Energy & Buildings 285 (2023) 112838

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Multi-objective optimization of the solar orientation of two residential multifamily buildings in south Brazil

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ARTICLE INFO

Article history:
Received 29 September 2022
Revised 8 January 2023
Accepted 28 January 2023
Available online 8 February 2023

Keywords:
Multi-objective optimization
Genetic algorithm
NSGA-II
Energy efficiency
Cooling demand
Heating demand
EnergyPlus
Python

ABSTRACT

The shape and orientation of a building influence the energy demand, therefore optimal decisions should only be made rigorously supported by energy evaluation programs, which allow for measuring the energy demand of a building more precisely. The main purpose of this research is to evaluate the shape and orientation of massive residential social housing multifamily buildings to find the best solar positioning to minimize cooling and heating demands simultaneously in the bioclimatic zone 2 (Cfa) in the southern region of Brazil. To do this, this study utilizes multi-objective optimization with a genetic algorithm (NSGA-II) simulating the thermal behavior in EnergyPlus and performing the optimization with a Python language programming code, totalizing 80,000 simulations. The main results showed that solar orientation optimization could reduce the total demand by 4% for the "H" shape and 22% for linear buildings in the isolated scenario. For the condominium condition, the reduction is 2% for the "H" typology and 8% for the linear shape. The results presented can help engineers and architects to design more energy-efficient buildings and address the energetic vulnerability in the same building. Moreover, future work can be carried out to improve the constructive pattern replicated all over the country, improving the surroundings.

1. Introduction

Rising energy prices, global economic pressures, and the effects of climate change are the main factors for the growth in energy poverty worldwide. Currently, 75 million people who have recently gained access to energy will not be able to pay for it [1]. Energy poverty means being deprived of essential services such as cooking, heating, or cooling at home and other subsidies for individual and collective development [2 –4].

The leading causes of high energy loads in homes derive from using ineffective air conditioning equipment (heating and/or cooling) that is not up to date, with little maintenance; inefficient household and lighting appliances; lack of thermal insulation; high level of infiltration by openings, but also by behavioral and cultural factors of society [5 –7].

To improve this scenario, energy efficiency measures are needed at a global level, thus reducing the impacts of energy poverty, achieving the proposed climate objectives, essential to increase the annual energy-intensity improvement rate from 1.9 % (2010 – 2019) to 3.2 %. Regarding social housing, there are 1 billion slums worldwide, formed by the increase in population in urban areas, lack of planning, lack of urban policies, and ineffective financing for the low-income population [8,9].

In this context, buildings accounted for 30 % of total final energy consumption and 15 % of greenhouse gas emissions in 2021. In the construction sector, there has been a growth of 0.5 % per year (since 2010) in emissions linked to an increase in energy demand. According to the World Energy Outlook 2022, the sector will present a 20 % increase in floor area by 2030, with 80 % in developing countries [1].

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https://doi.org/10.1016/j.enbuild.2023.112838
0378-7788/

Nomenclature

ANN	Artificial Neural Networks
ASHRAE	American Society of Heating, Refrigerating and Air- conditioning Engineers
BESOS	Building and Energy Simulation, Optimization and Surrogate-modeling
BPNN	Back Propagation Neural Network
BTO	Building Technologies Office
BZ	Bioclimatic Zone
CMA-ES	Covariance Matrix Adaptation Evolution Strategy
COP	Coefficient of Performance
DEAP	Distributed Evolutionary Algorithms in Python
DOE	U.S. Department of Energy's
EPPY	EnergyPlus and Python Library
EUI	Intensity of Energy Use
GA	Genetic Algorithm
GEATPY	Genetic and Evolutionary Algorithms toolbox for Python
GIS	Geographic Information Systems
GLSSVM	Group Least Square Support Vector Machine
GMDH	Grouped Method of Data Handling
GSPSO	Particle Swarm Optimization
HDE	Hybrid Differential Evolution
HVAC	Ventilation and Air Conditioning
HypE	Hypervolume-Based Many-Objective Optimization
INI-R	Inmetro Normative Instruction for the Classification of the Energy Efficiency of Residential Buildings
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LCE	Life Cycle Energy
LSSVM	Least Square Support Vector Machine
MOEA	Multi-objective Evolutionary Algorithms
MOGA	Multi-Objective Genetic Algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
MVHR	Mechanical Ventilation System with Heat Recovery
NBR	Brazilian Normative
NREL	National Renewable Energy Laboratory
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
NSGA-III	Non-Dominated Sorting Genetic Algorithm III
nZEB	Nearly Zero Energy Building
PCM	Phase Change Material
PYMOO	Multi-Objective Optimization in Python
RTQ-C	Brazilian Technical Quality Regulation for the Energy Efficiency Level of Commercial Buildings
RTQ-R	Brazilian Technical Quality Regulation for the Energy Efficiency Level of Residential Buildings
SPEA-2	Strength Pareto Evolutionary Algorithm – II
WWR	Window-to-Wall Ratio

Analyzing the Brazilian context, the country presents a housing deficit of almost 6 million homes in 2019, 75 % of which were for families with an income of up to 3 minimum wages [10]. Between 2010 and 2018, more than 1,500 million housing units were delivered throughout the national territory designated for these families [11]. These facts show that there is great interest by the scientific community in improving and adapting the reality of these homes, however, there is no thorough analysis of poverty and energy efficiency issues [12 –15].

Considering the breakdown of final electricity consumption in Brazil, the industrial sector consumes 37.4 %, residential buildings, 26.4 %, and commercial buildings, 15.7 %. That is, buildings consume 42.1 % of the energy generated by the country [16]. For the residential sector, electricity consumption is expected to increase by 3.9 % between 2018 and 2029 due to increased purchasing power and thermal comfort demands (primarily for cooling) [16,17]. Added to these factors, in the last five years, the country's electricity cost has risen by 47 % [18].

Even with a mostly renewable energy matrix of 78.1 % [16], the reality of social housing in Brazil needs to be improved. It can be highlighted that the performance regulations are less restrictive compared to the European ones, for instance. Most housing units use natural ventilation systems, where the user opens the windows without considering the outside temperature, either due to habit or to reduce mold and the feeling of claustrophobia. They are built out of masonry or concrete, using low-quality materials, and without thermal or acoustic insulation, with high-thermal transmittances, low-quality windows, significant infiltration problems, even of rainwater, and simple glazing, but more expressively replicating an architectural model without considering the climatic conditions and generally built by unskilled labor [14,19 –24].

In this scenario, improving social housing quality is needed, in terms of thermal comfort and performance, to overcome energy poverty and reduce the impacts of climate change [7,21,25,26]. Moreover, several governmental, economic, cultural, technological, and market barriers exist, and a lack of specialized professionals is observed [5,27]. Searching for low-cost energy demand optimization strategies according to the climate, considering the construction of mass housing adapted to the country's reality, is a way to demonstrate and encourage the replication of these tactics.

1.1. Optimization inserted into the urban context

The concern for energy consumption in buildings is highly linked to its surroundings. Thus, several researchers have sought to improve the urban context from the energy point of view. Studies by Rode et al. (2014), Zucker et al. (2016), Salvati, Coch and Morganti (2017) and De Luca and Dogan (2019) aim to present data and methods for improving energy efficiency from the urban level, presenting guidelines for urban planners, architects, governments, and decision-makers.

Furthermore, the studies mentioned above present strategies to access and improve solar radiation, shape the urban fabric and improve outdoor comfort. They also indicate that compact and vertical urban contexts have better energy performance than more sparse typologies [28 –31]. Taking into account the need for solar incidence, the reviews by Allegrini et al. (2015) and Shi et al. (2016) reinforce the importance of optimizing urban forms designed for their energy performance [32,33].

When evaluating the scale of the building, the main design variables that determine the performance are the shape, transparent surface, orientation, and the properties of the materials, as the previous researchers outline the characteristics of the urban space in which it is inserted. Passive solar strategies are a preferred option in the initial phases of the project, considering the main benefits of reducing the demand for conditioning and lighting and configuring a low-cost approach. Moreover, coordinating the site and climate is essential to achieve these benefits [34,35].

Thus, several studies have analyzed the performance of buildings without the urban context, as common practice in the academic field. Few studies have predicted the building's energy performance, comparing it in an isolated and urban context, such as Pisello et al. (2012), Samuelson et al. (2016), Han et al. (2017), Lima, Scalco and Lamberts (2019) and Jayaweera, Rajapaksha and Manthilake (2021).

1.2. Multi-objective evolutionary algorithms

In this context, one of the biggest challenges when simulating the energy behavior of buildings is to automate, parameterize and optimize conflicting objectives involved in the project. For this reason, there is a trend in multi-objective research that seeks alternatives that minimize thermal discomfort, energy consumption, and demand, in addition to costs, LCE, and LCC. In this new field of investigation, artificial intelligence has been an ally of researchers, reducing processing times and significantly increasing the number of iterations between variables [36,37,46 –51,38 –45].

The search for strategies with fast data convergence has expanded the investigation of methods that prioritize the performance of the optimal confluence curve in fewer solutions. According to Deb et al. (2002), there is a set of efficient multi-objective solutions for each numerical problem called the Pareto Front. Thus, multi-objective optimization methods or multi-objective evolutionary algorithms (MOEA) mainly aim to minimize the distance between the non-dominated front and the Pareto optimal front, finding various solutions for a given problem. This approach is used in problems with two or more conflicting objective functions, which can be minimized or maximized according to what is intended with the analysis [52].

GAs are based on natural selection and adaptation, miming biological evolution. As in genetics, these algorithms can cross information (genes), combine, and mutate them to deliver diverse solutions. Due to the elitist taxonomy, it accelerates the convergence of results and is an excellent solution to engineering problems [43].

Due to this, several types of research were carried out using MOEA to minimize the impacts of global warming, improve energy efficiency and user comfort, meet the new stricter regulations, such as nZEB requirements, and analyze the cost of optimized solutions and the life cycle. In this context, Table 1 summarizes the most current related articles that perform multi-objective analysis allied to GA.

As observed in the literature, among the most used MOEAs, the NSGA-II, proposed by Deb et al. (2002), is widely replicated in studies and has other versions and variants. It is best suited for solving multi-objective optimization problems of an architectural and engineering nature. This algorithm uses crowding distance, which means it seeks the convergence of the fittest genes after the first random generation [40,52,95].

The Asian continent was the most studied and continues to update and demonstrate parameters to improve its buildings. In the existing literature, several climatic contexts were analyzed, showing the concern of researchers regarding the use of tools, strategies, and systems allied to the climatic context, as well as the need to evaluate conflicting objectives to achieve the desired performance.

The main energy simulation engine used is the Energyplus software developed by the U.S. Department of Energy's (DOE), Building Technologies Office (BTO) and managed by the National Renewable Energy Laboratory (NREL). The optimization tools vary among different software, in which Matlab is the most replicated in the studies. The Python programming language appears as a trend in studies and has been gaining strength as an optimization engine used in collaboration with specific libraries.

The trend of current publications is to analyze multiple variables, showing that the studies use from 4 to 54 different optimization features in the same research, usually linked to the geometry, envelope, systems, and facilities of the building, and common practice is to optimize them without the surroundings. In 22 articles, solar orientation was analyzed as a variable. The evaluation of the solar orientation in conjunction with the shape of the building was carried out in 7 studies [6,53,76 –78,84,93]. However, the study by Yan, Ji, and Yan (2022) analyzes two building models considered archetypes (point and slab block buildings with 18 floors), developed by the Housing and Development Board of Singapore. All other papers cited optimize a generic form.

As seen from the literature results, there is no trend for the best solar orientation that varies even within a similar climatic context. The main findings of the multifamily building optimizations, in an isolated scenario, to the Cfa climate, are the following orientations: Milan 90°, Florianópolis 292.50°, Guangzhou 14° and to Hong Kong 201°; 5° and 358° [6,80,82,89,90].

It depends on the constructive pattern, shape and precepts of the building use. Regarding the analysis in isolated scenarios, this work corroborates the evidence of other authors of not neglecting the immediate/urban surroundings of the building being studied to optimize energy efficiency [96 –100]. Considering the enormous replication of large residential condominiums in Brazil, the energetic evaluation has to be performed taking into account the surroundings.

Among these, the studies by Shadram and Mukkavaara (2019) and Ciardiello et al. (2020) analyzed the multifamily building with an "H" shape, using multi-objective evaluation to optimize heating, cooling and total energy demand and embodied and operational energy, respectively.

Research by Chen et al. (2017), Li et al. (2018), Lima et al. (2019), Jayaweera, Rajapaksha, and Manthilake (2021) and Chen et al. (2022) addressed an urban context. Only the study of Li et al. (2018) analyzed residential multifamily with the assistance of GA. Lima et al. (2019) explored the cooling thermal load for office buildings, decomposing by floors and with and without surroundings, with parametric simulations and without multiobjective analysis. None of the research compares the impact of heating and cooling demand for each apartment separately or in the context of large and massive residential condominiums.

The simultaneous minimization of heating and cooling, as two conflicting objectives, is necessary for the climatic context under study, which is predominantly cold [101], making it more challenging to optimize the building with strategies that are only addressed to a season of the year. Likewise, as a climate trend, optimizing cooling to avoid using ventilation and air conditioning systems (HVAC) as a consequence of climate change. These objective functions were investigated by Chen et al. (2019) and Ciardiello et al. (2020), analyzing multifamily buildings, focusing on energy improvements, and no work aims to present energy vulnerability individually.

1.2.1. Brazilian context

In the Brazilian context, optimizations using GA are still recent. Most studies optimize the degree of heating and cooling hours, as in Santana et al. (2016), Fonseca et al. (2017), Linczuc (2020), Linczuc and Bastos (2020) and Berleze, Brasileiro and Silvoso (2021).

They use generative modeling to achieve energy efficiency level A according to the Brazilian Technical Quality Regulation for the Energy Efficiency Level of Commercial Buildings (RTQ-C) [102]. Optimizing an office building reduces initial costs by 6.7 % in one solution and a 1.3 % increase in LCE [103]. Minimizing the annual energy consumption and the constructive cost of a hypothetical office building achieved 50 % energy savings with a return on investment of fewer than three years [6].

A few studies were carried out to evaluate single-family houses in the southern part of Brazil. Dalbem et al. (2019) and Vettorazzi et al. (2021) aimed to meet the rigorous Passivhaus standard. Both studies showed a significant decrease in energy demand and dis-

Table 1
Multi-objective Optimization with GA studies.

Reference	GA	Typology	Case Study	Location	Simulation Tool	Optimization Tool	Variables	Objectives Functions
[53]	NSGA-II	RMF	HB	Singapore (Af)	Rhino + grasshopper/Ladybug + Honeybee	Python + N/a	2 shapes, orientation + 16 variables	Daylight performance, energy efficiency, and thermal comfort
[54]	GMDH (ANN) + NSGA-II	RMF	HB	Yazd (BWh), Tehran (BSk), Tabriz (BSk), Rasht (Cfa), Bandar Abbas (BWh), Iran	EnergyPlus	–	4 variables	Payback period and the predicted percentage dissatisfied
[55]	GLSSVM + NSGA-II	I	RB	Kjevik, Norway (Cfb)	IDA ICE	Dynamo	17 variables	Energy consumption and thermal comfort
[56]	BPNN – MOEA/E, NSGA-II and NSGA-III	O	RB	Qingdao, China (Cwa)	EnergyPlus	Python + PYMOO toolkit	Orientation + 27 variables	Carbon emissions, discomfort hours and global cost
[57]	NSGA-II + ANN	I	RB	Guangzhou, China	Grasshopper	Python + Geatpy	Orientation + 29 variables	Energy, thermal comfort and daylighting
[58]	ANN, NSGA-II and MOPSO	I	HB	Nanjing, China (Cfa)	EnergyPlus	Python + N/a	22 variables	Daylighting, thermal comfort, energy savings and economy
[59]	NSGA-II	I	RB	Tianjin, China (Dwa)	EnergyPlus	Python + N/a	13 variables	Improve energy efficiency and thermal comfort
[60]	LSSVM – NSGA-II	I	RB	Wuhan, China (Cfa)	DesignBuilder, EnergyPlus	MATLAB	6 variables	Energy consumption and indoor thermal comfort
[61]	NSGA-II	RSF	HB	Niš, Serbia (Cfb)	DesignBuilder, EnergyPlus	DesigBuilder	7 variables	Improve energy efficiency and thermal comfort
[62]	NSGA-II, MOPSO, MOGA + ANN	RSF	HB	Marrakech, Morocco (Csa)	TRNSYS	MATLAB	7 variables	Improve thermal comfort and energy performance
[63]	NSGA-II	RMF	HB	Agadir (Bsh), Tangier (Csa), Fez (Csa), Ifrane (Csb), Marrakech (Bsh) and Errachidia (BWh), Morroco	TRNSYS	MOBO	Orientation + 8 variables	LCC, energy saving, and thermal comfort
[64]	NSGA-II	RSF	RB	Darwin (Aw), Alice Springs (BWh), Brisbane (CfaB), Perth (Csa), Sydney (CsaS), Mildura (Bsk), Melbourne (CfbM) and Hobart (CfbH),	TRNSYS and Daysim	jEPlus + EA and Python + N/a	9 variables	Thermal discomfort hours, unsatisfied daylight hours, and LCC

Table 1 (*continued*)

Reference	GA	Typology	Case Study	Location	Simulation Tool	Optimization Tool	Variables	Objectives Functions
				Australia				
[65]	NSGA-II	–	HB	Boston, USA (Dfa)	EnergyPlus	jEplus + EA	Orientation + 4 variables	Energy consumption for annual heating, cooling, and electric lighting
[66]	NSGA-II	RMF	RB	Osmaniye (Csa) and Erzurum (Dfb), Turkey	EnergyPlus	MATLAB	Orientation + 7 variables	Thermal energy and investment cost
[67]	NSGA-II	RMF	RB	Hanzhong (Cwa), Chengdu (Cfa), Wuhan (Cfa), Changsha (Cfa), Xinyang (Cfa), Yichang (Cfa), Chongqing (Cfa), Shaoguan (Cfa), China	EnergyPlus	Python + N/a	Orientation + 13 variables	EUI for heating and cooling, thermal discomfort rate, and LCC
[68]	CMA-ES and HDE	RSF	HB	Bento Gonçalves (Cfb), Santa Maria (Cfa) and Florianopólis (Cfa), Brazil	EnergyPlus	MATLAB	4 variables	Energy demand and thermal discomfort
[69]	HypE	RSF	HB	Chapecó (Cfa), Brazil	EnergyPlus + Archsim	Octopus	Window orientation + 12 variables	Degrees of hours of cooling and heating
[70]	NSGA-II + ANN	RMF	HB	South Korea (Dwa to Cfa)	TRNSYS	MATLAB	12 variables	Building energy demand, LCA and LCC
[71]	HypE	RMF	HB	Budapest, Hungary (Dfb)	Rhinoceros3D Grasshopper EnergyPlus	Ladybug&Honeybee – Octupus	Number of floors, building width + 12 variables	Embodied and operational impact
[72]	aNSGA-II	RMF	HB	Roma, Italy (Csa)	EnergyPlus	Python + Eppy	11 variables	Investment cost, energy cost, energy demand and CO_2 emissions
[73])	aNSGA-II	RMF	HB	19 different cities	EnergyPlus	Python + Eppy	11 variables	CO_2 emission, annual energy costs, and energy retrofit costs.
[74]	NSGA-II	O	RB	Hohhot (Cfa), Tianjin (Dwa), Shangai (Cfa), Guangzhou (Cfa), China	DesignBuilder	jEPlus + EA	Orientation + 9 variables	Heating, cooling, lighting energy consumption and discomfort hours
[75]	NSGA-II	–	HB	Curitiba, Brazil (Cfb)	EnergyPlus	JEPlus + EA	Orientation + 6 variables	Degrees of hours of cooling and heating
[76]	aNSGA-II	RMF	HB	Roma, Italy (Csa)	EnergyPlus	Python + Eppy	(Phase I): Shape, shape proportion, orientation + 5 variables	Total energy demand, heating and cooling demand
[77]	NSGA-II	O	HB	Athens,	Rhino and Grasshopper software via the	modeFRONTIER	4 shapes + 4	Energy

(continued on next page)

Table 1 (*continued*)

Reference	GA	Typology	Case Study	Location	Simulation Tool	Optimization Tool	Variables	Objectives Functions
				Greece (Csa)	plugins Honeybee and Ladybug EnergyPlus		orientations + 5 variables	demand, energy production and adaptive thermal comfort
[78]	SPEA-2 and HypE	RMF	HB	Stockholm, Sweden (Dfb)	Grasshopper, EnergyPlus, Honeybee,	Octopus	rectangular, H, U, L, T and cross shapes, orientation + 10 variables	Embodied and operational energy
[79]	NSGA-II	RSF	HB	Singapore (Af)	EnergyPlus	JEPlus + EA	Phase I: Orientation + 8 variables – Phase II: 4 variables	Phase I: thermal discomfort rate and daylighting ineffective time. Phase II: LCC and energy consumption
[80]	Variant of NSGA-II	RMF	HB	Palermo (Csa), Naples (Csa), Florence (Csa) and Milan (Cfa), Italy	EnergyPlus	MATLAB	Orientation + 15 variables	Primary energy consumption, energy-related global cost and discomfort hours
[81]	Variant of NSGA-II	RSF	RB	Naples (Csa), Italy and Athens (Csa), Greece	EnergyPlus	MATLAB	9 variables	Global cost and primary energy consumption
[82]	NSGA-II e GPSPSO	RMF	HB	Hong Kong, China (Cfa)	EnergyPlus	jEPlus, GenOpt	Orientation + 10 variables	Heating, cooling and lighting demand
[83]	NSGA-II	RSF	HB	Québec, Canada (Dfb)	–	Phyton + DEAP	39 variables	LCC, greenhouse gases emissions and the thermal discomfort
[84]	MOGA	O	HB	Milan, Italy (Cfa)	EnergyPlus	MATLAB	Orientation + 53 variables	Primary energy consumption, global cost and CO_2-eq emissions
[6]	PAES	–	HB	Curitiba (Cfb), Florianópolis (Cfa), Campo Grande (Aw) and Belém (Af), Brazil	EnergyPlus	Python + N/a	Shape of a module (array), orientation + 6 variables	Energy consumption and constructive cost
[85]	CMA-ES and HDE	RSF	HB	Curitiba (Cfb), Santa Maria (Cfa) and Florianopólis (Cfa), Brazil	EnergyPlus	–	4 variables	Heating demand and degree-hours of cooling
[86]	GA	O	HB	Beijing (Dwa), Shangai (Cfa) and Guangzhou (Cfa), China	Radiance + DesignBuilder	MATLAB	Rectangle, L-shaped, H-shaped, U-shaped, cross, *T*-shaped and trapezoidal + 11 variables	Building proportion, daylight and energy consumption
[87]	NSGA-II	RMF	HB	Embrun (Dfb), La Rochelle (Cfb), Nice (Csb), Nancy	TRNSYS	MOBO	14 variables	Thermal, electrical demands and LCC

Table 1 (*continued*)

Reference	GA	Typology	Case Study	Location	Simulation Tool	Optimization Tool	Variables	Objectives Functions
				(Cfb) and Limoges (Cfb), France. Beirut (Csa), Qartaba (Csb), Zahle (Csa), Cedars (Cfa), Lebanon				
[88]	NSGA-II + ANN	RMF	HB	Shanghai, China (Cfa)	EnergyPlus	jEPlus	Orientation + 19 variables	Comfort Time Ratio and Energy Demand
[89]	NSGA-II	RMF	HB	Hong Kong (Cfa), Guangzhou (Cfa), China. Taipei (Cfa), Taiwan. Bangkok (Aw), Thailand. Singapore (Af).	EnergyPlus	jEPlus + EA	Orientation + 6 variables	Lighting and cooling energy consumption
[90]	NSGA-II	RMF	HB	Hong Kong, China (Cfa)	EnergyPlus	jEPlus + EA	Orientation + 9 variables	Lighting energy and cooling energy
[91]	NSGA-II	RSF	RB	Paraná, Argentina (Cfa)	EnergyPlus	Python	Orientation + 6 variables	Comfort of naturally ventilated rooms and energy consumption in air-conditioned rooms
[92]	SPEA-2 and HypE	RSF	HB	Viçosa, Brazil (Cwa)	Rhino + Grasshoper + Archsim + EnergyPlus	Octopus	8 variables	Degrees of hours of cooling and heating and cost
[93]	NSGA-II + ANN	O	HB	Naples, Italy (Csa)	EnergyPlus	MATLAB	Orientation + 47 variables	Energy consumption, thermal discomfort hours and global cost for energy
[94]	Variant of NSGA-II	I	RB	Benevento, Italy (Csa)	EnergyPlus	MATLAB	10 variables	St1: discomfort hours, heating and cooling demands/St2: investment cost, primary energy consumption and LCC

RMF: Residential multifamily; RSF: Residential single-family; O: Office building; I: Institutional building.
RB: Real Building; HB: Hypothetical building.

comfort hours, with an increase of 40 % in the total construction cost [68,85].

1.3. Research aim and contribution

As observed in the literature, there is a research gap regarding energy vulnerability within the same building and a lack of analysis of the energy performance of a building connected to its urban context [28,31,97 –100,104], which can directly impact the cooling demand, essential to meet the increase with the current scenario. Optimization of heating demand, without neglecting cooling in colder climates, entails reducing the intensity of use of air conditioning for cooling [17].

Therefore, as mentioned above, this study aims to optimize two multifamily building shapes using the Python programming language, combined with NSGA-II as an optimization tool and coupled with EnergyPlus to find the optimal solar orientation to minimize cooling and heating demand simultaneously to the representative city of Passo Fundo, Brazil (Cfa).

Furthermore, studies regarding energy performance are well established in the academic field, and the novelty of this study is characterized by gaps revealed throughout this study and by reviewing the publications presented so far, as follows:

The analysis of two scenarios (isolated and condominium) to compare how the shadows of the surroundings can impact the demand of the building was studied allied to multi-objective analysis and using GA.

A comparison was made between two architectural typologies of the multifamily building.

Unlike previous works, the optimization of only one variable was performed to reduce computational costs and present a friendly tool to architects, engineers and stakeholders.

The energy demand was shown in the building regarding the apartment positioning.

This study implements and evaluates the presented multi-objective optimization framework in the case study buildings based on real models replicated all around the country.

The most significant contribution of this research is that it is viable for use by architecture, engineering and construction firms, in which the framework is developed in open access software. It also presents relevant data on the potential for improving Brazilian social housing.

As a motivation to carry out the study, the demands were verified and highlighted separately for each apartment, and energy discrimination within the same building was discussed, highlighting energy vulnerability as a way of facing the consequences of energy poverty and climate change.

2. Materials and methods

This study uses a computer simulation and the NSGA-II algorithm for optimization as a research strategy. EnergyPlus (version 9.0.1), validated by ANSI/ASHRAE Standard 140 [105], meets the criteria established by NBR 15575 [106] and Inmetro Normative Instruction for Classifying the Energy Efficiency of Residential Buildings – INI-R [107] was used as thermal energy engine calculation software and the Python programming language coupled to the Jupyter Lab interface as an optimization tool. The modeling was carried out in Sketchup using the Euclid plugin (Version 0.9.4.1) that transfers all the constructive and geometric information of the model to the EnergyPlus. All the pieces of software used are open source.

This article presents the problem of how to solve heating without neglecting cooling by optimizing solar orientation. Considering the analyses carried out, it can be observed that it is important to consider both parameters when designing a building. Moreover, solar orientation is one of the easiest and cheapest strategies to make the most of the existing solar radiation to improve the heating and comfort of residential social housing multifamily in the cold climate in the south of Brazil.

This research recreates the context of the chosen typologies, simulating the thermal behavior of two residential social housing multifamily buildings with different geometric shapes in the climatic context of the city of Passo Fundo, bioclimatic zone 2 (BZ2 and Cfa, Brazil). The optimal solar orientation was sought that simultaneously reduced the cooling and heating thermal demand in the isolated and condominium scenarios and presented the thermal load of energy per apartment, separately. Fig. 1 shows the research framework.

The research framework is proposed in 3 main steps. Initially, the typologies to be studied were selected according to the analysis carried out by Triana, Lamberts and Sassi (2015), establishing the two typologies of multifamily social housing buildings most replicated in Brazil [108]. Next, the climatic context was selected to simulate the energy demand.

As observed in the literature, there are few studies on multi-objective optimization for buildings in an "H" shape and several for the linear typology (most common in Europe) and no research on multifamily buildings in the Brazilian context. This analysis is important because these building shapes are replicated in the country without considering each region's climatic conditions. The Brazilian climate is predominantly hot, making it clear that the particularity of each location needs to be analyzed. For this purpose, this work is applied to a case study in the cold region of the country [15].

2.1. Description of case studies

The two evaluated buildings belong to the Brazilian social housing program, designed for target audience 1 (families with income up to 1.8 thousand reais), and were designed for the BZ2. Both cases consist of a kitchen, bathroom, living room, and two bedrooms (single and double), and are part of a housing complex of more buildings. Both buildings were constructively modified for this experiment and are models based on existing constructions but without in situ measurements.

The "H" shape is a five-story building with four apartments per floor. The useful interior area is 37.05 m^2 and the balcony is 3.00 m^2, totalizing 1,011.25 m^2 of the built space. The linear edification has two stair cores and each apartment has a useful floor area of 36.95 m^2 totalizing 1,010.50 m^2 of built area. Both shapes do not have solar protection on the façades or windows.

The building shape and the constructive characteristics directly affect the thermal exchange between the interior and exterior. To describe the shape of a building and its consequences on thermal behavior, the shape coefficient is used to demonstrate the relationship between the external envelope and the volume of the building as presented in Eq. (1) [109].

$$Sc = \frac{se}{vt} \tag{1}$$

Where S_e is the total envelope surface (façades and roof) and V_t is the total volume of the building.

2.2. Climatic context

The study is applied to Passo Fundo, in southern Brazil. The city belongs to BZ2, as the NBR 15220 classification, which divides the Brazilian territory into eight different bioclimatic zones [101]. Regarding the Köppen-Geiger classification, the city is classified as Cfa climate [110]. As in the studies of Bre and Fchinotti (2017); Chen et al. (2018); Gou et al. (2018); Chen et al. (2019); Dalbem et al. (2019); Vettorazzi et al. (2021); Berleze et al. (2021); Jung et al. (2021).

The city is located at an altitude of 687 m above sea level and has well-defined seasons. Negative temperatures may be reached on winter nights. It has sparse rainfall and a large temperature range during the day and night. The predominant direction of the winds is northeast. Table 2 presents the respective climatic data.

This context was chosen by the representativeness demonstrated by Linczuc (2020), who carried out a cluster analysis, evaluating 5 climatic variables from 71 cities of the 3 southern states of Brazil (Rio Grande do Sul, Santa Catarina and Paraná). The evaluation demonstrated that Passo Fundo represents 19 cities of the southern climatic context [111].

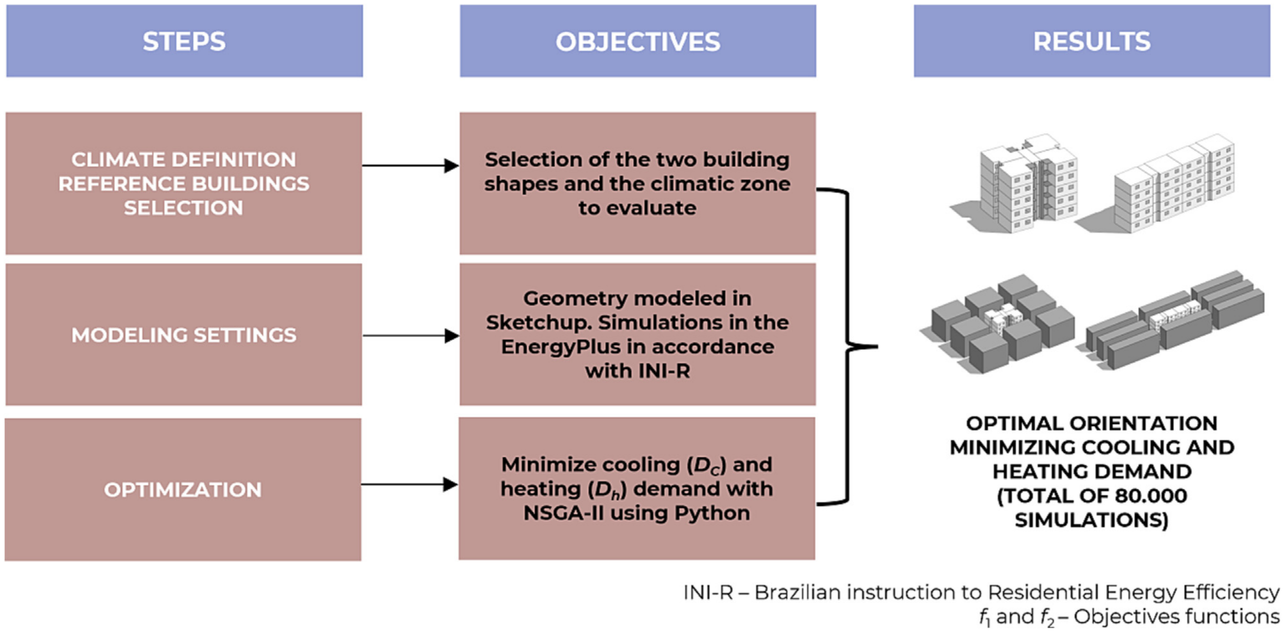


Fig. 1. Research framework.

Table 2
Normal Climate of Passo Fundo –1981 to 2010.

Month	Average temp. (°C)	Relative Humidity (%)	Precipitation (mm)	Wind (m/s)	Insolation (h)
Jan	22.2	72.6	159.7	3.9	236.9
Feb	21.7	75.6	140.9	3.9	203.5
Mar	20.7	74.5	121.5	3.8	213.3
Apr	18.0	73.1	138.9	3.8	189.1
May	14.8	75.9	159.4	3.8	177.1
Jun	13.1	78.2	148.0	4.0	146.0
Jul	12.4	76.4	180.9	4.2	169.8
Aug	14.1	71.7	137.9	4.3	173.8
Sept	15.1	72.2	174.3	4.5	166.1
Oct	18.0	71.4	225.0	4.3	186.9
Nov	20.0	66.3	158.8	4.2	229.2
Dec	21.8	66.5	162.2	4.1	250.1
Year	17.7	72.9	1,907.5	4.1	2,341.8

2.3. Modeling and settings for simulation and optimization

The modeling of the buildings was performed in Sketchup 2017. The simulation setups were run in EnergyPlus, with a simulation timestep of 4 simulations per hour. According to INI-R guidelines (still in the probationary period), NBR 15575 was for transmittance values and NBR 15220 for the physical properties of materials [101,106,107]. The FullExterior object of EnergyPlus, was configured taking into account the effect of shadows. Fig. 2 summarizes the setting and definitions of the shape and orientation optimizations.

The optimizations of the two architectural typologies are performed in the isolated and condominium scenarios. Using the Python programming language, the NSGA-II optimization codes were executed, supported by the Jupyter lab interface, and associated with the Building and Energy Simulation, Optimization and Surrogate-modeling (BESOS) platform developed by the University of Concordia in Canada, as proposed in the research conducted by Leitzke (2021) [112]. Table 3 shows the range of variability of the optimization variable.

As a decision-making criterion, a Python code was used to add the result of Pareto points to find the optimal solution, the one with the lowest total demand for heating and cooling, according to Nguyen, Reiter and Rigo (2014), Ascione et al. (2019), Bre and Fachinotti (2018) and as cited in Costa-Carrapiço, Raslan and González (2021), as the main decision criterion of the articles studied in the review.

All optimizations were executed in a 2-core laptop with an Intel Core i7-4500U processor of 1.8 GHz, with 16 GB of RAM and a Windows 10 operating system of 64bits.

2.3.1. Internal loads

As a simulation strategy, to standardize the models, the thermal zones were simplified in apartments, due to the robustness of the optimizations and unlike the INI-R that distinguishes the zone of long-term occupation (bedroom and living room) [107]. Thus, the solar orientation can be found more easily.

The conditions of occupancy (people and schedule) and metabolic rate were adapted from the INI-R, as well as the lighting system and its agenda, and internal load density. INI-R does not differentiate workdays, weekends, summer, or winter for these agendas [107]. Table 4 presents the occupancy schedule.

The lighting schedule is shown in Table 5.

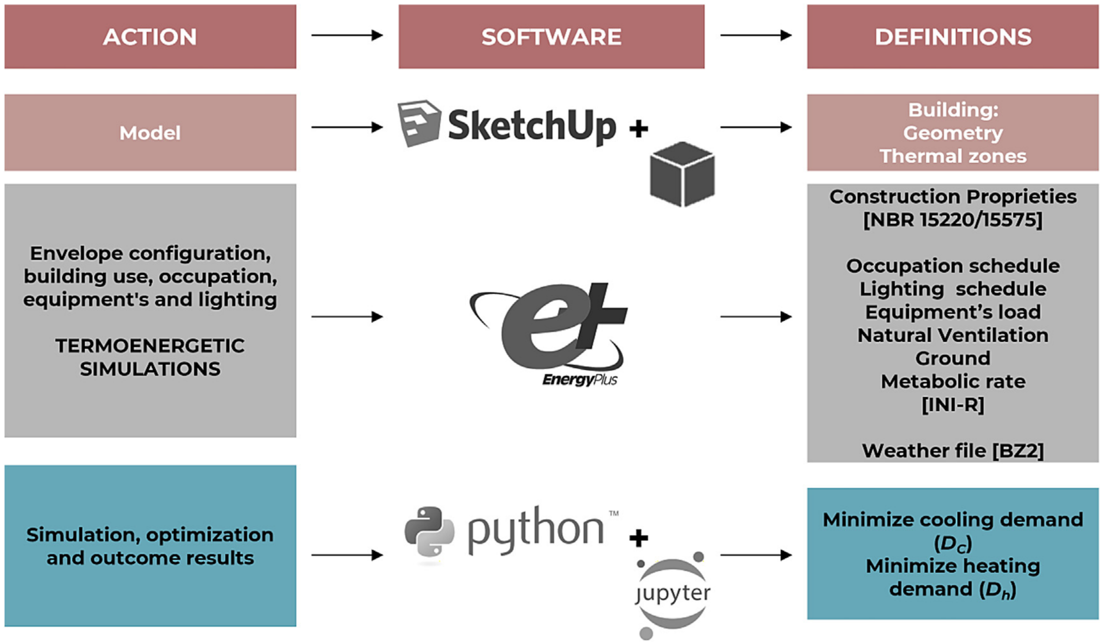


Fig. 2. Settings of the environment and shape optimizations.

Table 3
Range of variability of the optimization.

Variable	EnergyPlus (field name)	Range of variability
Orientation	North Axis	0° to 360°

Regarding the metabolic rate, the average between the living room (sitting or watching TV – 108 W) and the bedrooms (sleeping or resting – 81 W) per unit of area was used, totalizing the metabolic rate of 94.5 W total heat [107,113]. Moreover, 4 persons per apartment were stipulated. As defined by the INI-R, the installed lighting power density adopted was 5.0 W/m^2, and the internal load density adopted the power of 120 W, which was used between 2 pm and 10 pm.

2.3.2. Constructive parameters

NBR 15575 defines a minimum performance value according to the 8 bioclimatic zones of the country [106]. The building envelope's thermal configuration was established with the limits recommended by the NBR 15220 [101] for their material and physical proprieties and the NBR 15575 [114,115] observing thermal transmittance, thermal absorptance, and thermal capacity, as presented in Table 6.

For the configuration of the external wall, a calculation of the equivalent thickness of the red clay ceramic brick of 6 holes was made as the EnergyPlus considers that all components are constituted by layers transverse to the heat flow, disregarding the calculation of thermal resistance in parallel. To resolve this matter, Ordenes et al. (2003) calculation method was used for the construction model of an equivalent component that takes into account the heat fluxes through transverse layers for the correct insertion in the software [116]. Table 7 presents the characteristics of the opaque envelope of the buildings (exterior walls and roofs).

Regarding the translucid envelope, the windows comprise single glazing of 3 mm, with a solar transmittance factor of 0.837 and thermal transmittance of 5.8 W/m^{2}K.

It is important to mention that the "H" shape has its own shading, caused by the indentations of the constructed format. It has two facades with larger openings (location of bedrooms and living rooms), with a window-to-wall ratio (WWR) of 18.45 %. The room comprises a balcony with a glass door, which increases solar radiation entering, however this door is shaded because of the existing slab of the upper balconies. The other two facades (location of kitchens and bathrooms) are set back and have a WWR of 2.66 %.

The linear building has a different WWR for each facade, the largest with 12.8 % and 12.26 % and the smallest facades without windows.

To summarize the building composition, Table 8 outlines the settings for both typologies.

2.3.3. Natural ventilation

The natural ventilation settings were made in the *AirFlowNetwork* object of the EnergyPlus, as used in Bre et al. (2016), Bre and Fachinotti (2017) and Vettorazzi et al. (2021) [68,91,117].

The ventilation was set to be always on (possibility of leaving the window open with and without occupancy) because opening the windows was limited to a controlled temperature, in the range of 5 °C. Below 20 °C, the program considers the windows closed, avoiding energy loss. Above this value, windows are considered as remaining open until 25 °C, if the external temperature is between 20 °C and 25 °C, when the program considers the win-

Table 4
Occupancy schedule.

Time	00:00 to 08:00	08:00 to 14:00	14:00 to 18:00	18:00 to 24:00
Occupancy rate	100 %	0 %	50 %	100 %

Table 5
Lighting schedule.

Time	00:00 to 06:00	06:00 to 08:00	08:00 to 16:00	16:00 to 23:00	23:00 to 24:00
Lighting	0 %	100 %	0 %	100 %	0 %

Table 6
Thermal performance by NBR 15575 (2021).

	Bioclimatic Zone 2		
Local	U-value	Thermal capacity	Absorptance
Roof	2.3 $W/m^2.K$	Not specified	Not specified
Exterior walls	2.7 $W/m^2.K$	$\geq$130 $kJ/m^2.K$	Not specified

dows closed to avoid overheating due to energy gains, as in Bre and Fachinotti (2017) and Vettorazzi et al. (2021).

The main natural ventilation settings used the *AirflowNetwork* control in multizone without distribution and initialization type linear method. For leakage and airtightness, the settings shown in Table 8 were applied. The sliding windows with a crack factor and minimum venting open factor were set to 0.45. The ventilation control mode was in the Zone Level. The indoor and outdoor temperature difference upper limit for minimum venting open factor was at 5 deltaC. The outdoor air flow rate per person was 0.00944 m^3/s.

The value range stipulated was based on the study by Martins et al. (2009) and according to the limit of comfort from the Passive House Institute to warmer climates [85,118]. The buildings do not have active systems, such as air conditioning. Regarding the infiltration rate of the openings, it was used according to the INI-R prescription, as shown in Table 9.

2.3.4. Ground temperature

Silva and Ghisi (2013) used SLAB to determine the soil temperature in their work as the iteration of the simulations analyzed by the authors depended directly on the average temperature of the indoor air of the building, where the soil temperature generates influence [119].

The choice of SLAB to configure the soil temperature was due to the influence of the soil in relation to the heat exchange with the internal environment of the building, attempting to make the building as close as possible to reality. The values defined in the SLAB program were used in all simulations and are shown in Table 10.

2.3.5. Cooling and heating demand assessment

The *HVACTemplateZone:IdealLoadsAirSystem* routine of the EnergyPlus was used, as in Dalbem et al. (2019), Gou et al. (2018) and Vettorazzi (2021), which analyzes the energy necessary to heat and cool the thermal zone. This setting of the EnergyPlus simulates an HVAC system with a Coefficient of Performance (COP) equal to 1, therefore the energy demand may be taken directly from the results [68,85,88].

The setpoint was set to 19 °C for heating, and 26 °C for cooling. This configuration makes it possible to reduce the time of using the installations and increases the comfort time using natural ventilation. Thus, it prevents the thermal engine software from calculating the active system (*IdealLoadsAirSystem* routine) and the natural ventilation at the same time.

2.4. Multi-objective optimization

To characterize a multi-objective optimization, two or more objective functions must be delimited to proceed with the evaluation, and the results of these objectives are presented as a set of Pareto optimal solutions (Pareto front). In the case of two objective functions, the Pareto front is a curve in a two-dimensional space. Each Pareto Front point is a non-dominated solution. For example, improving one objective function without hindrance to the other is impossible. For this matter, a set of optimal solutions is presented instead of just one [36,37,46,103,110].

Thus, this article uses two objective functions, selected according to the climatic characteristics of the study site, represented by a greater demand for heating. Thus, evaluating two conflicting objectives to find the solution that minimizes both parameters simultaneously generates a curve with the optimal solutions. The objective functions of this experiment are to minimize the heating demand (D_h) and cooling (D_c) of the two typologies in the study.

Furthermore, this optimization seeks to minimize the cooling and heating demand at the same time, concerning the variables of the solar orientation. The multi-objective problem is presented as:

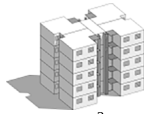
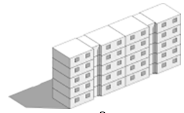
$$Min\{D_h\}\ \{D_c\} = [x_1] \tag{2}$$

Table 7
Opaque envelope- physical properties.

Exterior wall	t (m)	λ (W/mK)	ρ (kg/m^3)	s (kJ/kgK)
Exterior mortar	0.025	1.15	1,800	1.00
Red clay ceramic brick	0.18	0.90	785	0.92
Interior mortar	0.015	1.15	1,800.00	1.00
Roof	t (m)	λ (W/mK)	ρ (kg/m^3)	s (kJ/kgK)
Fibercement tile	0.008	0.65	1,800	0.84
Air gap	>0.05	–	–	–
Concrete slab	0.10	1.75	2,400.00	1.00
Floor	t (m)	λ (W/mK)	ρ (kg/m^3)	s (kJ/kgK)
Ceramic tiling	0.01	1.3	2,300.00	0.965
Mortar	0.02	1.15	1,800.00	1.00
Concrete slab	0.10	1.75	2,400.00	1.00

t = thickness; λ = thermal conductivity; ρ = density; s = specific heat.

Table 8
Building configurations.

Item	"H" Building	Linear Building
		
Total built area	1.011.25 m^2	1.010.50 m^2
Useful area of apartment	37.05 m^2	36.95 m^2
Shape coefficient	0.49	0.38
WWR north	18.45 %	12.8 %
WWR south	18.45 %	12.26 %
WWR east	2.66 %*	0 %
WWR west	2.66 %*	0 %
Floor height	2.7 *m*	
N° of floors	5	
N° of apartments	20 (4 per floor)	
Lighting load	5.0 W/m^2	
Equipment load	120 W	
Occupancy load	94.5 W/person	
Uvalue window	5.8 W/m^2.K	
Uvalue ext. Wall	2.6 W/m^2.K	
Thermal capacity ext. Wall	130 kJ/m^2.K	
Thermal absorptance wall	0.2	
Uvalue roof	2.3 W/m^2.K	
Thermal capacity roof	252.10 kJ/m^2.K	
Thermal absorptance roof	0.6	

WWR: Window-to-Wall Ratio.
* Recessed windows with shadows cast by the building itself.

Table 9
INI-R infiltration settings.

Field	Value
Air mass flow coefficient when the opening is closed	0.001 kg/s.m
Air mass flow exponent when the opening is closed*	0.66
Minimum density difference for two-way flow	0.0001 kg/m^3
Discharge coefficient*	0.6

* Dimensionless.

Where f_1 (D_h) minimizes the cooling demand and f_2 (D_c) minimizes the heating demand. Moreover, the principal variable in analysis x_1 is the solar orientation of the buildings. The optimal solutions will be presented in the Pareto front.

2.4.1. Optimization algorithm

To carry out this experiment, optimizing solar orientation, the NSGA-II was selected to carry out the multiobjective analysis, given its efficiency and well-established use in the building performance simulation [37,120]. It is a metaheuristic method, which works like human DNA, based on the selection, crossover, and mutation of genes in their various generations. It has an iterative application where the new generations replace the old ones. It is elitist, which speeds up the convergence process and can efficiently put the best solutions in order. They are less likely to converge at the local optimum, use random choice operators, and are efficient at solving nonlinear problems [37,38,45,48,91].

The NSGA-II uses the concept of Dominance to evaluate each individual of its population so that, where *p* and *q* are two individuals of population P, *p* dominates *q* if *p* is better than *q* in at least one of its goals, the rest of the *p* goals are no worse than *q*. This strategy allows the algorithm to classify the fittest individuals and determine the distance from the crowding distance-sorting algorithm for each of them to the optimal point (origin of the representation plane in the case of minimization functions or the constant enlargement of the identified values for the maximization functions). The behavior occurs in such a way that the greater the number of individuals dominated by *p* and the smaller its distance to the optimal point, the better its classification [52].

Table 11
NSGA-II parameters.

Parameter (NSGA-II)	Value
Population size	100
Maximum number of generations	200
Crossover	0.9
Mutation probability	1.0
Total simulations	20,000.00 per building (x4) 80,000.00 simulations

The NSGA-II implementation also has a *Q* data structure, which stores non-dominated individuals, that is, those that at a given moment of execution were part of the set *P* but were discarded in the execution of the current generation due to better results. The existence of *Q* allows the ordered elements not to lose interesting characteristics at a given moment of execution, ensuring the heterogeneity of the population set and avoiding elitist aspects that disregard the diversity of individuals. Table 11 present the parameters of the NSGA-II utilized in the experiment.

The population size has to be large enough to verify the variable. In this case, 100 buildings were selected as the population. Regarding the termination criteria, the number of generations was fixed at 200, as in Ascione et al. (2016) and as referenced in Ciardiello et al. (2020), as 2 – 6 times the number of genes [76,121]. This value must be significant but not excessive, which can extend the computational time. Thus, 20,000,000 simultaneous simulations were performed per building. Evaluating the 4 different scenarios, this research achieved a total of 80,000,00 simulations.

3. Results

As mentioned throughout this article, the importance of the solar orientation of buildings focusing on the quality of the north solar orientation for the southern hemisphere can be mentioned [122,123]. Thus, the first step of the optimization research was to seek the solar orientation that ensures the energy demand of heating and cooling and analyzes the shape ("H" or linear) for the same reasons. In this section, the results obtained from the optimizations of the two architectural typologies will be presented for the two analyzed scenarios.

3.1. Isolated scenario

This scenario evaluated the two typologies without surroundings with no external shadows. Fig. 3 presents the Pareto Front results for both buildings.

The Pareto Front shows the 100 individuals analyzed, after the 200 generations and how the GA distributed the optimization between the two objective functions (D_h and D_c). The "H" building

Table 10
Ground temperatures for Passo Fundo from Slab (EnergyPlus).

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
°C	23.2	23.3	23.3	20.9	18.9	18.6	18.5	18.5	19.3	20.2	21.2	22.9

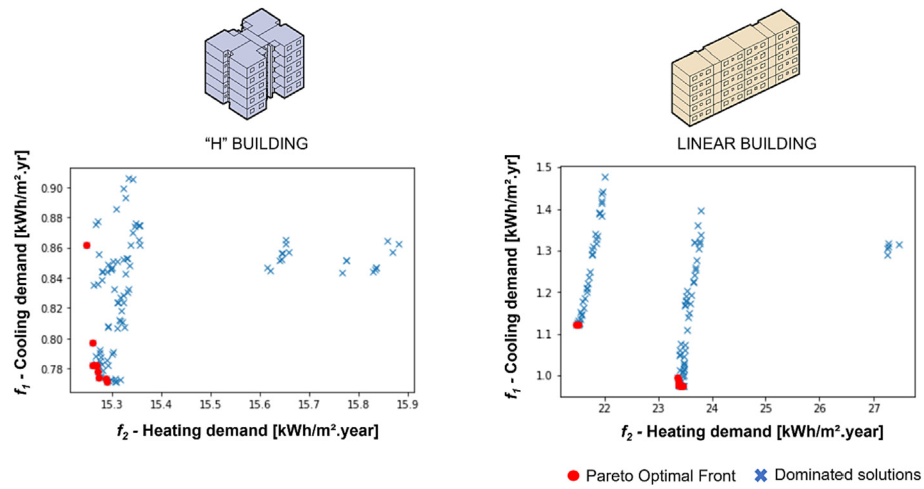


Fig. 3. Pareto Front – Isolated situation – "H" and Linear buildings.

achieves 10 Pareto Front solutions, and the optimization took 5 h 53 mins. The linear building reached 11 solutions in the Pareto Front set and the optimization was run in 4 h 52 mins.

Analyzing the evolutionary behavior of the samples, the "H" building achieved a greater convergence of solutions compared to the linear building. The linear shape presents three large groups of results, divided by different cooling intervals in the same heating interval, that is, with Pareto solutions that will be between the first part of this set that were between 1.0 and 1.15 kWh/m^2.yr of cooling and others of the second set that were between 1.35 and 1.3 kWh/m^2.yr of cooling. However, both with little variation in heating, indicating that it is an evolutionary pattern for this shape, are able to reduce heating, while the set that achieves a greater reduction in heating is not able to reduce cooling significantly.

The behavior of the Pareto Front of the linear building is due to several factors. Initially, because the initial population generated by the NSGA-II is random, and from this point onward, it creates the optimal solutions according to these initial premises due to its elitist character. The configuration of the initial population and the number of generations highlights the need to go deeper in this sense, finding the most suitable combination to find the best solar orientation. Furthermore, the architecture of the building itself is a limiting factor for the convergence of solutions on the Pareto curve.

Thus, Fig. 4 shows the parallel coordinate graph of the "H" building, presenting the solar orientations evaluated.

To understand the optimization and parameters found by the GA, the parallel coordinate graph shows the evolutionary behavior and the optimal orientation search. The graph shows the solar orientation angles analyzed by the algorithm for the "H" building and presents that from 0.98° to 45°, it can achieve major reductions in both heating and cooling. From 180° to 210° and those close to 350° are the best for optimizing heating. On the other hand, the orientations around 130° and 310° are the angles with a major demand for heating and cooling.

The same analysis is performed for the isolated scenario, for the linear building, where the optimizations are well defined in three heating intervals. Fig. 5 presents the parallel coordinate graph for the linear building shape.

The graph illustrates that the orientations from 150° until 175° and the closest to 350° are the best solutions to achieve the lower demand of heating, although the best angles to reduce the cooling demand are closer to 0.28° until 25° and around 150° until 170°.

The selection of the initial random population identified the regions mentioned above with the most significant reductions in the heating demand, concentrating the search for solutions close to these intervals, as the GA seeks the results that are best executed in one generation, thus concentrating the crowdistance function between them.

As the cooling demand has a smaller impact on the total demand, and as described in the method, for both shapes, the optimal solution achieved is to reduce heating and cooling simultaneously. Thus, Table 12 presents the best solutions for both shapes and also shows the solution that achieves better heating and cooling demands separately. Additionally, it presents the worst case reached by the optimization to evaluate the improvement in the orientation and demand.

The convergence of the optimal solutions was reached among the first 10 generations for both buildings, as in Lopes (2020). The term "convergence" can be defined when future generations do not improve the defined function objectives, reaching the optimal solutions. Nonetheless, it does not necessarily mean that it has reached the minimum location. This phenomenon occurs due to the elitist nature of the NSGA-II, and the crowdistance function, which searches for the genes that had the best performance [52,103,124].

Analyzing the optimization results for the "H" building, it is clear that the orientations that have the largest glazed areas (WWR – 18.45 %) are facing north, to retain solar radiation, as in Ciardiello et al. (2020) [76]. Comparing the optimal solution with the worst case, there is a reduction of 4 % in the total demand. From this value, there was a decrease of 10 % for cooling and 4 % for heating.

For the linear building, the same pattern occurs, the optimization seeks to orient the large facades with a greater glazed area (WWR – 12.8 %) to the north, a characteristic for colder climates, aiming to accumulate the heat from solar radiation in the winter period. For this shape, the optimal solution that minimizes heating and cooling matches the solution that most minimizes heating. In this case, the difference between the optimal solution and the worst solution is a decrease of the 2 % of the total demand, in which there is a 15 % reduction in the cooling and 22 % in the heating.

3.2. Condominium scenario

As an isolated scenario, the condition of the condominium was optimized, with the same configurations. It was differentiated because eight adjacent buildings separated 5 m from the central building in each direction so as to replicate the reality of large condominiums in Brazil. The behavior of the building with the influ-

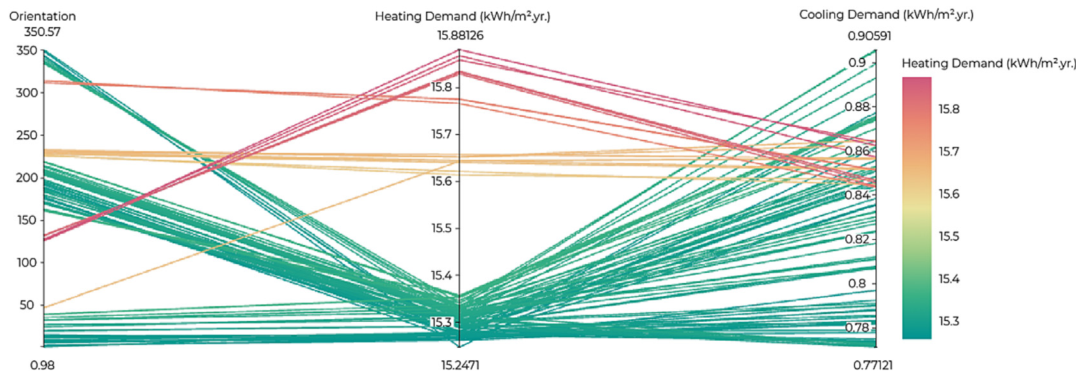


Fig. 4. Parallel coordinate graph – Isolated situation – "H" building.

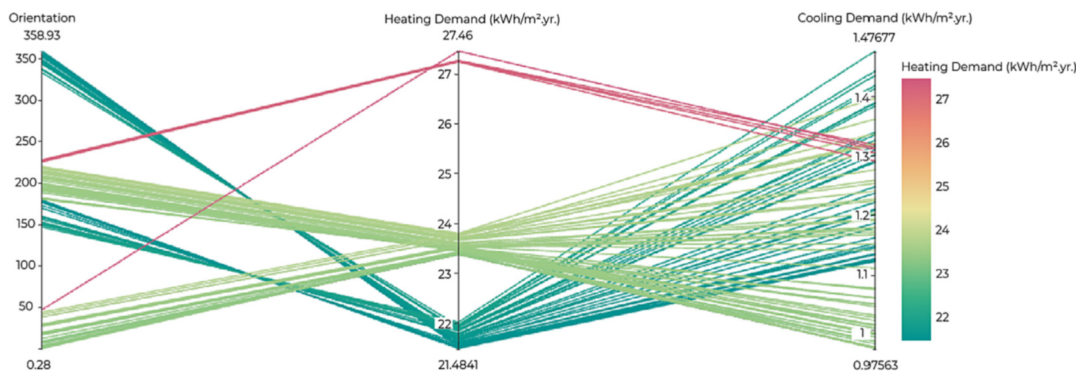


Fig. 5. Parallel coordinate graph – Isolated situation – Linear building.

ence of the shadows was observed. Fig. 6 presents Pareto Front results for the two typologies.

Similar to the isolated scenario, the Pareto Front solutions for the condominium condition had the same pattern. The "H" building had more sparse solutions and the linear shape with two heating intervals was well defined. The "H" building optimization achieves 10 Pareto Front solutions and ran in 8 h. The linear building achieved 14 Pareto Front solutions and took 4 h 42 mins to finish.

For a better understanding of the orientations optimized, Figs. 7 and 8 present the parallel coordinate graph for both shapes, in the condominium scenario.

By analyzing the "H" shape, it can be said that it had the same evolutionary behavior as in the isolated scenario. In this case, three groups of orientations can be seen, those that reduce heating are between 340° and 357°, from 150° to 200° and those from 0.76° to 30° are presented as the orientation angles that can decrease demand simultaneously.

Regarding the linear shape, four orientation groups can be observed, two that reduce cooling and two that reduce heating, as illustrated in Fig. 8.

The solar orientation around 150° until 180° and 330° until 360° are the ones that optimize the heating demand, following the same pattern in the isolated case, where the large façades are exposed to the north. On the other hand, the angles 0.07° until 25° and 180° until 200° have the most reduction in cooling.

Table 13 presents the Pareto Front solution to the "H" and linear buildings for heating, cooling and the optimal solution. It also shows the worst case achieved by the optimization to evaluate the improvement made in the orientation and solution.

The "H" shape obtained the best reduction in heating and cooling in the 350° orientation, which was the same solution that minimizes heating the most. Comparing the optimal solution and the worst optimized solution, there is a 2.7 % reduction in total demand. There was a 2.5 % reduction in cooling and 2.7 % in heating.

Regarding the linear format, the orientation that obtains the greatest reduction is 175°, with a difference in thermal demand 8.2 % that is smaller compared to the worst optimized solution.

Finally, the best relationship between the cooling and heating demand, named as the optimal solution in this article, for both scenarios and shape are presented in Fig. 9.

Due to its more compact form, the "H" building has less demand in both scenarios compared to the linear building, it has several setbacks. It has a shadow of the volume and this does not happen in the linear form, where the facades are fully exposed. Comparing the two scenarios, it can be said that there was an increase in the total demand of 4.5 % of the isolated building for the condominium case. For the linear shape, there was a 6.5 % increase in total thermal demand, comparing both scenarios. In both cases, the increase is due to the shading generated and the increase is all in heating. The solar orientation for the two scenarios is close to the same angle.

3.3. Demand for each apartment

The apartments were evaluated separately to understand the thermal behavior in each scenario. Fig. 10 compares the cooling and heating demand for each apartment separately in both scenarios to the "H" building. The demand is in accordance with the orientation optimizations carried out (3° – isolated scenarios and 350° – condominiums).

As shown in Fig. 10, the thermal behavior of the apartments is similar for different orientations. In the 5 apartments facing north

Table 12
Pareto Front solutions × worst solution.

"H" building				
Generation (#)	Orientation (°)	Cooling demand (kWh/m².yr)	Heating demand (kWh/m².yr)	Total demand (kWh/m².yr)
0	184	0.77	15.29	16.06
1	349	0.86	15.25	16.11
2	16	0.80	15.26	16.06
3	189	0.77	15.27	16.05
4	188	0.77	15.29	16.06
5	3	0.78	15.26	16.04
6	6	0.78	15.27	16.05
7	7	0.78	15.27	16.05
8	192	0.78	15.27	16.05
Worst solution				
99	126	0.86	15.88	16.75
Linear building				
Generation (#)	Orientation (°)	Cooling demand (kWh/m².yr)	Heating demand (kWh/m².yr)	Total demand (kWh/m².yr)
0	182	0.98	23.47	24.44
1	179	1.12	21.48	22.61
2	9	0.99	23.37	24.36
3	359	0.98	21.52	22.64
4	7	0.98	23.37	24.36
5	6	0.98	23.37	24.36
6	2	0.98	23.39	24.37
7	3	0.98	23.38	24.36
8	3	0.98	23.38	24.36
9	3	0.98	23.38	24.36
10	3	0.98	23.38	24.36
Worst solution				
95	47	1.32	27.47	28.78

Optimal solution
Minimize cooling
Minimize heating
Worst solution

and east, there is a greater thermal demand of heating similar to those facing south and east. The thermal demand increases from the first floor to the roof, where there is more sun exposure and thermal changes, as observed by Jayaweera, Rajapaksha and Manthilake (2021) and Lima, Scalco and Lamberts (2019).

Comparing the graphs, it can be seen that the apartment facing south and west is the one with the highest cooling load, due to the west facade in summer, which receives more radiation at the end of the day. In all orientations, there is an increase in the heating demand in the condominium condition compared to the isolated scenario. For cooling, the difference between the two scenarios is a small decrease in the condominium.

It can be seen that for the facades facing north, the behavior is similar, reaching a difference of 18.8 kWh/m^2.yr between the ground floor apartment and the penthouse for the isolated scenario and of 19.1 kWh/m^2.yr with the urban context.

Fig. 11 presents the thermal behavior of each apartment to the linear typology as the optimized orientations and scenarios (178° – isolated and 175° – condominium scenarios).

In this case, the lateral apartments have 3 orientation façades. The same arrangement of the "H" building is repeated in this shape, the first floors have the lowest demand, increasing the demand by floor until the highest demand on the roof apartment. Comparing the apartments, the increase in the total thermal demand from the first floor to the last floor can be observed. In this typology, the lateral apartments have the same thermal behavior and the same occurs with the middle apartments.

This behavior is due to the poor quality of the building envelope, making the linear building unfavorable energetically in all orientations, when compared to the "H" building. It is more evident for the lateral apartments with 3 façades, when the "H" shape is more compact and has apartments with only two exposed façades.

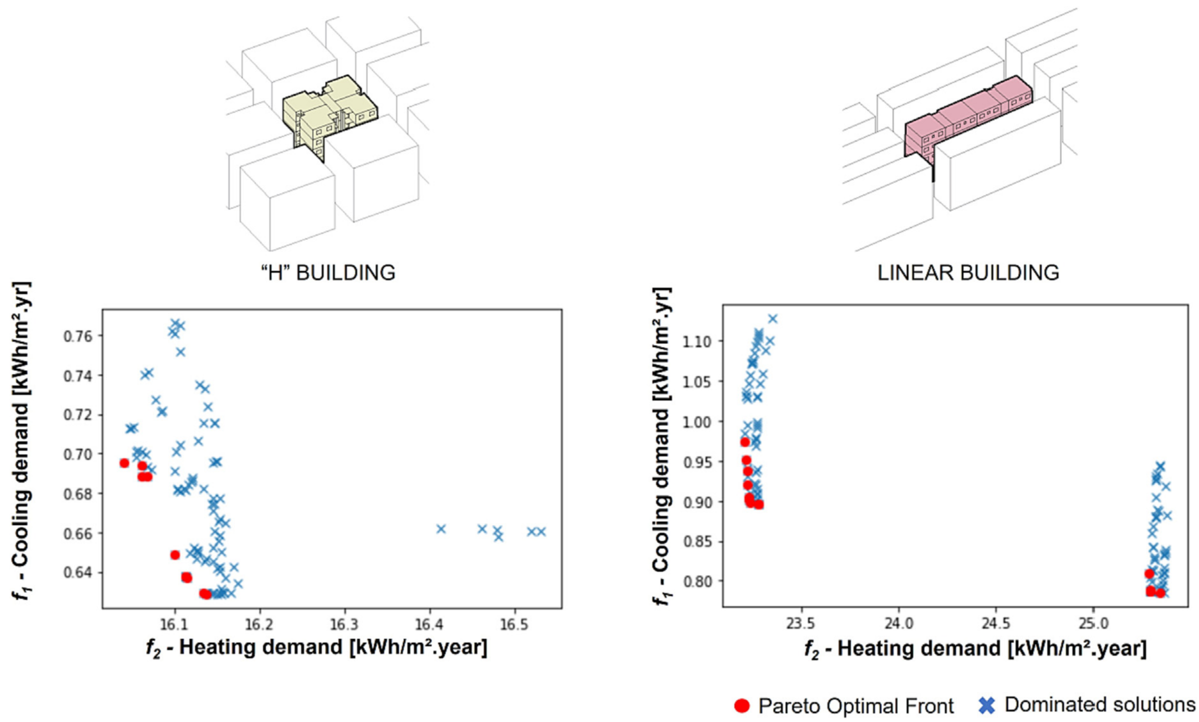


Fig. 6. Pareto Front – Condominium condition – ‘‘H” and Linear buildings.

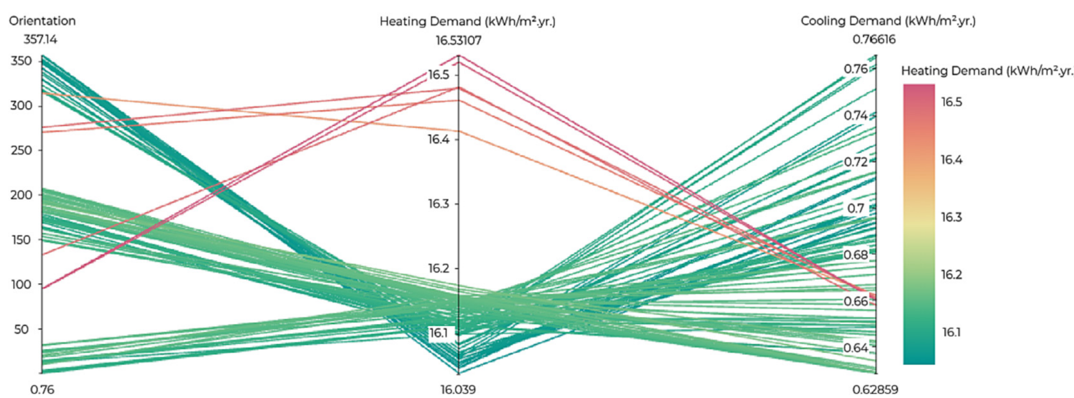


Fig. 7. Parallel coordinate graph – Condominium condition – ‘‘H” building.

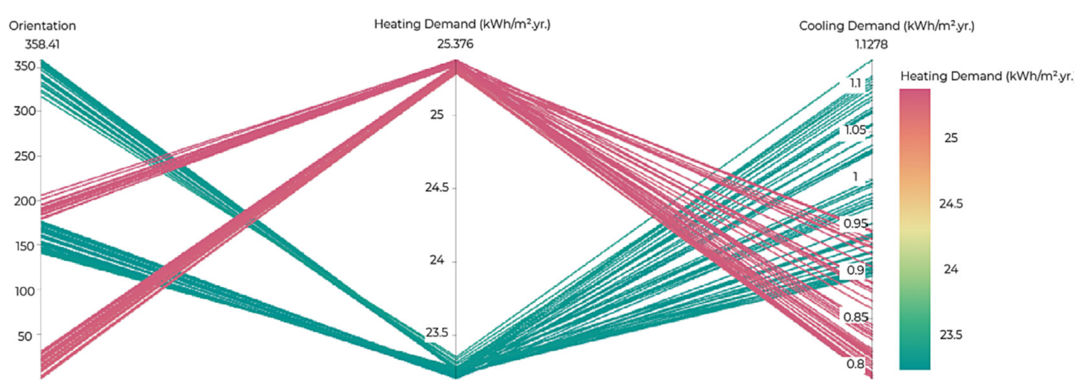


Fig. 8. Parallel coordinate graph – Condominium condition – Linear building.

Table 13
Pareto Front solutions × worst solution.

Generation (#)	Orientation (º)	Cooling demand (kWh/m².yr)	Heating demand (kWh/m².yr)	Total demand (kWh/m².yr)
"H" building				
0	185	0.63	16.14	16.77
1	350	0.70	16.04	16.73
2	13	0.65	16.10	16.75
3	257	0.69	16.07	16.76
4	182	0,63	16.13	16.76
5	351	0.69	16.06	16.76
6	4	0.64	16.11	16.75
7	1	0.64	16.11	16.75
8	356	0.69	16.06	16.75
9	2	0.64	16.11	16.75
Worst solution				
87	95	0.66	16.54	17.19
Linear building				
Generation (#)	Orientation (º)	Cooling demand (kWh/m².yr)	Heating demand (kWh/m².yr)	Total demand (kWh/m².yr)
0	162	0.97	23.21	24.18
1	180	0.79	25.34	26.12
2	10	0.81	25.28	26.09
3	358	0.90	23.28	24.18
4	165	0.95	23.22	24.17
5	170	0.92	23.22	24.14
6	167	0.94	23.22	24.16
7	3	0.79	25.29	24.08
8	174	0.90	23.23	24.14
9	177	0.90	23.24	24.14
10	175	0.90	23.23	24.13
11	358	0.90	23.28	24.17
12	0	0.79	25.29	24.08
13	1	0.79	25.29	24.08
Worst solution				
99	206	0.92	25.37	26.29

Optimal solution
Minimize cooling
Minimize heating
Worst solution

The central apartments behave better, but compared to the "H" shape, still perform worse due to the good orientation of one facade and the bad orientation of the other. This is also because of the transparent envelope, where the losses due to the bad façade cannot be compensated for by better orientation.

It can be observed, for both shapes, that the condominium scenario, has an increase in the heating demand and a small reduction in cooling. This fact occurs because the simulated building is in the shade, on the first floors up to approximately the fourth floor, in winter periods. With the highest sun in the summer, the ground floor apartments are still in the shade, but those closer to the roof are more exposed to solar radiation.

The solar orientation influences the demand of the apartments separately and it is an important factor of comfort in the buildings. This compact shape of the "H" building works very well from a whole point of view, but when scrutinizing the demand separately by apartments, the disparity is a condition for energy efficiency equality. This article aimed to highlight the importance of designing the building by its parts, so as not to damage one or the other.

4. Discussion

This section will present the main findings of the experiment and insights into the results obtained with optimization. Thus, ana-

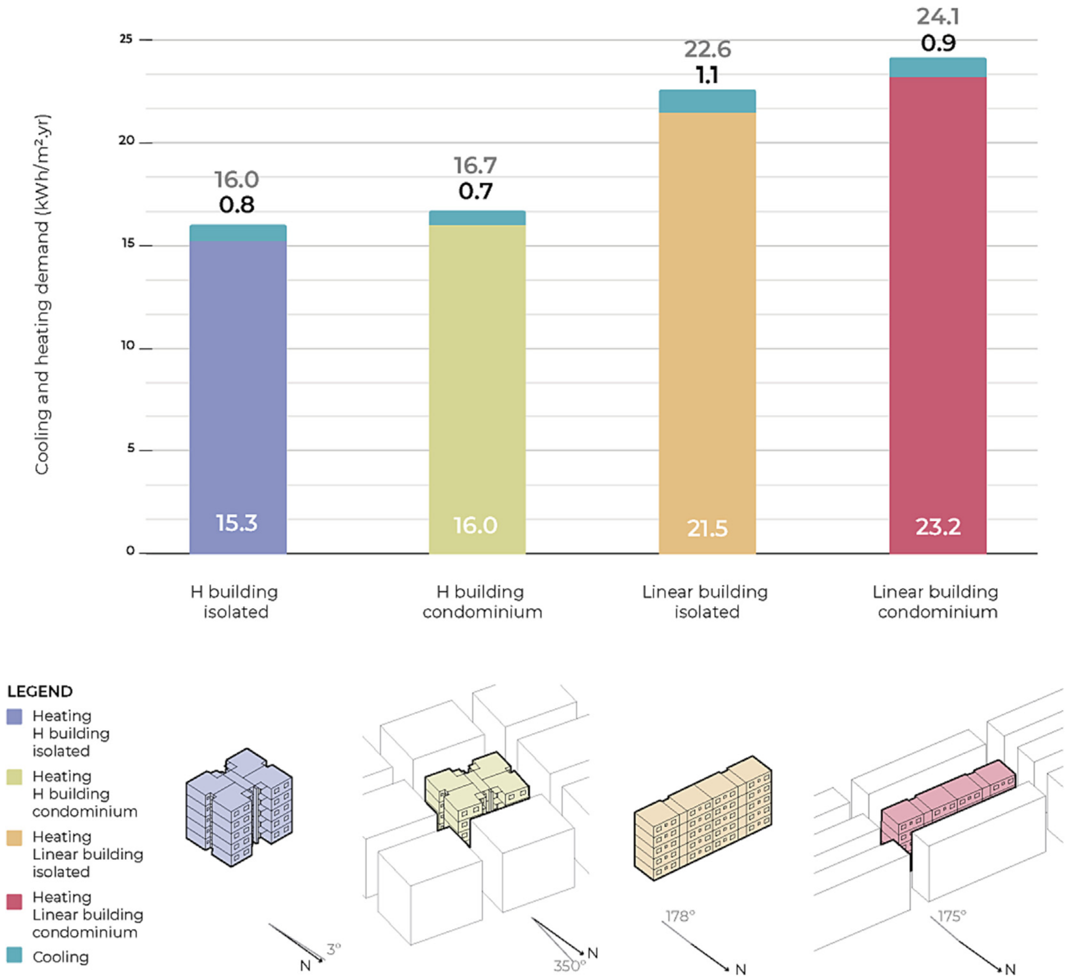


Fig. 9. Comparison of the optimal solution for both scenarios and typologies.

lyzing the framework's application and comparing it with the previous studies identified in this article.

4.1. Multi-objective optimization performance

The application of a multi-objective method for energy demand optimization, combined with a GA and an energy calculation engine, provides various benefits in decision making for more efficient buildings. It is an agile tool in the data and variable convergence process, can be helpful in all project phases, and it is seen an increase in the use of this tool to achieve conflictive objectives [37,44,45,75,82,84,88,90,121].

In this experiment, the use of a genetic algorithm allowed the execution of 80,000.00 simultaneous simulations, reaching a wide spectrum of possibilities, resulting in a group of solutions that optimize the demand for heating without neglecting cooling, one of the current concerns due to the climatic exchange [1,17]. Thus, this research presents the results of applying a simplified framework for optimizing the solar orientation of multifamily buildings in a Cfa climate, predominantly cold.

4.2. Climatic context and objective functions

The function objectives used significantly reduce energy demand in the climate context studied. Since, as we improve the energy benefits for winter, with the increase in solar radiation, the demand for refrigeration increases, it is necessary to introduce contradictory measures to achieve a demand that minimizes heating and cooling simultaneously. This was observed by Ciardiello (2020) and Chen (2019), who analyzed the Csa and Cfa climate [76,82].

4.3. Solar orientation

Regarding solar orientation, as mentioned in the research conducted by Morrissey et al. (2011), for the southern hemisphere, the search for the best orientation will optimize the entry of light during the day and increase the thermal gains for the winter [122]. This fact is outlined in this paper, with the convergence of the GA to the orientations with major WWR facing the north.

In this context, this experiment guided the following orientations: "H" building 3° in the isolated scenario and 350° in the condominium, the linear building 175° in isolation, and 178° in the condominium. Demonstrating that there is a difference between optimizing energy demand and considering the context in which it is inserted. The search for better solar orientation is increasingly difficult to achieve, given the predominance of buildings built in the urban context, which is already consolidated, generating impact on neighboring buildings [28,30,31].

The behavior of GA was to seek the set of solutions that places the largest areas of windows for the best orientation; in this case, the north. It is an easy strategy to achieve in linear typology. However, complex in the form "H". The results were observed by parallel graphs, demonstrating a trend and accumulation of optimal

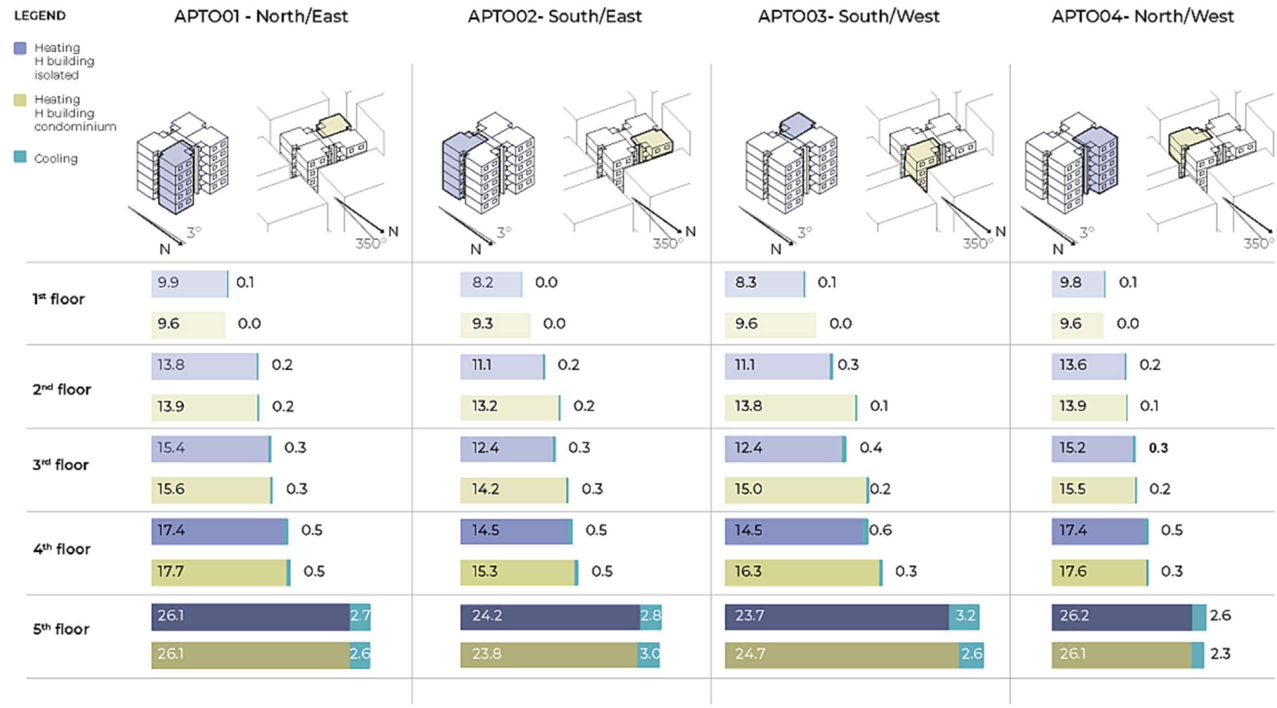


Fig. 10. Comparison of cooling and heating demand for each apartment by facade and scenario to "H" building.

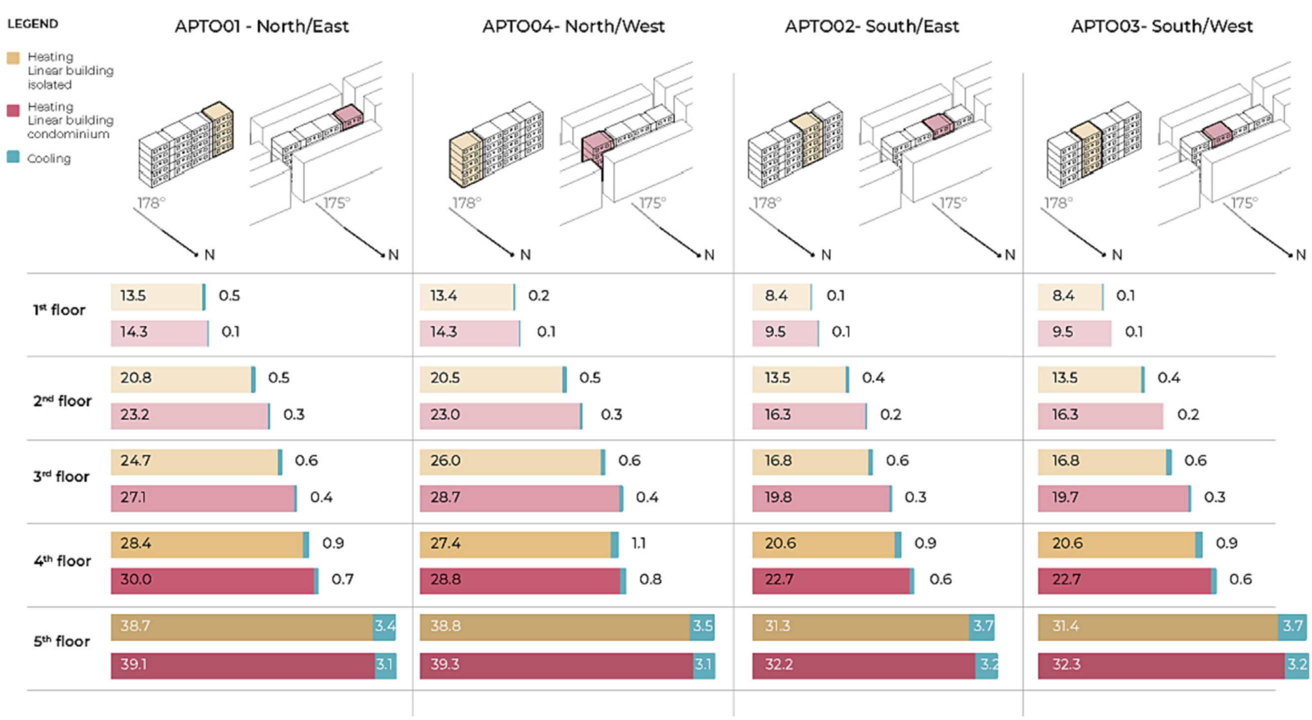


Fig. 11. Comparison of cooling and heating demand for each apartment by facade and scenario to linear building.

orientations in well-defined groups, given by the elitist characteristic of the algorithm.

Condominium scenario – urban context.

Furthermore, the urban context needs to be inserted into the optimization of buildings. According to Pisello et al. (2012), analyzing a building without considering its surroundings can lead to distortions and oversizing of equipment. The distortion can reach 42 % for summer and 22 % for winter [98]. Continuing this investigation, Han et al. (2017) showed that shading significantly impacts solar reflection, with a more significant effect in warmer climates [99].

Samuelson et al. (2016) demonstrated an increase in energy consumption for heating and artificial lighting when considering the urban context, highlighting that ignoring the surroundings can lead to misled in the optimal design solutions [97].

The analysis of the cooling load of two hypothetical office buildings, isolated and without urban context (in two orientations), underlines the importance of thermal energy simulation by considering the surroundings. The study, applied to Maceio in Brazil, reached a reduction between 16 and 18 % in the thermal load with the presence of the surroundings [100].

Comparing the energy consumption with or without the surroundings can reduce the cooling load for buildings by 3 to 6 % compared to the isolated situation for colder climates [96]. In the case of warmer climates, it can be between 16 and 18 % of the difference [100]. The findings were validated in this article with an increase in the total demand of 4.5 % of the isolated building for the condominium case. For the linear shape, there was a 6.5 % increase in total thermal demand, comparing both scenarios, with a reduction in cooling.

Most studies disregard the urban context, focusing on the urban fabric, the comfort of outdoor spaces, and urban dimensions. This is relevant, given that the world population is increasingly urban, where land is scarce and expensive, and pressures are increasing for the verticalization of buildings to meet the housing demand, generating large and massive condominiums, where Brazil still has a long way to go to meet household demand.

4.4. Shape

Regarding the shape of buildings, Depecker et al. (2001) demonstrate that energy consumption is inversely proportional to the compactness of the building [108]. Thus, the best performance of the "H" building is the result of its more compact shape compared to the linear building, where the side apartments are more exposed, with three facades.

Exposing the typologies to a crisis, it can be observed that the academic and construction sector have analyzed linear format buildings in more depth, from the energy point of view, which are more common in Europe as regulations are demanding and better determine thermal performance with the mandatory insulation of facades, as is the case of the Basic Building Standard – Thermal Conditions in Buildings (NBE-CT/79) in force since 1979 in Spain [125].

One of the major normative challenges in Brazil is where cultural and technical barriers still do not allow the insertion of new technologies in civil construction, especially regarding social housing [5,15,27].

Thus, comparing a format already consolidated and known in the world context for having a more compact format, and various setbacks and self-shading, identifies that the compactness factor is relevant for climates with milder temperatures. Similarly, the optimized solar orientation, in isolation, does not reach significant results when compared with isolated constructive models [53,54,80,82,84,87,126,63,66,67,70,71,73,76,78].

The simultaneous evaluation of solar orientation and the shape of a building, in the initial phases of the project, up to 36 % energy reduction can be achieved [127]. Comparing typologies shows that poor quality and construction are the main barriers to achieving better energy performance [22,27,108]. A maximum of 22 % reduction in demand in the isolated scenario was achieved with the best orientation.

4.5. Shapes comparison

The two most replicated shapes in Brazil are analyzed. These typologies are little studied in the Brazilian context when studies explore single-family buildings. As previously commented, the "H" building presents lower total energy demand compared to the linear one. Thus, Table 14 presents the difference between the two shapes.

There is more than a 40 % difference in energy demand for the linear shape, due to the potential for self-shading and minimization of the "H" building's shape coefficient. Comparing the scenarios, isolated and condominium, the greatest reduction is presented when the building is inserted in the urban context, where the total demand of the linear building is greater due to the need for heating.

Methodological approach.

Unlike the cited articles, as a methodological choice, this research optimizes only one variable, simplifying the process, reducing processing time, and serving as a quick decision-making tool in the early stages of the project. As seen in the revision of Machairas et al. (2018) and the research of Gagnon et al. (2019), the large number of variables can make it difficult to search for the best solutions, generating uncertainties in the results and directly impacting unnecessary computational time [44,83].

To perform the 80,000.00 simulations in a 2-core laptop with an Intel Core i7-4500U processor of 1.8 GHz took 23 h and 45 min to finalize the procedure. Demonstrating that this framework is agile and does not require investment in large computer processors.

Developed in open-access software (Sketchup 2017, Euclid/OpenStudio, EnergyPlus, and Python 3, with code written in Jupyter Lab and connected to the BESOS library) with a friendly interface based on Leitzke's dissertation (2021) [112]. After adopting the model, modeled in Sketchup, and configured in EnergyPlus, the code is opened in a browser and the file name (.idf) and optimization parameters are changed, if required. This methodology is uncommon in the literature and has been gaining ground.

4.6. Energetical vulnerability

After analyzing the individualized demand for an apartment, showing its behavior, verifying the existing inequality between the neighbors of the same building, taking advantage of the GA and optimizing the solar orientation, to the best of our knowledge there is no other research using this methodology. Assessing the intensity of energy poverty in multifamily buildings is little discussed in the existing literature.

When analyzing the apartments individually, as seen in Lima et al. (2019) and, Rajapaksha and Manthilake (2021), the thermal demand increases, the closer the floors are to the roof. Analyzing the impact of the simulations by floors, little difference was noticed in the thermal load. In the case without surroundings, only the ground floor and the roof behave differently. However, in the analysis of the urban environment, there was a variation of 13–24 % for the different floors [100,104].

The energy demand trend, individually by apartment, shows that ground floor owners have a lower demand than those more exposed on the roof floors, with a difference of approximately 19 kWh/m^2.yr between these apartments in the "H" building and 28 kWh/m^2.yr for the linear, both in the condominium condition. This shows the vulnerability and the need to investigate the improvement not only of energy efficiency but also because of the integration of solutions that are addressed to optimize the demand among the neighbors.

Table 14
Shapes comparison.

Typology	Isolated	Condominium
H	16.0 kWh/m^2.yr	16.7 kWh/m^2.yr
LINEAR	22.6 kWh/m^2.yr	24.1 kWh/m^2.yr
Difference	41.3 %	44.3 %

4.7. Implications for stakeholders

As affirmed in Stevanović (2013), the GA tool is a complex procedure to use in architecture firms [123]. For this reason, this tool can be replicated in other typologies and climate contexts. Moreover, when it is expanded, the analysis can optimize more variables or parameters. Optimizing only one variable reduces processing time without the need for powerful machines to perform robust data processing and it is more attractive for decision-makers and stakeholders. It can be used in the early stages of the project when there is still not much information about the building.

The results of the implementation of the framework demonstrate that it is a helpful tool that assists in decision-making aligned with measures to mitigate the effects of poor constructive quality of buildings and can be allied to new regulations and future enterprises. The biggest obstacle to the effective use of the tool is still connected with cultural aspects and the lack of specialized professionals in the construction sector in issues related to energy efficiency. Topics normally passed on to consultancies, which last longer than the project, are unfeasible for social projects.

4.8. Energy savings potential

As the average energy consumption for the southern region of Brazil is 177 kWh/month [75], if all 170,000.00 buildings built in the southern region had optimized solar orientation, 812,430.00 kWh/month could have been saved, or 9,749,160.00 kWh/year, just using the best solar orientation for the "H" building.

5. Conclusions

This article carried out a multi-objective optimization, aiming to simultaneously minimize the cooling and heating demand. The proposed method was applied in two architectural typologies, isolated scenario and condominium, and disclosed the energy demand of each apartment. As a methodological strategy, the optimization was performed using a Python code written in the Jupyter Lab interface, coupled to the BESOS library. The models were designed in Sketchup with the Euclid plugin that sends the model data to the EnergyPlus energy calculation engine.

As a result, for the "H" building, a reduction of 4 % in the total thermal demand was obtained for the isolated scenario and 2.7 % for the condominium condition. For the linear shape, there was a 22 % reduction in the isolated case and 8.2 % in the condominium. These values were only achieved with the best positioning of the building according to the solar incidence. Based on these results, the "H " building obtains the best overall performance due to its more compact format, as affirmed by Depecker et al. (2001). However, the improvement found is still relatively low due to the constructive pattern replicated in the country.

The best solar orientation in the early stages of the project should be carried out, as it is a quick and low-cost strategy given the need to build new homes in urbanized contexts. It should also consider the great potential for energy savings concerning the high housing deficit in Brazil.

The main limitations of this study are related to the adoption of a single pattern of occupancy, lighting, and natural ventilation. Thus, it is suggested that future studies consider many of these characteristics, which are so sensitive to the conditioning of residential buildings. For this study, it can be observed that only the optimization of solar orientation is not enough to reach efficient performance levels, thus showing the need to adopt the analysis of constructive parameters to improve the energetic performance.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors acknowledge the financial support from CAPES (Brazilian Federal Agency for Support and Evaluation of Graduate Education) and CNPq (National Council of Scientific and Technological Development – Brazil). The participation of Ana Carolina Passuello is sponsored by CNPq through the research fellowships PQ 2021: Grant number 310208/2021-1.

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