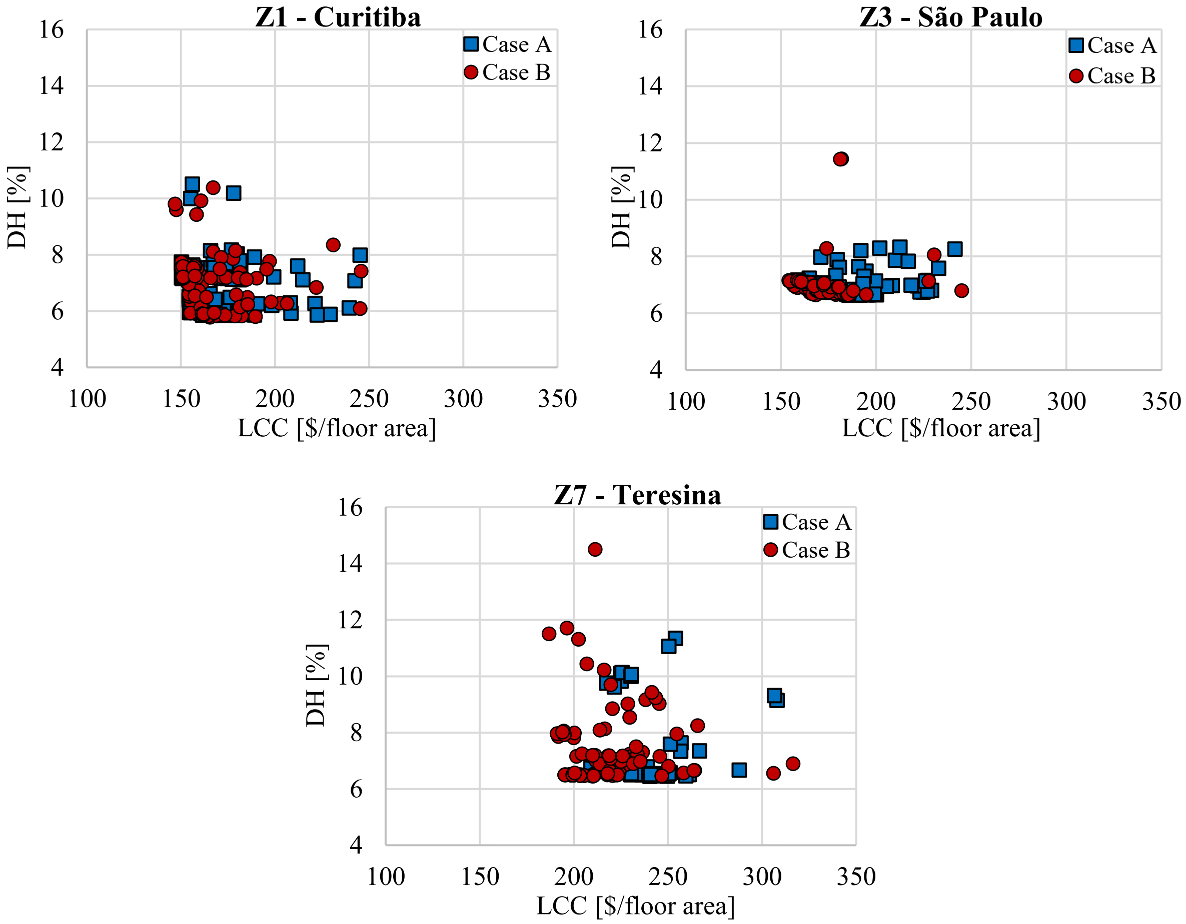
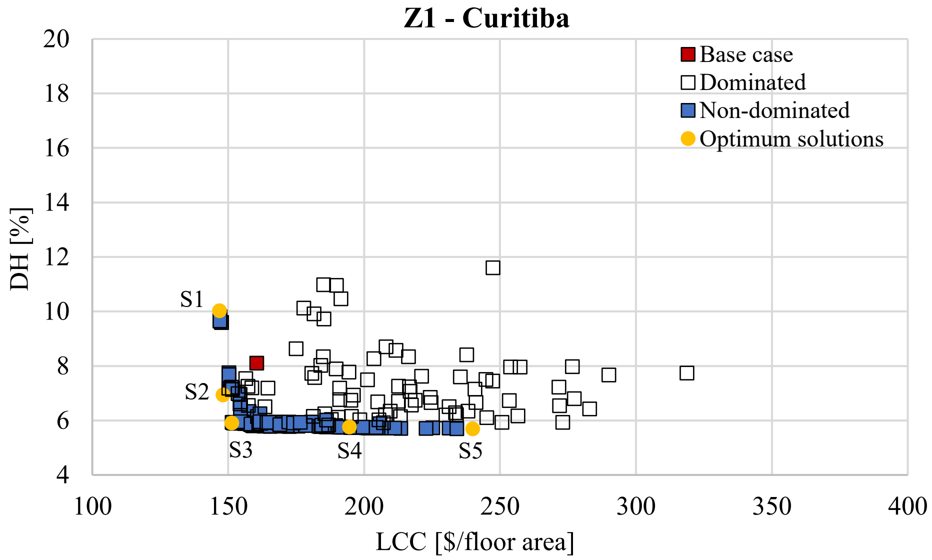


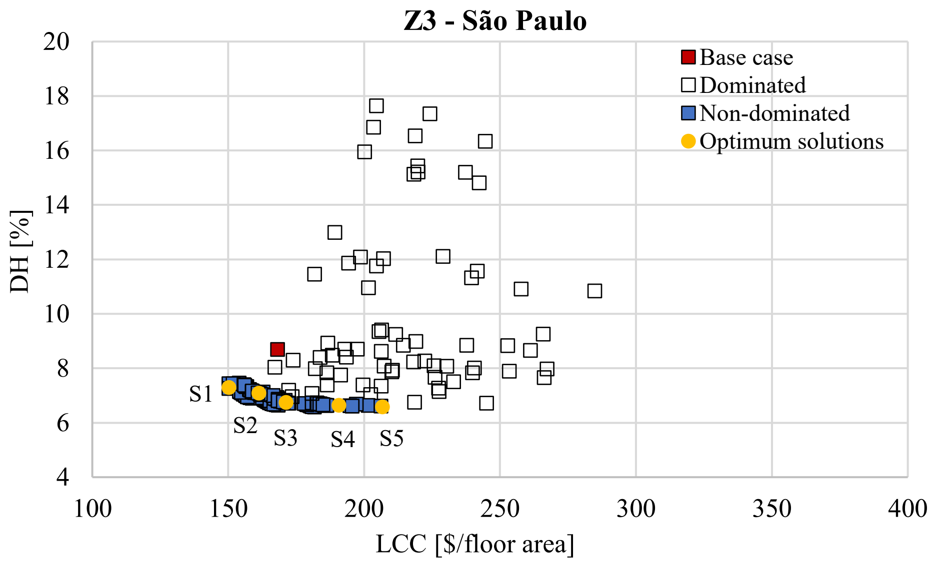
Figure 5.8: Comparison between the last ten generations from Case A and Case B of the optimization procedure

5.4.2 Analysis of the optimization model

The compiled results from the three runs for each city in Case B are shown in Figure 5.9, where the horizontal axis represent the life-cycle cost (LCC) values, and the vertical axis represent the discomfort hours (DH), calculated over the occupancy period. The black squares are the dominated solutions, the blue squares are the non-dominated solutions in the Pareto front, the red squares are the base cases, and the yellow circles represent the optimum solutions selected from the non-dominated cases in the Pareto front.

For each city, five optimum cases (S1, S2, S3, S4, and S5) were selected for comparison with the Brazilian energy efficiency regulation in the next section. They were chosen based on the following criteria: two cases (S1 and S5) are in the extremities of the Pareto front. The intermediate cases (S2, S3, and S4) were selected considering and equal physical distribution along the Pareto front.





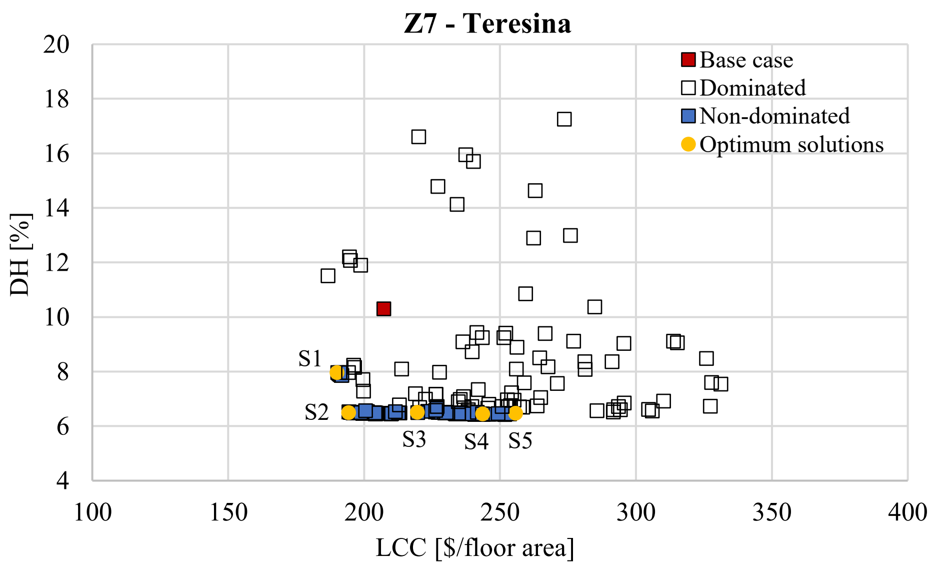


Figure 5.9: Compiled results from the three runs for the final generation versus the initial population

It can be seen from Figure 5.9 that the dominated solutions are widely distributed, while the final non-dominated solutions are more clustered towards the bottom left corner of each graph. This indicates that the genetic algorithm was successful in finding results that satisfied the objective functions, i.e., to minimize both life-cycle cost and discomfort hours. The results for dominated and non-dominates solutions are summarized in Table 5.6.

Table 5.6: Summary of results for life-cycle cost (LCC) and discomfort hours (DH) in the dominated (D) and in the non-dominated (ND) solutions

Zone (City)	**LCC [$/floor area]**		**DH [%]**	
	D	**ND**	**D**	**ND**
Z1 (Curitiba)	164 – 320	147 – 210	5.9 – 11.6	5.7 – 7.9
Z3 (São Paulo)	182 – 285	150 – 210	6.7 – 17.7	6.5 – 7.5
Z7 (Teresina)	220 – 331	194 – 249	6.7 – 17.3	6.2 – 8.2

It is important to highlight that a true Pareto front is difficult to obtain in most practical problems. However, the non-dominated solution points resemble Pareto curves where the tradeoff between LCC and DH can be seen. At this point in the early stage design, the decision-making lies with the knowledge and experience of the architects and engineers involved in the process. The professionals may select a feasible solution from the Pareto front based on their needs or goals [10]. For example, if there is a limited initial construction budget, the solutions from the left side of the front can be selected, with the risk of increasing the number of hours of thermal discomfort. However, if indoor thermal comfort is a more critical concern, a more expensive design solution, from the right end of the front, may be selected.

5.4.3 Comparison with the Brazilian regulation (RTQ-C)

As this research is intended as a contribution for future Brazilian building energy codes, a comparison with the current RTQ-C regulation was carried out. For each city, five optimized solutions were chosen from the non-dominated solutions (Figure 5.9) and compared with the base case design that complies with RTQ-C (Table 5.2). The base case and the selected optimal solution were labelled using the simulation method from RTQ-C [28]. The label, design parameters and results for each solution are shown in Table 5.7. Only the envelope label was selected, as both the lighting and HVAC systems were kept constant through all simulations and received a Level A for all cases in the prescriptive method. However, it is worth mentioning that the final label can be different from the envelope label once the lighting and HVAC systems are considered.

As mentioned in section 5.2.3, the base cases were designed according to envelope elements requirements for a Level "A" label from RTQ-C. Even so, the base case in Curitiba (Z1) was labelled as Level C, while São Paulo (Z3) and Teresina (Z7) received Level B. This could be explained because of a rather large WWR (40%), especially on the west façades, which contribute for the solar heat gains in tropical and subtropical regions buildings.

Table 5.7: RTQ-C label for the base case and the average optimal case for each city in the study

Case	**Label (envelope)**	**Shape**	**Orientation [deg]**	**Overhang**	**WWR [%]**	**Wall type**	**Roof type**	**Glazing type**	**Setpoint (heating / cooling)**	**COP**	**Heating [kWh/m^2-yr]**	**Cooling [kWh/m^2-yr]**	**LCC [$/floor area]**	**DH [%]**
Z1 (Curitiba)														
Base	C	R	0	0.75m	40	W5	R5	G2	20 / 24	4.65	1.5	6.7	**160.5**	**8.1**
S1	B	S	90	None	20	W1	R4	G1	19 / 26	4.84	0.6	4.4	**146.9**	**10.0**
S2	B	S	0	None	20	W1	R4	G1	22 / 25	4.84	3.1	6.2	**150.3**	**7.2**
S3	B	S	270	None	20	W5	R5	G1	22 / 23	4.70	2.7	7.0	**151.3**	**5.9**
S4	A	R	90	0.50m	20	W5	R5	G3	22 /23	4.70	2.4	11.6	**194.6**	**5.8**
S5	C	R	270	None	40	W6	R2	G3	22 /23	4.70	2.4	14.6	**240.0**	**5.7**
Z3 (São Paulo)														
Base	B	R	0	0.75m	40	W1	R2	G2	20 / 24	4.65	0.36	10.5	**168.1**	**8.7**
S1	B	S	180	None	20	W1	R5	G1	22 / 25	4.84	1.27	5.8	**150.2**	**7.3**
S2	B	R	90	None	20	W2	R4	G1	21 / 25	4.70	0.7	9.2	**161.4**	**7.1**
S3	B	R	270	None	20	W5	R5	G1	21 / 25	4.70	0.4	9.6	**171.4**	**6.7**
S4	A	R	270	1.00m	20	W6	R2	G3	21 / 25	4.70	0.3	9.9	**190.8**	**6.6**
S5	C	R	90	None	40	W5	R4	G3	22 / 25	4.70	0.8	11.4	**206.8**	**6.6**
Z7 (Teresina)														
Base	B	R	0	0.75m	40	W1	R2	G2	20 / 24	4.65	-	52.3	**207.2**	**10.3**
S1	A	S	270	1.25m	20	W1	R5	G1	19 / 25	4.84	-	39.8	**190.0**	**8.0**
S2	A	S	270	1.25m	20	W1	R4	G1	20 / 24	4.84	-	45.6	**194.3**	**6.5**
S3	A	L	0	1.25m	20	W2	R6	G3	18 /24	4.84	-	46.3	**219.6**	**6.5**
S4	C	R	90	None	40	W2	R4	G1	19 / 23	4.84	-	65.4	**243.7**	**6.4**
S5	E	R	90	None	60	W2	R4	G1	21 / 23	4.84	-	66.9	**255.8**	**6.5**

For Curitiba (Z1), there was an improvement from the base case label (Level C) in four of the five selected optimum cases. Solutions S1, S2, and S3 received a Level B label, while S4 was labelled as Level A, and S5 received Level C. Most of the optimized cases had a square shape (S1-S3). However, the best case (S4) is a rectangular-shaped building, just like the base case. The main observed difference from S4 to the rest of the cases regarding geometry is the presence of horizontal overhangs. This could have been determining for the best RTQ-C performance. Regarding the envelope properties, there was diverse types of wall, roof, and glazing. Insulated walls (W5-W6) and roofs (R4-R5) prevailed in the optimized cases. As for the glazing, a most efficient, double insulated glass (G3) was selected in the best case (S4). However simple glazing (G1) also appeared in three optimized models.

In São Paulo (Z3), most optimized cases (S1-S3) were labelled as Level B, following the base case. Like in Curitiba, there was only one Level A selected case (S4). However, there was a worse envelope performance in RTQ-C for case S5, which received a Level C. This probably occurred because of the large WWR (40%) and no shading element to block sunlight heat gains. Stull regarding geometry, only case S1 was a squared-shaped building. All other cases were rectangular buildings, like the base case. The best case (S4), like Curitiba, also had a shading device (1.00m horizontal overhangs) on the windows and a small WWR (20%). As for the envelope elements, there was not a clear pattern on types of wall, roof, and glazing. Walls with higher U-values (W1-W2) figured in S1, S2, and S3, while well-insulated walls (W5-W6) showed on cases S4-S6. Most optimized cases had simple glazing (G1), but the best case had a more efficient insulated glazing (G3).

In Teresina (Z7) results were slightly different from the other two cities. Most optimum cases (S1-S3) were labelled as Level A in RTQ-C. However, two cases had a worse performance from the base case. S4 presented a Level C, while S5 presented a Level E, indicating that even suitable solutions from the non-dominated cases can be deemed inappropriate for the Brazilian energy efficiency regulation. Regarding the geometry, the best cases were squared-shaped buildings (S1-S2), which indicates that more compact buildings have a better performance in tropical, hot regions. Also, cases S1-S3 had deep horizontal overhangs (1.25m) to protect the windows from direct solar radiation. The WWR for the best cases as 20%, while larger WWR values tend to lead to worst performance. As for the envelope elements, walls for all best cases were composed of simple elements (W1-W2), of clay or concrete blocks, while the roof were composed of well-insulated elements (R4-R5-R6). Simple (G1) or double insulated (G3) glazing can be used together with shading devices.

For the optimum cases geometry in the three cities, the WWR showed a value of 20%, indicating that large glazed facades are not recommended for either hot and subtropical climate regions, as solar heat gains through the glazing increase cooling loads and consequently the electricity consumption. For the best cases, the glazing type G3 is most indicated, for its energy efficiency, despite the higher cost per square meter. Should larger glazing area be desired, better performance windows and shading may be needed, which may add cost. A sensitivity analysis can be later conducted to determine if a more efficient glazing in larger WWR would be selected if market prices are reduced, for example.

Regarding the opaque elements, a well-insulated wall type (W5), composed of exterior tile, EPS insulation, concrete block and interior gypsum board, with a U-value of 0.72 W/m²-K is preferred for colder climate cities, like Curitiba (Z1) and São Paulo (Z3). For Teresina (Z7), a simple clay brick wall with exterior plaster and interior gypsum board (W1), with a U-value of 2.00 W/m²-K can be used. These results follow the work of Liang Wong and Krüger [32], where the RTQ-C technical requirements were compared with the European regulation. The authors stated that in Brazil the importance of U-values is significantly lower in warm climates than in colder climates.

As for the roof, it has a more significant impact on solar heat gains in medium-sized buildings. So, all best solutions presented in the case study should have well insulated roof elements composed of exterior pebble, waterproof membrane, EPS insulation, concrete slab and a gypsum board ceiling (R4-R5), with U-value of 0.79 and 0.58 W/m²-K, respectively. For all opaque elements, the solar absorptance was kept constant ($\alpha = 0.5$). However, as pointed out by Nakamura et al. [33], for a Level A label, RTQ-C requires lower α values, which can explain some cases presenting RTQ-C Levels B and C. The authors evaluated energy efficiency measures in conditioned buildings and found out that in some cases, higher solar absorptance values can result in more thermal comfortable buildings in some Brazilian climates.

The energy performance of the buildings can also be compared. For Curitiba (Z1), in most optimum cases there was an increase in annual heating and cooling electricity consumption compared to the base, with an increase from 1.5 to 3.1 kWh/m² in heating (S2) and from 6.7 to 14.6 kWh/m² in cooling (S5). The life-cycle cost (LCC) was reduced by up to 8.4% in S1, and thermal discomfort hours (DH) were reduced by up to 29% in S5. However, in S1, DH were 10% (23% more than the base case), mainly due to the high cooling setpoint of 26 ºC for the HVAC system. The best case (S4) presented a 28% reduction in DH, but a 21% increase in the

LCC. These intermediate values could be considered in the decision-making process during early stage design, should a more efficient solution be desired.

In São Paulo (Z3) there was an increase in heating consumption from 0.36 to 1.27 kWh/m² in S1, but a reduction to 0.3 kWh/m² in S4. Cooling demand was reduced in most cases, followed by a reduction in discomfort hours up to 24% in S4 and S5. LCC was reduced by 11% in S1 but increased by 23% in S5. The best case presented a 13% increase in LCC but with the lowest value for DH. In Teresina (Z7), there was no heating demand whatsoever in the simulations, as the city is in a tropical climate region. Cooling demand was reduced by 24% in S1 (52.3 to 39.8 kWh/m²) and increase by 28% in S5 (the worst case in terms of energy efficiency label). LCC was also reduced by 8% in S1, and DH was reduced by up to 37% in S4. The best cases S2 and S3, however, presented similar DH reduction, but with a Level A label in RTQ-C, and a reduction in LCC of 6% in S2.

The HVAC parameters of the optimum cases were also compared to those of the base cases. The system coefficient of performance (COP) defined by the MOGA procedure for the best solutions were higher than the base cases, 4.70 and 4.84 in Curitiba and São Paulo and 4.84 in Teresina. The HVAC heating and cooling setpoints in Curitiba can be highlighted. For the best case, having a 22 ºC / 23 ºC heating/cooling setpoint is not practical, as the mechanical system usually operates with a higher margin for turning on and off. For São Paulo, operating the HVAC with 21 ºC for heating and 25 ºC for cooling is a feasible situation in the best case (S4). In Teresina, as there is no heating demand, operating the cooling system with a 24 ºC or 25 ºC setpoint is also a possible solution.

From the results of Table 5.7, for the three analyzed cities, one can see that both objective functions of the optimum solutions were reduced from the base cases. As the Brazilian Regulation for Energy Efficiency Labeling of Commercial Buildings (RTQ-C) does not include life-cycle cost or thermal comfort analysis in its requirements, it would be interesting for future national codes to include these criteria for energy-efficient and sustainable building design. In this case study, there was an improvement in one out of five optimum cases in Curitiba (Z1) and São Paulo (Z3), labelled as Level A in RTQ-C, with lower discomfort hours but higher life-cycle costs. In Teresina, three optimized cases received a Leve A label, all with significant reduced DH and reduction in LCC in two of them.

5.5 Conclusion

In this chapter, a multi-objective genetic algorithm procedure was proposed to minimize two objective functions, life-cycle cost, and indoor thermal comfort. A case study was carried out to find optimal design alternatives for an office building in three Brazilian climatic regions and the results were compared with the current Brazilian energy efficiency regulation (RTQ-C). The optimization procedure using jEPlus+EA tool could be applied to improve energy efficiency and thermal comfort in office buildings located in different Brazilian climatic regions. The results indicated a clear trend in minimizing the two conflicting criteria with various parameters in early design stage.

When selecting optimal solutions from the Pareto front in the non-dominated compiled solutions, there was a significant reduction in indoor thermal discomfort (up to 37%), and in life-cycle cost of the building (up to 11%). Five optimal solution were selected as best cases from the Pareto fronts, and results were compared with the base cases for Curitiba, São Paulo, and Teresina. In Curitiba (Z1) and São Paulo (Z3), one out of five optimized cases presented an improvement in the RTQ-C label (Level A). In Teresina (Z7), three cases were labelled as Level A. With this case study, architects and engineers have enough data to make a well-informed decision. Depending on the professional and/or client needs, design, envelope, and system parameters can be chosen to their best interest.

This case study assessed the life-cycle cost and thermal comfort for the analyzed office building. RTQ-C regulation does not include these criteria, which are critical for energy efficiency and sustainable building design, especially in the early stages of the architectural process. This indicates a potential of the multi-objective genetic algorithm procedure to achieve higher energy efficiency and thermal comfort in different climatic regions of Brazil.

The current stage of this research focuses on the building envelope and some system parameters. Some uncertainties and limitations can be pointed out for future analysis. There are many variables involved in parametric studies such as this optimization procedure. A deep and careful sensitivity analysis mut be carried out to determine which variables and design parameters have more influence in the objective functions. A more holistic approach towards Life-cycle assessment can be drawn to include the buildings' environmental impact, as well as operating and demolition costs. Further studies should also be conducted to compare the potential of the proposed multi-objective genetic algorithm procedure in achieving energy efficiency and indoor environmental comfort for office or other types of buildings in different

Brazilian climatic regions for a later improvement of the current RTQ-C and RTQ-R regulations. The initial intention of this research was to conduct the optimization method to develop a procedure that architects can use to achieve more efficient and sustainable buildings. This procedure is summarized in the next discussion chapter.

5.6 References

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Chapter 6

Discussion

In building thermal energy performance simulation, optimization methods have been proven successful allies in the process since they allow the achievement of optimized solutions in the early design stage [1–5]. The Systematic Literature Review on the topic has shown that there are many well-justified, implemented cases in the area [4,6–9]. However, the technical difficulties experienced by architects is still one of the greatest hindrances to the best development of building performance simulation coupled with optimization methods, such as genetic algorithms. The basic training of these professionals does not include disciplines such as programming, statistical analysis, and in-depth knowledge in the areas of energy efficiency and environmental comfort [10].

Even so, over the last few years, increasing number of studies, and the availability of more friendly graphic have allowed the coupling of genetic algorithms to simulation tools, like jEPlus+EA, a tool used in this research [11]. From the literature review, the main objectives for optimization were identified, which were used in the validation and optimization procedure studies. Minimizing energy consumption, construction costs and thermal discomfort hours are crucial to guarantee high performance design, guided by the principles of sustainability.

The most used design variables were also identified as input data in the simulations. The variation of parameters such as geometry (shape, orientation), envelope (walls and roofs properties, window-to-wall ratio, types of glass, shading elements), and of the mechanical systems (machines efficiency, cooling and heating setpoints) configure the main elements that directly impact the thermal energy and economic performance of a building [12–18].

Despite the positive aspects of this procedure, its application in Brazilian regulations does not keep pace with the results obtained in academia. Several works point out that the current method of the Regulation for Energy Efficiency Labeling of Commercial Buildings (RTQ-C) has limitations to certify in fact the energy efficiency of an architectural design or construction. The new method proposed by PROCEL Edifica is certainly an improvement over the current method, since it considers annual and monthly consumption of primary energy, CO2 emissions and water saving potential [19–23].

On the other hand, the proposed method still does not consider the economic aspects of implementing the design strategies, life-cycle energy (LCE), life-cycle cost (LCC), or detailed parameters of environmental comfort. It was based on this aspect that this research was developed, aiming to present a procedure that takes these aspects into account and may in the future contribute to the improvement of the Brazilian energy efficiency regulation.

The validation study presented in Chapter 4 demonstrated that the application of the method with genetic algorithms reduced envelope initial construction cost, and the energy consumption during the building's life cycle. The study results allowed demonstrating the potential of GA as an optimization method in comparison with traditional design methods, using computer simulation in the early design stage, automating the process quickly and efficiently.

With the procedure presented in Chapter 5, the optimization results for three cities in different Brazilian bioclimatic zones were obtained. After three simulation runs to minimize the life cycle cost (LCC) and the discomfort hours (DH), there was a reduction of LCC by up to 11% in São Paulo and of DH by up to 37% in Teresina, when compared with the office buildings base models. The best selected cases were also compared with the base cases regarding the energy efficiency label from RTQ-C. In Curitiba (Z1) and São Paulo (Z3), one out of five optimized cases presented an improvement in the RTQ-C label (Level A). In Teresina (Z7), three cases were labelled as Level A. This demonstrated that an architectural project with different geometry, envelope and system characteristics can have the same or an improved classification in the Brazilian regulation, but the optimized cases showed a significant improvement in the performance criteria.

From this research, an outline of the optimization procedure proposed in the initial objectives of the work is presented below (Figure 6.1). The procedure starts in the early stage with the architect's design definition, with some pre-established parameters according to the specificity of the project. Energy efficiency and environmental comfort strategies must be established according to the climate region of the project, based on the literature and on current regulations. Then, computer simulation parameters such as occupancy profile, lighting systems, air conditioning and equipment must be defined. An initial simulation must be performed using EnergyPlus software.

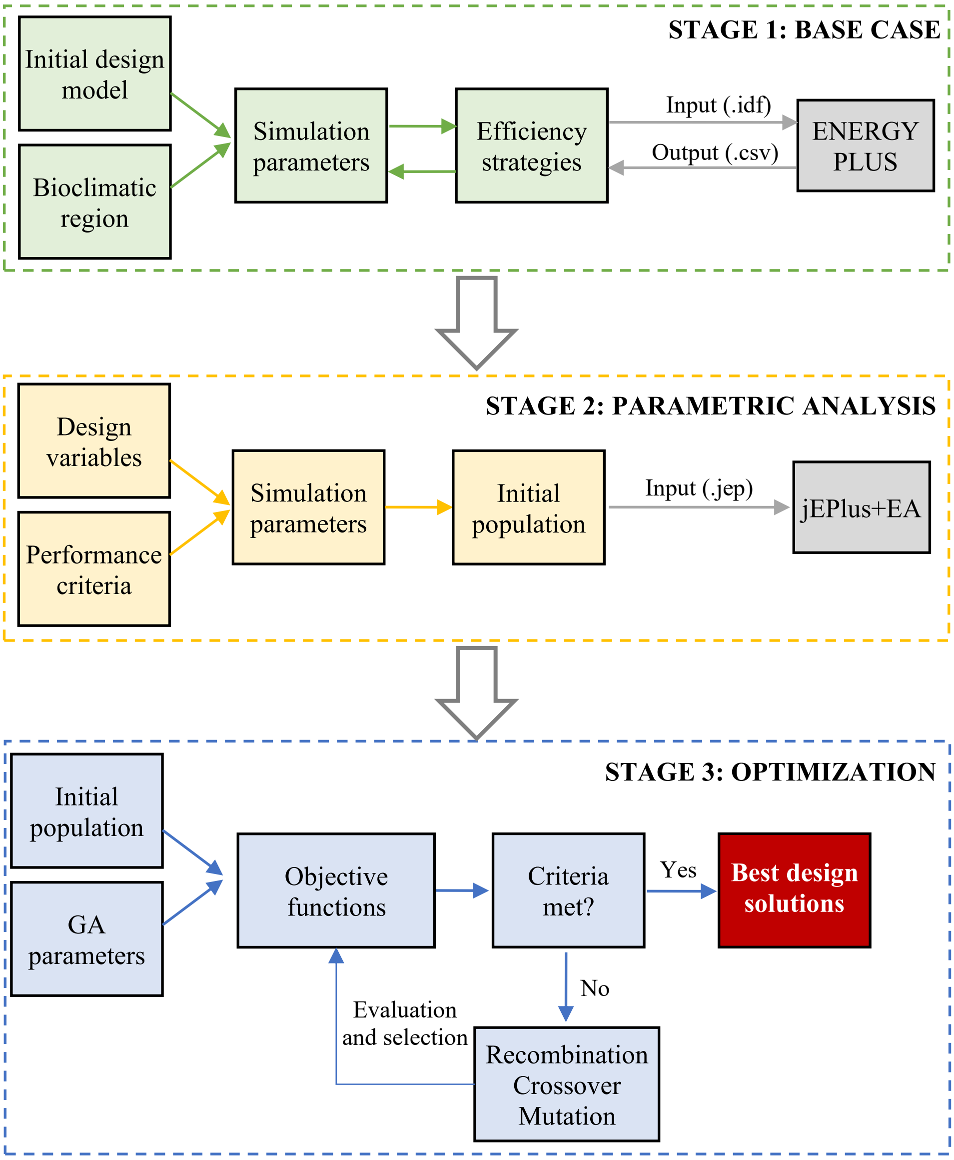

Figure 6.1: Outline of the proposed optimization procedure for achieving optimized design solutions

The second stage consists of defining the design variables that can be modified to obtain more efficient solutions, especially related to geometry (such as orientation and shape), envelope (types of wall, roof and glazing), and systems (lighting, mechanical, etc.). Thus, parametric analysis is defined in the jEPlus software. In the third stage, the optimization method with genetic algorithms is used in the extension jEPlus+EA from the parameters established in the interface for the NSGA-II method. Then the optimization objectives must be defined, such as energy consumption, thermal comfort, life-cycle analysis, among others, at the discretion of the professional and client.

The optimization must be run in at least three rounds so that the diversity and convergence of results is achieved. With the results of the procedure, it is expected to obtain the non-dominated solutions on the Pareto Front, i.e., feasible options for the initial design problem, where the decision-making process is based on pre-established criteria decided between professionals and clients.

This study reiterated the original hypothesis of the doctoral research, which states that in commercial buildings design, there are optimal solutions for conflicting objectives, such as thermal energy performance and cost analysis, which present both technical and economic viability to be applied in early stage design. Therefore, it is suggested, as future applications of this research, the integration of GA in future revisions of the RTQ-C regulation for commercial buildings, as well as in the regulation for residential buildings (RTQ-R).

Chapter 7

Conclusion

The concern with the thermal energy performance in buildings and the many variables involved in the decision-making process in the early stage design of an architectural project can lead to conflicting criteria such as energy consumption, construction costs and thermal comfort. Thus, this research aimed at evaluating the application of a method with genetic algorithms to find optimal solutions in the early stage design, based on performance criteria of commercial buildings. The exploratory research was based on a literature review to develop case studies, demonstrating the potential of the optimization method as a possible improvement for the current Brazilian energy efficiency regulation.

Based on the content covered in this doctoral thesis, it is possible to draw several conclusions in each chapter presented. In Chapter 3 a Systematic Literature Review was developed to analyze work on applications of genetic algorithms in energy efficiency and thermal comfort studies. Results showed that:

- The review returned 1186 documents that were carefully analyzed to find 115 relevant works for the study. There is a clear trend in interest growth in the field that demonstrated that the most used tools to couple building performance simulation with optimization methods are EnergyPlus and MATLAB software.
- With the papers' division into four main themes, besides concern with energy efficiency and thermal comfort, papers with life-cycle assessment and lighting use in buildings applications were also analyzed.
- From the study, future research may use genetic algorithms in early stage design considering reducing energy consumption, improving economic and environmental aspects as objectives, to find optimum solutions regarding building geometry, envelope, mechanical systems, and construction costs.

In the validation study presented in Chapter 4, the jEPlus+EA interface is used to find optimum solutions for a medium-rise office building model in São Paulo. The results demonstrated that:

- From the case study, 213 solutions were simulated, with seven possible optimal results. There was a reduction in initial construction cost of 6.7% in one solution, and life-cycle energy cost was reduced by 5.8% in other solution.

- For São Paulo, medium-rise office buildings can have different orientations, small window-to-wall ratio is more adequate, insulated flat roofs and simple brick wall materials.

- The used genetic algorithm method led to various possible solutions, when conflicting criteria are considered in early stage building design.

In Chapter 5, the optimization procedure used a similar method from the previous chapter to minimize life-cycle cost and thermal discomfort hours for an office building model in three cities from different Brazilian bioclimatic zones. With the study, it can be concluded that.

- The procedure using jEPlus+EA can be applied to improve energy efficiency and thermal comfort in a simplified way in early stage design.

- Results indicate a clear tendency in minimizing two conflicting objectives (life-cycle cost and discomfort hours). There was a significant reduction in indoor thermal discomfort (up to 37%), and in life-cycle cost of the building (up to 11%). In Curitiba and São Paulo, one optimized case presented an improvement in the RTQ-C label (Level A). In Teresina, three cases were labelled as Level A.

- Architects and engineers have enough data to make a well-informed decision, depending on the professional and/or client needs. However, a deep and careful sensitivity analysis mut be carried out to determine which variables and design parameters have more influence in the objective functions.

Future work recommendations

The use of optimization methods with genetic algorithms in building performance simulation is a complex, thought-provoking and challenging topic that must be further explored. Some developments of the research can be suggested as future works:

- Propose active and passive design strategies for all other Brazilian bioclimatic regions with a multicriteria optimization, such as energy consumption, environmental comfort, life-cycle analysis, among others.

- Perform simulations for other types of buildings, with more design parameters, as a way of comparing results with the current RTQ-C and RTQ-R regulations.

- Develop a computer tool with a more friendly graphical user interface, allowing architects to integrate genetic algorithms in their design process.

- Consider not only thermal comfort, but also lighting and acoustic aspects in the design process, according to Brazilian performance requirements.

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