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Research Article

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Multi objective optimization of existing buildings: "A Study of a Higher Educational Laboratory in Cairo, Egypt"

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Abstract:

This research presents a comprehensive methodology for optimizing building performance in the context of visual and thermal comfort of a computer laboratory in higher educational buildings in hot dry climates, focuses on minimizing energy use intensity (EUI) and maximizing annual thermal comfort ratio and daylighting through maximizing useful daylighting illumination (UDI) and spatial daylighting Autonomy (sDA). This study conducts a parametric optimization approach of building envelope openings and materials to integrate multi-objective optimization (MOO), aiming to explore and find optimal solutions for improving the laboratory's overall performance. Throughout Rhino Grasshopper platform for simulation purpose. The methodology begins with the development of a parametric model of the computer laboratory, which allows for the manipulation of key design variables, including window size, Window wall ratio (WWR) orientation, shading devices, wall materials and properties, glazing types. These variables are used as design parameters linked to performance metrics that capture the visual comfort (via daylighting analysis), thermal comfort (evaluating indoor temperature variations and HVAC loads), and EUI (calculated through energy simulation). The design space is explored using multi-objective optimization by Genetic algorithms NSGAII with Wallacie solver, which balance trade-offs between the 124 key design parameters to enhance five objective functions performance criteria. The results show that significant improvements can be achieved in the computer laboratory's visual and thermal comfort, while simultaneously reducing energy use intensity by around 2.35% maximizing (sDA) and (UDI) to 1.3%, maximizing annual thermal comfort ratio (ATCR) to 1.9%. The optimized solutions exhibit a balance between natural and artificial lighting, effective thermal insulation, and strategic shading. In some cases, up to a 26% reduction in energy consumption (EUI) is observed, with notable improvements in both daylight quality and occupant thermal satisfaction.

1. Introduction

Building Performance Optimization (BPO) is a crucial approach in sustainable architecture, aimed at enhancing energy efficiency, occupant comfort, and environmental impact. It involves using simulation tools and optimization algorithms as genetic algorithms to evaluate design alternatives and improve key performance metrics such as energy use, thermal comfort, and lighting quality. Parametric design plays a vital role in this process, allowing designers to explore multiple design variables and their impact on building performance. Multi-objective optimization (MOO) methods are often employed to balance competing objectives, such as minimizing energy consumption while maximizing occupant comfort and daylighting, visual comfort. [1]. Many studies have been investigating (BPO) to enhance building performance through optimizing energy consumption, improving the daylighting performance, economic viability, to tackle local housing deficits improving sustainability issue, a study in Cyprus [2] used a mixed-method strategy that combines literature review, taxonomy classification of prefab systems, energy and daylight simulations (utilizing DIVA/Rhino), and comparative cost analysis, the study reveals a prototype that attains near-zero energy levels (53.7 kWh/m²/year) with embedded solar systems the results emphasize the cost benefit of prefab construction (€292.45/m² compared to traditional €440.78/m²) and enhanced daylight performance through adaptive shading.Another study in Egypt, focuses on combining disassembly and circular adaptive façades to introduce hybrid reusable, biodegradable façade module utilizing local resources and smart controls (Arduino) to enhance energy efficiency and minimize waste with an emphasis on Egypt's climate. Integrates computational simulations (Ladybug/Honeybee), empirical prototyping, and sensor-based automation to create adjustable shading conditions, diminishing glare (by as much as 50%) and thermal loads. tackling the absence of circular lifecycle strategies in adaptive façades [3]another research optimizes west-oriented façades in Vietnam to boost daylight efficiency while meeting LEED v4.1 standards, concentrating on balancing Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE). By employing the African Vulture Optimization Algorithm (AVOA) in conjunction with parametric modeling and ClimateStudio simulations, the approach attained 100% LEED compliance, surpassing random designs (6.7% compliance). Main discoveries emphasize that light-hued materials and clear glazing are ideal for achieving a balance between sDA and ASE. [4] a study examines how courtyard geometry—location, orientation, and aspect ratio—affects energy efficiency in residential structures in Al-Kharga City, in Egypt's arid and hot climate, the study reinstates classic courtyard techniques to lower energy usage. Through DesignBuilder simulations, 9 courtyard configurations, 6 aspect ratios (ranging from 1:1 to 2.5:1), and two orientations (east-west and north-south) were evaluated. Significant gaps involve scarce research connecting courtyard shapes to energy measurements in Egypt and dependence on traditional designs lacking quantitative verification. Constraints include the lack of accessible real-world energy data and an emphasis on individual low-rise homes in a single city. Findings revealed that a southwestern courtyard with a 2.5:1 ratio (north-south direction) is ideal, attaining 18.73% energy savings and 17.88% decrease in CO_2 emissions. The research promotes the inclusion of courtyards in contemporary designs while emphasizing the necessity for evaluations of vertical and economic scalability [5]another research focuses on optimizing building shape and window design to improve daylighting and thermal energy efficiency in three Egyptian cities (Cairo, Alexandria, Aswan) that exemplify different aspects of a hot-arid climate. it focuses on the oversight of intra-climate variations in current research and the dominance of inflexible building designs in Egypt that increase energy usage. Employing a multi-objective genetic algorithm (Octopus) combined with parametric modeling (Grasshopper) and simulations (Ladybug/Honeybee), the research optimizes various dynamic factors such as building expansion, orientation, WWR, skylights, and shading. Significant gaps consist of a restricted emphasis on sub-climate variations and an excessive focus on envelope retrofitting instead of form optimization in earlier Egyptian research. Constraints include static fixed parameters (e.g., ceiling height), in a study of optimizing building fenestration [6] to optimize an office building thermal energy and daylighting through dynamic parameters manipulation using Rhino 6 + Grasshopper Ladybug/Honeybee for EnergyPlus thermal simulations and Radiance daylighting analysis, and Octopus plugin implementing SPEA-2 genetic algorithms for Pareto-front optimization, Achieved significant improvements over baseline designs - up to 36.14% EUI reduction and 15.15% UDI enhancement, with optimal solutions showing city-specific characteristics: skylights beneficial for UDI in Cairo (20%) vs. Alexandria/Aswan (10%), and shading devices essential for all EUI-optimal solutions.Another study investigates the isolated impact of diverse building forms on thermal energy performance in Cairo's hot climate, addressing gaps in prior research that conflated form optimization with other parameters (e.g., WWR, HVAC). Four novel form families—polygon, pixels, letters, and round—are parametrically modeled by (Grasshopper/Rhino), simulated (Energy Plus), and optimized (genetic algorithm) to minimize energy use intensity (EUI). Results identify round forms as optimal (27.9% EUI reduction) but computationally intensive, prompting an ANN model (R^2=0.798) to expedite predictions. Limitations include climate specificity, exclusion of envelope parameters (e.g., windows), and constrained optimization iterations. [7] Energy consumption in laboratory spaces is high compared to other similar case studies of a full building assessment in previous studies (217.1 kWh/m^2 by Hamida et al. The findings are slightly higher those reported by [9] for university campus buildings in Australia across various classifications (academic, administration, library, research, teaching, etc.), Research buildings had the highest EUI at 379 kWh/m^2. However, values of 800 kWh/m^2, 338 kWh/$m^{2,}$ 404.7 kWh/m^2 and 270 kWh/m^2 are reported for lab spaces, Simulation labs require 36.79% more energy than other labs due to the prolonged use of computers [10].

2. Research Problem

"The efficient utilization of laboratory space in university buildings presents a complex Mult i-objective optimization challenge involving Energy Use Intensity (EUI), Annual Thermal Comfort Ratio (ATCR), Daylight Autonomy (DA), Useful Daylight Illuminance (UDI), and Spatial Daylight Autonomy (sDA). Despite advancements in building performance simulations and optimization techniques, there remains a significant gap in understanding how to simultaneously optimize these metrics to enhance both energy efficiency and indoor environmental quality in laboratory spaces. This study aims to develop a novel framework for the multi-objective optimization (MOO) of laboratory layouts and configurations that maximize EUI reduction, improve ATCR, achieve high levels of DA, UDI, and sDA."

3.Objective

The main objective of the research is to optimize the performance of the lab space at architectural engineering buildings using Wallacei optimization tool of Rhino. identifying a number of variables that improve the performance of energy, thermal comfort and daylighting comparing alternatives created during the optimization through different generations.

5.Methodology

Applying the experimental approach to propose a framework for integrating genetic algorithms with simulating the performance of buildings in order to narrow the scope for research in choosing optimal solutions from the set of solutions selected by the multi-objective performance optimization-MOO. This will help the decision-making process for designers and will be applied to the lab space of a university to achieve the objectives of improving energy efficiency and increasing the efficiency of the and visual Comfort performance of the thermal comfort as well. Figure.2

6. Case study description

The framework was applied to an existing building 3 at Cairo university faculty of engineering building was built and used in 1989. Figure.3 as a case study to assess its applicability, capabilities, and limitations. The building Figure.4 consists of 7 stories of which 4 stories are occupied by Department of Architectural Engineering (3rd to 6th floors), and each one is 3.6 m high. architecture students in the building on 4 floors, including the third, fourth, fifth, and sixth, as well as an office section, a library, printing center, and a conference hall in the fifth floor, drawing rooms, and lecture halls distributed on all floors,The rest are used for different departments (2nd floor) is a computer ICT lab. This research focuses on the 2nd floor labs ICT Figure.5 where it has the highest energy measures and needs to have an optimized solutions for energy efficiency and visual and thermal comfort. Climate data were conducted using the ladybug standard Energy plus Weather data files (.EPW) of with climate data for the location of Giza, Egypt (Energy Plus weather file (EPW), Typical Meteorological Year – TMY). the building located in Giza governorate 28.7666° N, 29.2321° E Figure.6. building geometry and systems were modelled in the Rhinoceros7 environment using Grasshopper, Ladybug 1.6.7.0, a Radiance 5.4-based plug-in for Grasshopper, was used to conduct grid-based comfort and daylighting analyses. energy calculations are provided by Honeybee which use the EnergyPlus23.1.0 engine and open studio 3.6.1, a genetic algorithm optimization solver is Wallacei from Jan to December 2023, the simulation performed on the laboratory zone at the second-floor Figure.5 including all the surrounding spaces.The building envelope components (exterior walls, structural column fenestration, roof, ground floor) are shown in **Figure.3** building facades are modularly designed, so taking a section in one of the facades can determine its components. laboratory room Figure.6 which is a 70m^2 rectangular room (7m×10m×3.6 m) with two large south facing windows (1.4m×2.8m). sill height 90cm with total WWR 0.43 form total wall, structural columns with 1m length and 0.25m width with 0.75m outside as outer shade modularly distributed every 1.4m, the building orientation is 15 degree to the north and also to the south. The wall on which windows are located, has been divided into three horizontal sections: a fixed part at the bottom; a dynamic part in the middle, all of the parameters in the model of the window and shades can be controlled parametrically to accommodate any change in the building geometry while searching for the optimum solutions.

6.1 Building program

the laboratory is occupied 5 to 6 days per week, from 8:00am to 4:00pm. Higher education buildings are used about 200 days per year with relatively long periods of non-occupancy. The building program were set to most recent ASHREA 29.1 2019 which is coordinated with the international energy conservation code. For the academic year 2023 at Cairo University's Faculty of Engineering, including the Architecture Department, the semester and holiday schedules followed the general academic calendar of the university about 19 holiday day. The **Fall Semester** began in late September 2023 and typically runs until January, followed by the **Spring Semester**, which generally starts in February and ends in June.

6.2. Parametric Model Setup

Among all parametric modeling programs Rhino/Grasshopper is the most extensively used platform for parametric optimization, Ladybug too provides the ability to conduct climate data to the model to peruse climate-based analysis, for calculating Energy use efficiency Energy plus is the simulation engine open studio for creating energy model, Radiance engine for the analysis of daylighting and comfort metrics. The research proposes a laboratory room unit with an area of about 70 m2 and a height of 3.6 m as a measurement model for applying the research methodology to enhance the performance of higher educational building with Multi Objectives Optimization (MOO) of visual, thermal comfort and energy efficiency using Wallacei plugin as genetic algorithm solver. Wallacei (which includes Wallacei Analytics and Wallacei X) is an evolutionary engine that allows users to run evolutionary simulations in Grasshopper 3D through utilizing highly detailed analytic tools, and make more informed decisions at all stages of the evolutionary simulations; including setting up the design problem, analyzing the outputted results and selecting the desired solution or solutions for the final output. Focuses on problem formulation, analysis of the outputted results, selection of the optimized solutions [8].

6.2.1 Performance Simulation

6.2.1.1 Energy consumption

The building was zoned into 4 main zones, laboratories was the highest energy consumer so it was isolated to conduct energy assessment the surrounding spaces classrooms, drawing halls, laboratories, and corridors, are calculated energy use intensity (EUI) is 273.346 kwh/m^2 for the total zones as the cooling loads are 38027. 8 kwh, heating loads 7536.1 kwh, lighting loads 2758.3 kwh, equipment loads 2047.2 kwh. energy simulation was conducted cooling loads are the highest energy consumer. Energy use intinsity breakdown shows that the cooling loads are the heighst between all air conditioned zones. In Figure(8) represents energy consumption per month it shows that the highst consumption are in summer season during summer courses due to solar gain and cooling loads and the lowest are in autumn and winter season , heat gains from Appliances and lighting are nearly the same throughout all semesters.

6.2.2 Comfort Simulation

According to the Adaptive Comfort Model [11], the acceptable indoor operative temperature can be determined from the mean monthly outdoor air temperature as expressed in the following equation (1) the annual operative temperature of the laboratory Figure (10), which includes the outside south wall, roof, and fenestrations. shows that the peak heat gain periods in summer are 21 June and August due to extreme hot temperatures highest indoor temperature of the year so comfort were calculated through it Figure (11) predicted mean vote PMV is slightly warm, and average zone operative temperature is 27c°. As a result, the power consumption of the air conditioning system increases significantly during these periods to achieve desired thermal comfort in the laboratory. **Materials**, custom Radiance materials were assigned to laboratory surfaces. As shown in Fig two different sets of adjacent walls were defined: one set as interior (adiabatic) walls and another set as exterior ones.

$$T0(comf) = 0.31\,Ta(out) + 17.8 \qquad (1)$$

Where, *T0(comf)* is the optimum comfort operative temperature in °C, and Ta(out) is the mean monthly outdoor air temperature in °C. Further, the 90% acceptability limits of indoor operative

temperature can be calculated with [12]

$$90\%\ acceptability\ limits = To(comf) \pm 2.5\,°C. \ (2)$$

For the predicted mean vote (PMV) is used to measure the comfort into a conditioned space and adaptive comfort is used to analyze comfort in non-conditioned spaces, the Annual thermal comfort ratio (ATCR) is 65.70% not meeting the comfort model as the average Operative temperature is a weighted average of the air temperature and the mean radiant temperature (MRT). It represents the combined effect of air temperature and the radiant heat exchange between the human body and the surrounding surfaces [13]. And it is 34.8 C, measures at 21 Jun, the Time Not Meeting the Adaptive Comfort Models during Occupied Hours for ASHRAE55 90% Acceptability Limits, Laboratories 27°C, PMV for laboratory room

6.2.3 Daylight Simulation

Daylighting simulations were run over the period of one year, The internal loads and schedules were set according to the actual building the standardized values for the Higher education buildings category a minimum illuminance level of 500 lx on the work plane at a height of 80 cm above ground. **Analysis grid** of the Daylighting performance was simulated on one plane, resulting in a set of analysis points a grid of 0.5 m × 0.5 m at a working level height of 0.8 m, with 210 sensor point at the grid. Daylight Availability (DA) metric is, 33.8% which is below the standard Figure (12), Useful Daylight Illuminance (UDI) is a used to assess the quality and quantity of natural daylight in a space where the lower limit is 100 LT >100 T >3000 UT figure (14) the Useful daylight illuminance is 89.3% for UDI between 500-3000, and 3.8% for UDI<100, and 7.2% for UDI>3000, While general lab lighting standards are around 500 lux, for daylight, the goal is a range that supports precision tasks. A useful range of 100-2000 lux is a common starting point. spatial daylight autonomy sDA percentage 31.5%, Aiming for Preferred Sufficiency of daylighting a target would be for at least 75% of the floor area to have an sDA300/50% of 75% or greater. Assesing metrics like sDA and UDI can go beyond simple illumination levels to evaluate the quality and consistency of daylight in a laboratory throughout the year. recommended by organizations like the IESNA, quantify the availability of sufficient and comfortable daylight over timeEnsuring visual comfort Glare autonomy was measured figure (13) So for a threshold of Daylight glare probability DGP > 0.45, a GA of 100% means that the probability of experiencing daylight glare at a given view never exceeds 45%. In this study it is 100% so the lab wont face problems with glare.

6.3 Optimization

Wallacei X employs the NSGA-II algorithm [14] as the primary evolutionary algorithm, and utilizes the K-means method as the clustering algorithm [10] The framework used NSGA-II as an optimizer to perform evolutionary Mult objective optimization simulations, is provided by Wallacei add-on for Grasshopper 3D Wallacei (including Wallacei Analytics and Wallacei X Components) is an Evolutionary multi-objective optimization engine that runs evolutionary simulations in Grasshopper 3D. Produces multiple solutions decisions during the evolutionary simulation, assessing the results, applying selection strategies, and exporting the resulting genotypes by a set of components it can analyze the fitness values generated by each generation. five objectives set in the optimization were to minimize the Energy use intensity use (EUI) by decreasing the energy consumption using Energy Plus and Open studio. a Radiance model to maximize the amount of adaptive comfort by calculating annual operative temperature, by maximizing annual thermal comfort ratio (ATCR), also maximizing daylighting level in the zone measured as the daylight autonomy (DA). Useful Daylight illuminance (UDI) to ensure uniform distribution of daylight into the space the occupancy hours, Spatial daylight Autonomy (sDA) to meet the LEED V4 standards in this category of buildings.

6.3.1 Description of the numerical model's objectives and settings

The optimization procedure was conducted out utilizing the Multi objective optimization (MOO) Genetic algorithms apply evolutionary concepts to identify optimal solutions to a problem based on certain objectives. To simulate the problem, a parametric approach is required. Variable inputs, such as, shade depth and distribution, count of louvers, and tilt angle of vertical of the louvre-blades, Window wall ratio, resistance of Exterior walls R-Wall, U-value for windows glass, windows height and sill (Table). The way the model is scripted, the vertical louvers move freely around the vertical axis z the table below describe the whole design parameters that set to optimize the lab. are utilized to adjust the model's measured outputs (EUI, ATCR, UDI, DA, sDA). The method evaluates output based on a fitness function to quantify solution performance.

6.3.2 Design parameters

This study taking into account several types of influential parameters affecting the optimization which are (WWR, shade depth, distance between shades, shade count, louver angle, U-value, R-Wall) affects cooling, heating loads, and also EUI, ATCR, UDI, DA, sDA, as shown Table (3). genetic algorithm begins by creating a random population of solutions and then evaluating their fitness. Then a loop begins, with each iteration representing what is known as a generation. The loop consists of selecting the best-fit individuals from the population for reproduction, breeding new people, evaluating the fitness of the new offspring, and eventually replacing a portion of the population with the fittest offspring. Breeding new people based on genetic operators such as crossover- and mutation rates, as well as crossover- and mutation probability, ensures that the genetic algorithm evaluates a wide range of solutions and discovers new alternatives. The number of solutions created is determined to maintain a balance between processing time and having a sufficient number of examples for the algorithm to find Pareto-optimal solutions. When these solutions are plotted, they form what is known as the Pareto front-in our instance, a 3-dimensional plot. All of the points on the Pareto front are non-dominated solutions, which means they reflect the optimal compromise (tradeoff) of performance between conflicting objectives. All other points developed during the optimization process are referred to as dominated solutions since at least one other solution consistently outperforms them. This stage involves many performance design characteristics to meet standards, including building envelope window to wall ratio (WWR), materials, and more. After creating parametric models, performance simulation evaluates performance for each criterion and passes decision-making to multi objective optimization stage.

6.3.3 Design Objectives

Design objective is shown in table (4), The framework.* can use objective functions to define design objectives, such as minimizing Energy use intensity, maximizing thermal comfort, or maximizing visual comfort. Performance optimization begins with converting or reconfiguring the design parameters to meet performance objectives. Evolutionary algorithms analyze the relationship between Design parameters and fitness values, generates design alternatives for improved performance, and identifies the Pareto front for trade-offs between objectives. After the optimization process, the solver component exports generated phenotypes (PHE), genomes (GE), and optimization parameters via export components. Furthermore, it enables the viewing of EMO simulation results in the form of objective space. Architects can analyze the performance of set objectives using charts such as fitness value (FVC), standard deviation (SDC), standard deviation trendline (SDTC), and mean fitness trendline (MFTC).

7. Results

Pareto front solutions in Figure (15) depicts the laboratory performance problem's 5th-dimensional objective space, which includes five energy efficiency targets (EUI, ATCR, DA, UDI, and sDA) The X, Y, and Z axes indicate the objective functions, respectively. The Pareto Front component calculates the non-dominance value for any generation within the population and draws the pareto front for any given generation. Parallel coordinate plot (PCP) method was used to visualize and represent the objectives' fitness values for all solutions over the entire population. (EUI) reached 202.98 kwh/m2, (ATCR) reached the value of 93.8%, (DA) reached 79.7, (UDI) reached 66%, and (sDA) reached 100% as shown in figure (16) it shows the optimum results of every objective function in all generations.each fitness objective is attributed a y-axis, in which the first objective is the left most y-axis, and the last objective is the right most y-axis. The polyline that connects the corresponding fitness values across the y-axes represents a solution. A colored form ranges from red to blue colors was used to indicate the first solution and the last solution respectively. The solver found 88 pareto front solutions for all generations the replicated solutions has been eliminated and below are the 10 solutions figure (17) that considered to be optimum solutions table (6)these solutions (chromosomes or genotypes) corresponding to Pareto front compared to baseline case study, managed to decrease (EUI) objectove and increase (ATRC), (DA), (UDI), (sDA) as shown in figure (17)

4. Conclusions

This research demonstrates the efficacy of abilities parametric multi-objective optimization in delivering high-performance building solutions, providing us with actionable insights for achieving energy-efficient and occupant-comfort-oriented design alternatives. This paper proposed methodology and workflow to optimize building performance by inducing optimum and near optimum solutions of the building envelope and inner walls which is highly adaptable and can be extended to other building typologies and performance criteria specially in existing buildings. Decreasing (EUI) by 26%, increasing (ATCR) by 1.9%, increasing (DA) by 2.35%, increasing (UDI) by 1.3%, and increasing (sDA) 3.17%. which is a complex tradeoff.The case studies reviewed in this research demonstrate the potential for significant energy savings and enhancements in occupant comfort when MOO techniques are applied. As the demand for energy-efficient, occupant-friendly buildings continues to grow, MOO techniques will become increasingly valuable in helping designers navigate complex performance trade-offs.

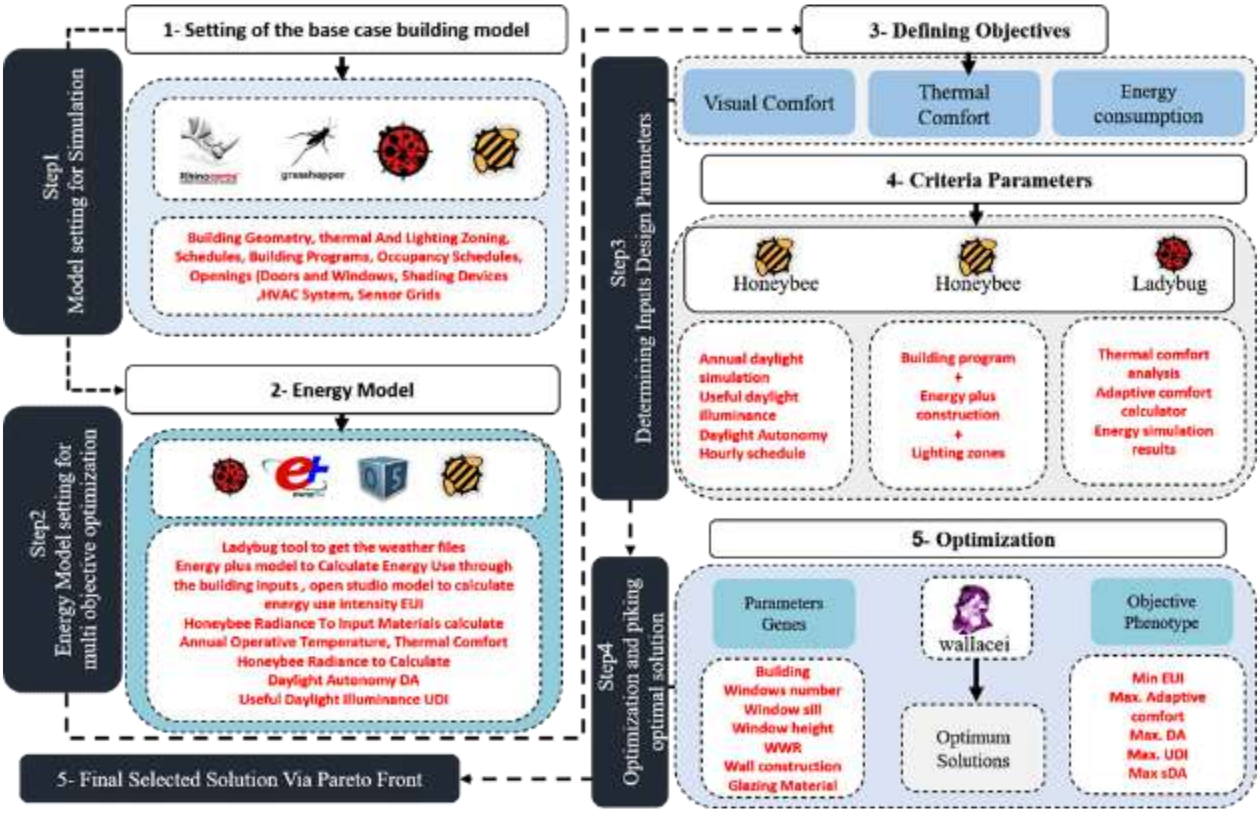


Figure 1 *Flowchart summary conducted from the literature to design the research methodology.*

Figure 2. *Building layout*

Figure 3. *Architecture Engineering Building*

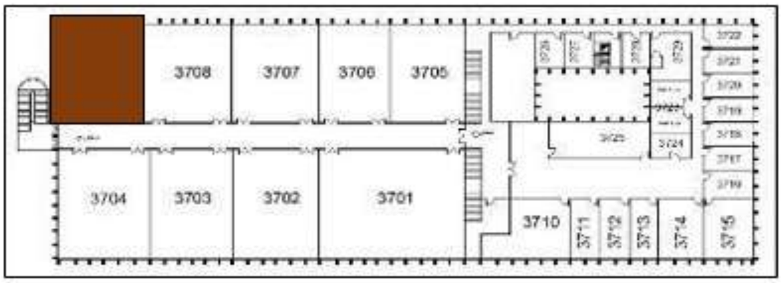


Figure 4. *Second floor plan*

Figure 5. *lab layout*

Figure 6. *Second floor of the architecture building, the Faculty of Engineering, University of Cairo, consists of a number of laboratories that differ in their orientation but are similar to the area.*

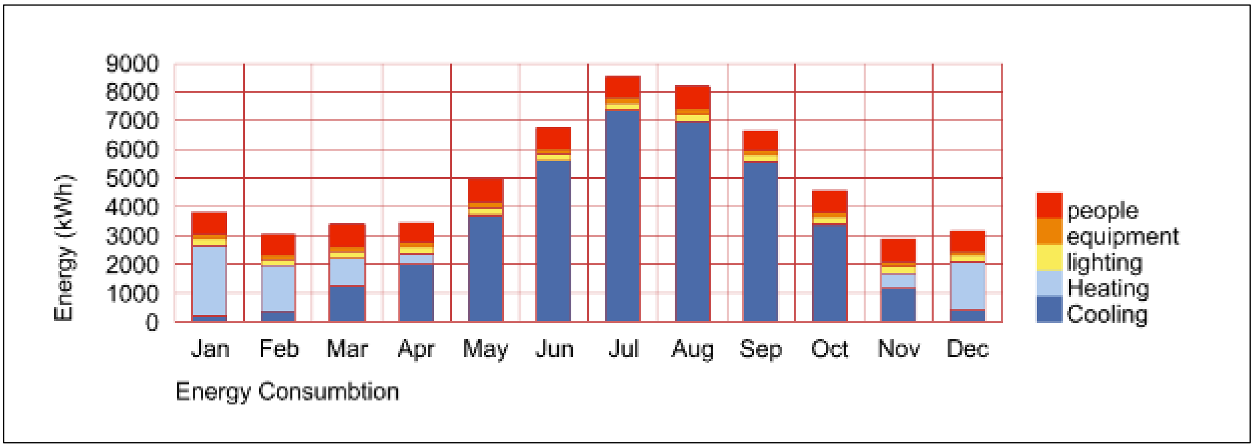


Figure 8. *Energy consumption simulation through a year*

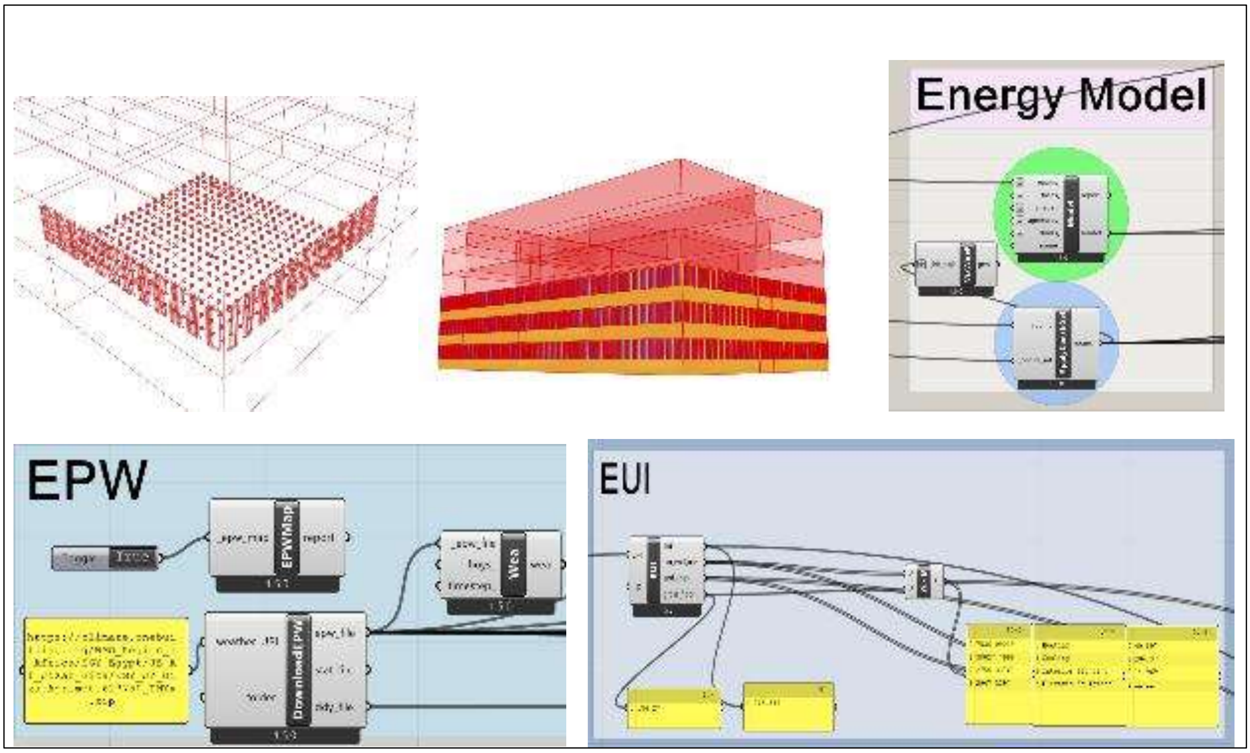


Figure 8. *Energy model created to conduct energy consumption and simulation*

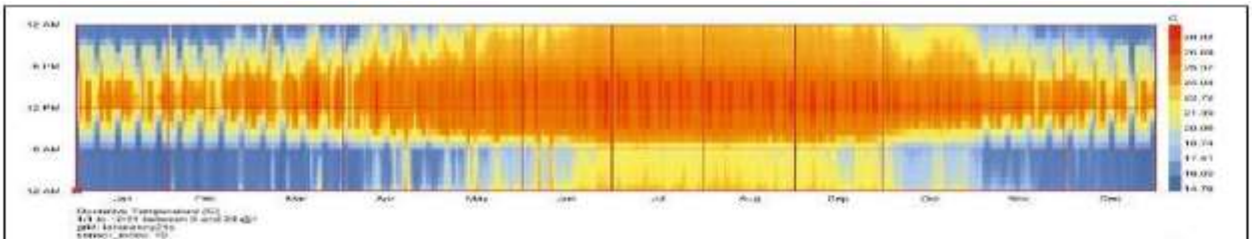


Figure 9. *Operative temperature for a year calculated from mean monthly outdoor air temperature*

Figure 10. *operative temperature from 1/6 to 30/9 from 8am to 20pm, zone average temperature 27°C, PMV for laboratory room*

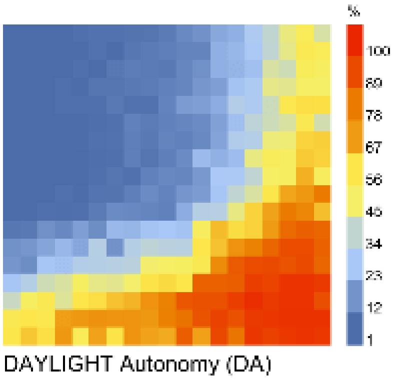


Figure 11. Daylight Autonomy through a year

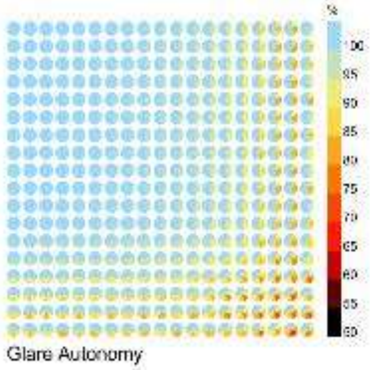


Figure 12. Glare Autonomy through a year

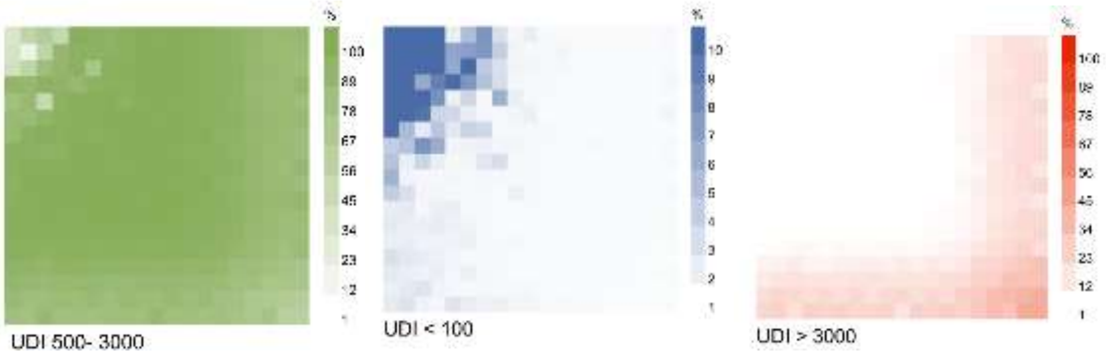


Figure 13. *Useful daylight illumenance*

Table 1 *Summary of base case energy, comfort, and daylighting metrics*

Metric	Value	unit
EUI	273.35	Kwh/m2
heating	7536.09	kwh
cooling	38027.78	kwh
interior lighting	2758.34	kwh
electric equipment	2047.24	kwh
ANNUAL THERMAL COMFORT RATIO (ATCR)	48.66	%
DAYLIGHT AUTONOMY (DA) %	33.85	%
UDI 100 - 3000	49.9	%
UDI < 100	3.89	%
UDI > 3000	7.22	%
SDA 50%	31.5	%

Table 2 *Evolutionary Multi-Objective Optimization Algorithm Settings (NSGA-II)*

Population	
Generation Size	10 Solutions
Generation Count	40 Generations
Population Size =	Generation Size x Generation Count 400 Solutions
Crossover Probability	0.9
Mutation Probability	1/n (n= No of Genes)
Crossover Distribution Index	20
Mutation Distribution Index	20
Random Seed	1

No. of Genes (Sliders)	9 Genes
No. of Design Variables	(Slider Values) 178
No of Objective Values	5
Size of Search Space	2 x 10^9

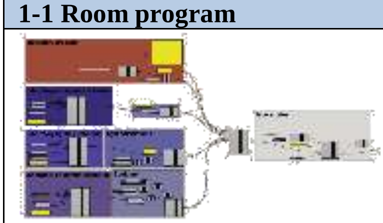
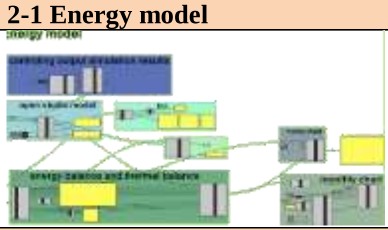
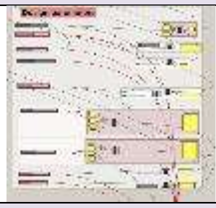
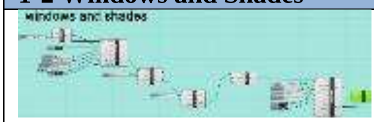
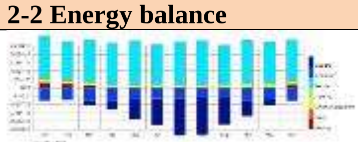
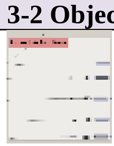
Table 3 *Design parameters*

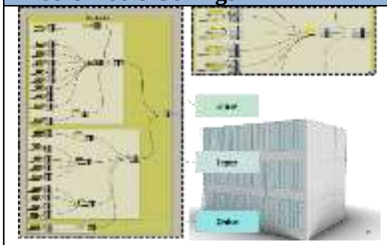
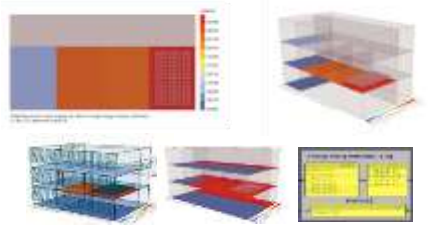
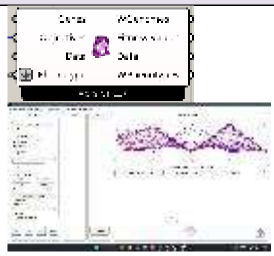
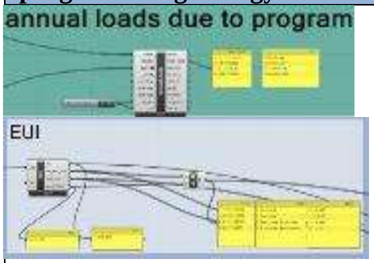
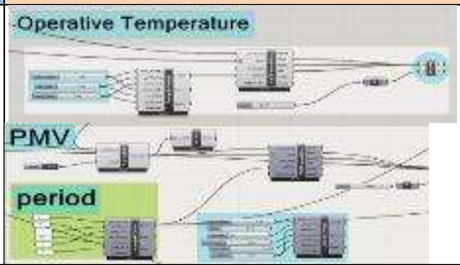
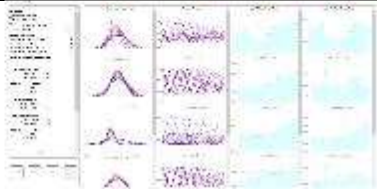
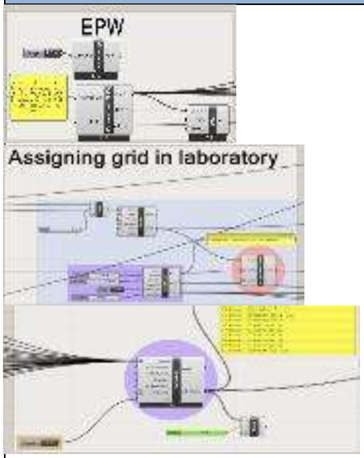
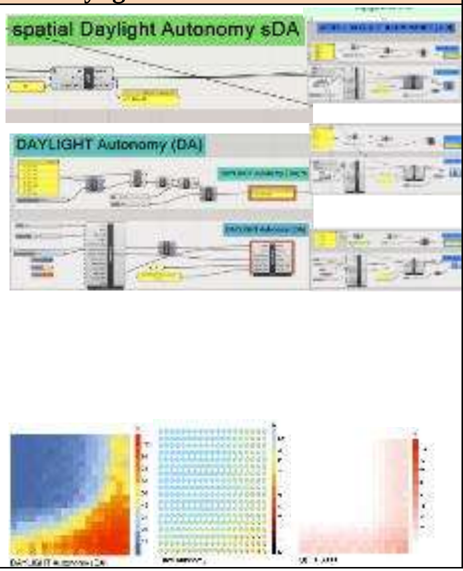
Variable	attributes	Number of values
Shade depth	0.15, 0.2, 0.25, 0.3	4
Distance between shades	Increment from 0.1 to 1	10
Shade count	From 1 to 12	12
Louver angle	From -50 to 50 with n increment of 10	11
WWR	from 18% to 82% with increment of 4	64
R-wall	Values from ASHREA 2019 of external walls materials 0.85, 0.9, 0.95, 1, 1.2, 1.4, 1.6	7
U-value glass	Several types of glass obtained from ASHREA 2019 0.81, 1.4, 1.5, 1.6, 2.6, 5.8 Generic Low-e Glass, Generic Window Air Gap, Generic Window Argon Gap, LoE TINT 6MM, U 0.32 SHGC 0.22 Simple Glazing, COATED POLY-55	6
Windows height	3.4, 3.2, 3, 2.8, 2.6	5
Windows sill	0.5,1, 1.5, 2, 2.5	5
Total design parameter		124

Table 4 *objective functions*

Objective functions	Reason of choose
Minimize Energy use intensity (EUI)	energy per meter per year. It is calculated by dividing the total energy consumed by the building in one year by the total gross floor area of the building
Maximize Adaptive comfort Annual thermal comfort ratio (ATCR) [16]	By using the adaptive thermal comfort model, the periods of discomfort, and so the potential energy demand for active cooling, are not overestimated.
Maximize visual comfort Daylight Autonomy (DA) [17]	it is signified as a percentage of annual daytime hours that a given point in a space is above a specified illuminance level
Maximize Useful daylight Illuminance (UDI) [18]	It is the annual time fraction that indoor horizontal daylight illuminance at a given test point reaches in a given domain. UDI contains lower and upper thresholds and an acceptable range as UDI u underlit, UDI overlit and UDI useful respectively.
Maximize Spatial Daylight Autonomy (sDA) [19]	sDA has become the most common due to its inclusion in LEED v4

Table 5 *Optimizing laboratory three stages modeling, simulation, and optimizing*

1- Parametric model	2- Performance Simulation	3- Optimization
1- Geometry	**2 -Energy simulation analysis**	**3-Design Parameters**
1-1 Room program	**2-1 Energy model**	**3-1 Genes**
		
1-2 Windows and Shades	**2-2 Energy balance**	**3-2 Objective functions**
		
1-3 Construction for Every Element of The Building Walls	**2-3 Laboratories are the highest cooling loads between all the Conditioned zones**	**3-3 Optimizing by Wallacei X 2.7**

1- Parametric model	2- Performance Simulation	3- Optimization
Floors Roofs Ceilings		
		
1-4 Annual Loads Due To program using Energy Plus	2-4 Comfort Simulation	3-4 Wallacei Analytics
		
1-0 Weather files	2-5 Daylight Simulation	3-4 Wallacei Selection
		

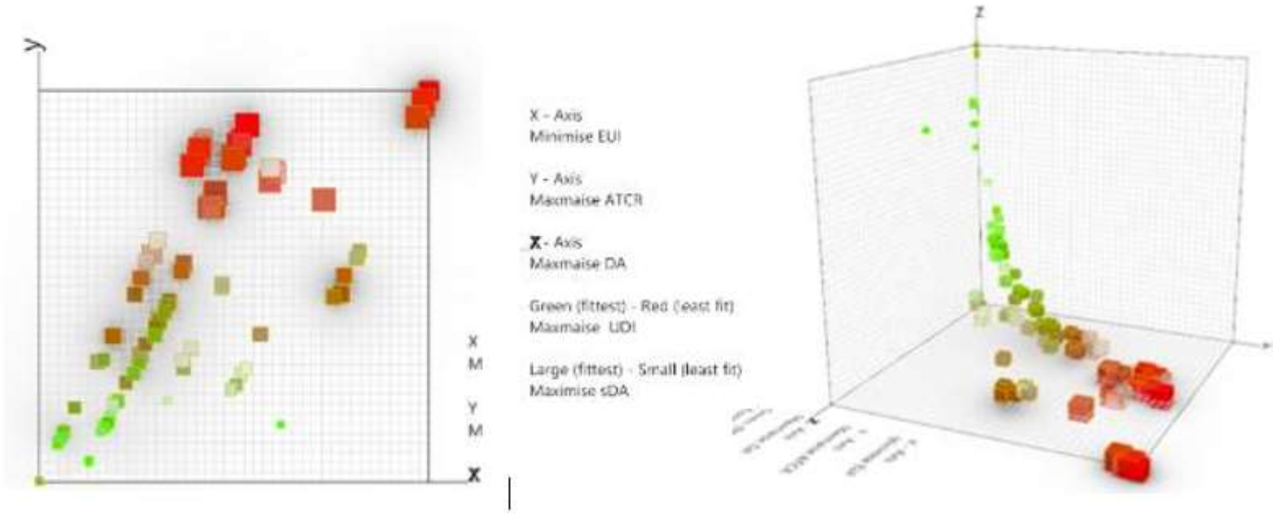


Figure 14. *Objective space pareto front solution*

***Table 6** objective functions results*

Objective function	Base case results	Optimum objective results	Variation ratio%
EUI Kwh/m^2	273.35	202.98	26
ANNUAL THERMAL COMFORT RATIO (ATCR)	48.66	93.84	1.9
DAYLIGHT AUTONOMY (DA) %	33.85	79.7	2.35
UDI 100 - 3000	49.9	66.03	1.32
SDA 50%	31.5	100	3.17

***Table 7** pareto front solutions genomes*

	shade depth	dist. Between shade	shade count	Louver Angle	WW R	R-Wall	U value glass	win height	win sill
(0,0)	0.15	0.2	6	30	0.62	1.2	1.5	3.4	0.75
(0,4)	0.2	0.2	7	0	0.34	1.4	2.6	1.4	0.75
(8,9)	0.2	0.2	12	0	0.34	1.6	5.8	2.6	0.75
(9, 9)	0.15	0.2	4	10	0.42	1.2	2.6	2.6	0.75
(10,0)	0.2	0.2	12	0	0.34	1.6	5.8	2.8	0.75
(11,8)	0.2	0.2	5	0	0.34	1.4	0.81	2.8	0.75
(17,7)	0.2	0.2	2	0	0.38	1.4	0.81	3.2	1.25
(21,6)	0.2	0.7	12	0	0.34	1.4	5.8	2.8	0.75
(26,6)	0.2	0.2	6	-10	0.34	1.6	5.8	3.2	0.75
(35,9)	0.2	0.1	7	10	0.34	1.4	5.8	2.8	0.75

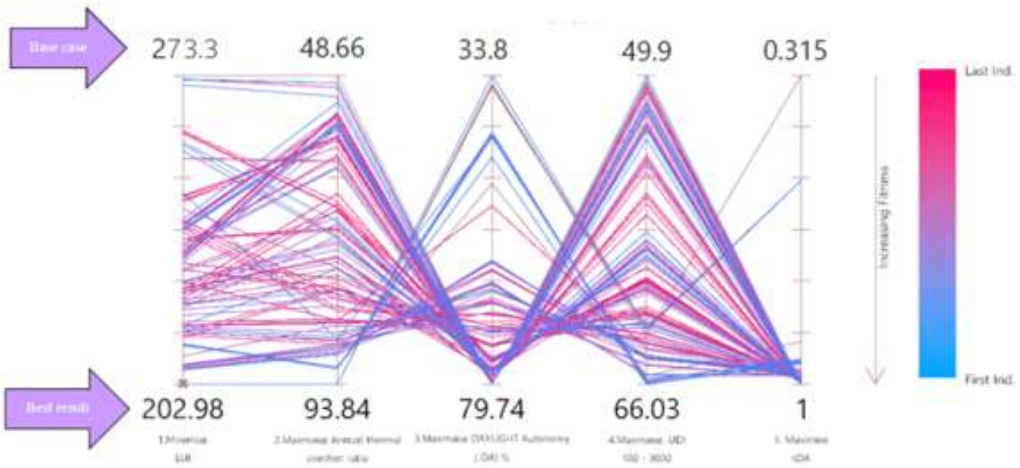


***Figure 15**. Parallel coordinate plot for objective function*

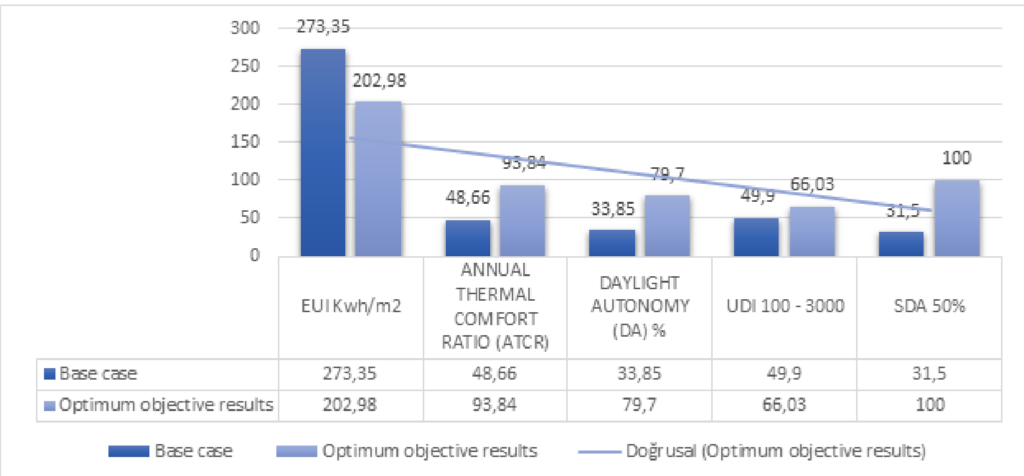


***Figure 16.** The variance of objective functions and fitness values*

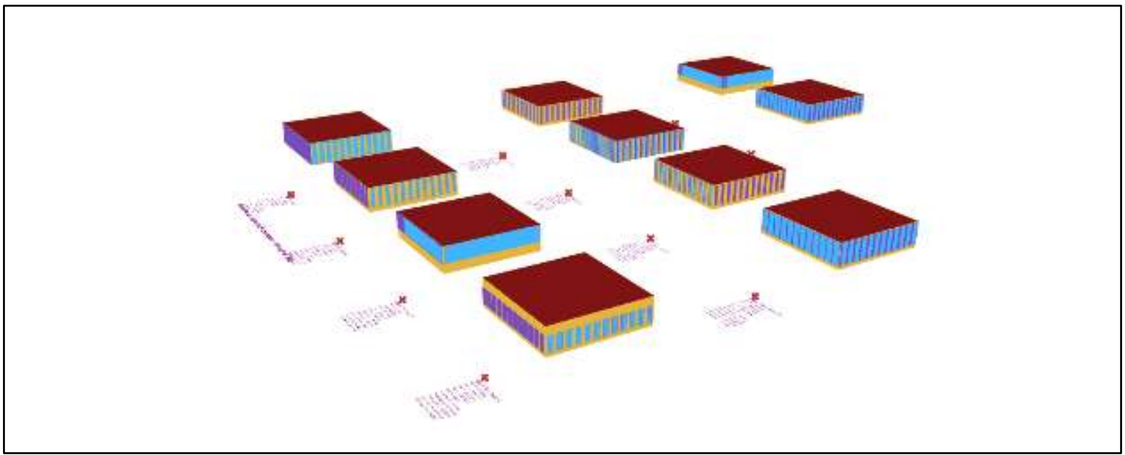


Figure 17. *A group of 10 pareto front solutions*

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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