Journal of Solar Energy Research (JSER)

Journal homepage: www.jser.ut.ac.ir

A Novel Design-based Optimization Method for Building by Sensitivity Analysis

Qodsiye Najafi[a], Yousef Gorji Mahlabani[b,*], Ali Goharian[c], Mohammadjavad Mahdavinejad[c]

[a] Faculty of Architecture and Urbanism, Imam Khomeini International University, Qazvin, Iran.
[b] Faculty of Architecture and Urbanism, Imam Khomeini International University, Qazvin, Iran.
[c] Department of Architecture, Tarbiat Modares University, Tehran, Iran.

Received: 07-12-2022
Accepted: 09-04-2023

Abstract

The important objective of a building must be to provide a comfortable environment for people. Heating ventilation and air conditioning systems provide a comfortable environment but they have high energy consumption. Therefore, designing an energy-efficient building that balances energy performance and thermal comfort is necessary. Choosing effective parameters for energy performance is an important factor in achieving this goal. This research aims to produce a methodology for multi-objective optimization of daylight and thermal comfort in order to study the effect of wall material and shading of an office building (Tehran a basic-location). The building simulation was developed and validated by comparing predicted daylight and thermal comfort hours based on tests and training in Jupiter Notebook. The sensitivity analysis uses a multiple linear regression method. Secondly, optimization is based on a genetic algorithm with effective parameters to optimize daylight and thermal comfort performance. For this, we developed a parametric model using the Grasshopper plugin for Rhino and then used Honeybee and Ladybug plugins to simulate thermal comfort and daylight, and finally used Octopus engine to find an optimization solution. The result of this paper is essential as a preliminary analysis for building optimization in the open-plan office.

Keywords: Thermal comfort, designedly approach to daylighting, Multi objective optimization, Daylight, Sensitivity analysis

DOI: 10.22059/jser.2023.352184.1269 DOR: 20.1001.1.25883097.2023.8.2.7.5

*Corresponding Author Email Address: gorji@arc.ikiu.ac.ir

1. Introduction

Considering the increased environmental challenges due to global warming, the energy efficiency of buildings has an effective role in architectural design. Today global approaches aim to reduce energy consumption to achieve a sustainable environment [1]. Solar radiation has a crucial role in hot climate regions that can lead to excessive energy consumption. Sustainable building attends to increase the quality of the environment [2],[3]. Good buildings incorporate thermal and lighting comfort conditions as they have a fundamental impact on building performance [4]. Although many researchers focus on thermal comfort and daylight, many have proposed theoretical results that are not practical [5], [6]. A place that has thermal comfort is a condition that people in place are satisfied with. The Predicted Mean Vote (PMV) and Percentage of Persons Dissatisfied (PPD) are the popular indices for thermal comfort [7], [8]. These indices are calculated based on environmental parameters, such as relative humidity, air velocity, air temperature and mean radiant temperature, and occupant-related parameters such as metabolic rate and clothing insulation [9], [8].

The main purpose of good design is to improve energy consumption and daylight access. On the other hand, building optimization is one of the cost-effective solutions to increase building performance [10]. The overall heat transfer of windows is usually about five times greater than other building components, but designers usually use a high window-to-wall ratio in their projects [11]. Research shows that measures of U-value, Solar Heat Gain Coeficient (SHGC), visible transmit (VT), glass, double-layer glass and window size could increase thermal comfort [12], [13]. Solar shading devices have a considerable advantage in the regulating solar radiation [14], [15].

Due to relatively little knowledge about optimization and uncertainties of design parameters, the designer's default values should be confident about the parameters, significantly affecting the simulation result. This effect will be small if the purpose is to compare several design options. If these parameters are examined for the optimization process, the effect will be longer; therefore, if these parameters are not selected correctly, simulation time and design cost will be increased. Also, due to the time-consuming optimization process and the uncertainty of the desired parameters, it is necessary to carry out sensitivity analysis (SA) before optimization [16].

Sensitivity analysis (SA) is the statistical method that can calculate the relationship between input and output parameters [17]. Statistical methods examine the effect of these parameters by examining many output parameters relative to the input parameter [18]. SA has a significant effect on understanding building simulation. SA's purpose is to predict the performance of design parameters, also research on these parameters is useful to achieve the optimal building [19], [20].

In recent years optimization algorithms have focused on solving the optimization problems in building design. Optimization is the process of finding the best solution or solutions between different alternatives. Building optimization is performed automatically by simulation and stochastic population-based optimization algorithms, including genetics and particle swarm [21], [22].

This research aims to address the knowledge gaps about the effect of sensitivity analysis in building simulation. The SA objective is to find the most influential design parameters with multiple linear regression and the optimization objective is to find the most optimum solutions which is usually a simple approach proposed by ranking the solutions on the Pareto frontiers. The optimization process is performed based on a genetic algorithm with the octopus plugin [23] Fig1.

This paper established a method for the office building, this method considered the effect of building design for thermal comfort and daylight with Honeybee and Ladybug plugins taking advantage of python's ability. The variable parameter in this study is wall construction Thermal resistance (R-Value), window to wall ratio (WWR), Window frame thickness, SHGC, Shading Reflectance and Shading Depth. The parameters have been proposed by many researchers, but these parameters are not always fully accounted for in the SA and optimization process; these parameters can interact with each other.

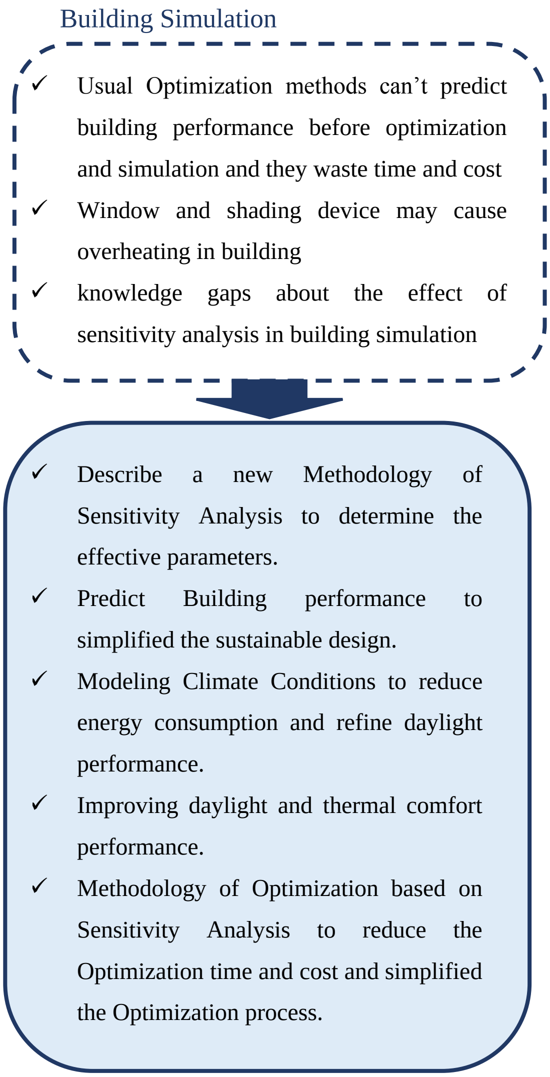

Figure 1. Strategy of research aim

2. Material & Method

This research is modeled in the Grasshopper plugin parametric environment that has been developed in Rhinoceros software. Honeybee and Ladybug plugins have been developed to simulate building performance; The present study, using the parametric potential of these plugins, has completed the optimization solution process more quickly and flexibly [23].

The building is located in Tehran. The office is occupied daily from 8 AM to 6 PM. The base case building represents the typology of the Reinhart office [24]. The selected office is located on the ground floor with a total area of 29.52m^2 Fig2.

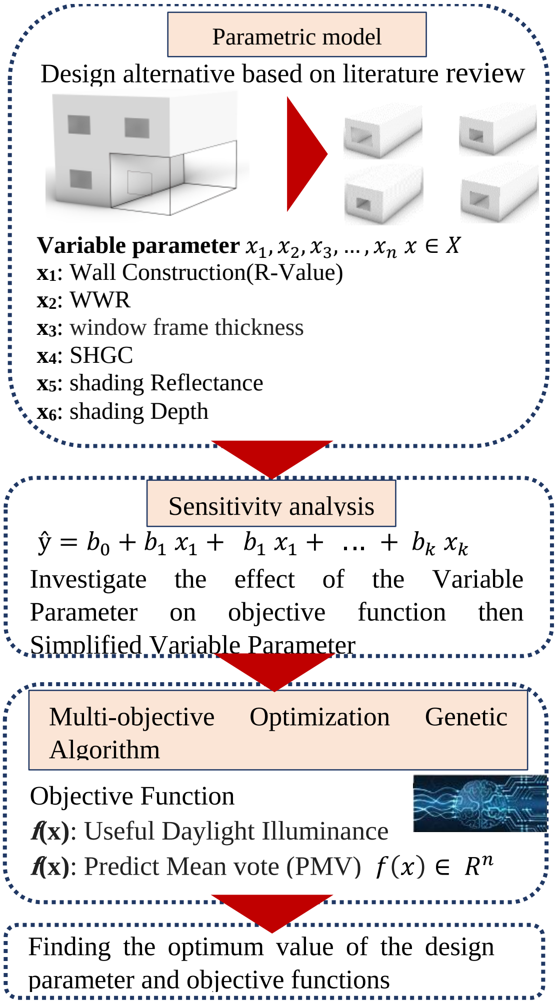

Figure 2. Case study design process

The shading system position is above the window located on the south façade. More details about the building construction are given in Table1.

Table 1. The detailed building construction information

Component	Description
Exterior wall (W/m^2 · K)	Concrete brick
Roof (W/m^2 · K)	Concrete - 0.10
Exterior window (W/m^2 · K)	Double glazing Window
Floor (W/m^2 · K)	Concrete - 11.76

The number of people per area (occupant density) is 0.06 (people/m^2). The Lighting density is 2.235 (W/m^2). Daylight sensors are placed on a grid 0.8 cm above the floor and the grid size is 0.40*0.40 cm. Lighting measurement IES LM-82-12 promotes climate-based daylighting metric [25].

It is generally considered that if the indoor illuminance were above 500 lx the indoor lighting requirements can provide. The present method has follows [26]'s studies, which are based on the SRC method. The range of design parameters have been selected by testing and training. This research uses the Monte Carlo method for Sensitivity analysis. This is a random sampling method [27]. Table2 shows this information for the building performance.

Table 2. Design variables parameters for sensitivity analysis

Parameter	Variable
Wall Construction(R-Value)	0.09, 0.14, 0.19
WWR (%)	14, 26, 32, 43, 52, 56
window frame thickness(m)	0.06, 0.07
SHGC (%)	0.35, 0.39, 0.46, 0.50
shading Reflectance	30, 40, 50
shading Depth(m)	0.05, 0.09, 0.15

Response variables are the average yearly, UDI, PMV, and PPD values. PMV index based on environmental parameters. Table3 reports the considered parameters and their corresponding levels.

Table 3. Investigated factors and their corresponding levels for thermal comfort simulation

Factor	Unit	Level
Clothing level	Clo	0.8-1.5
Metabolic rate	W.m^{-2}	58-125

Considering the objective of this research is the Multi-Objective Optimization (MOO) of daylight and thermal comfort so this objective can maximize the PMV and Useful Daylight Illuminance (UDI) and optimize the energy and daylight performance. The research framework is performed in three main steps shown in Fig3.

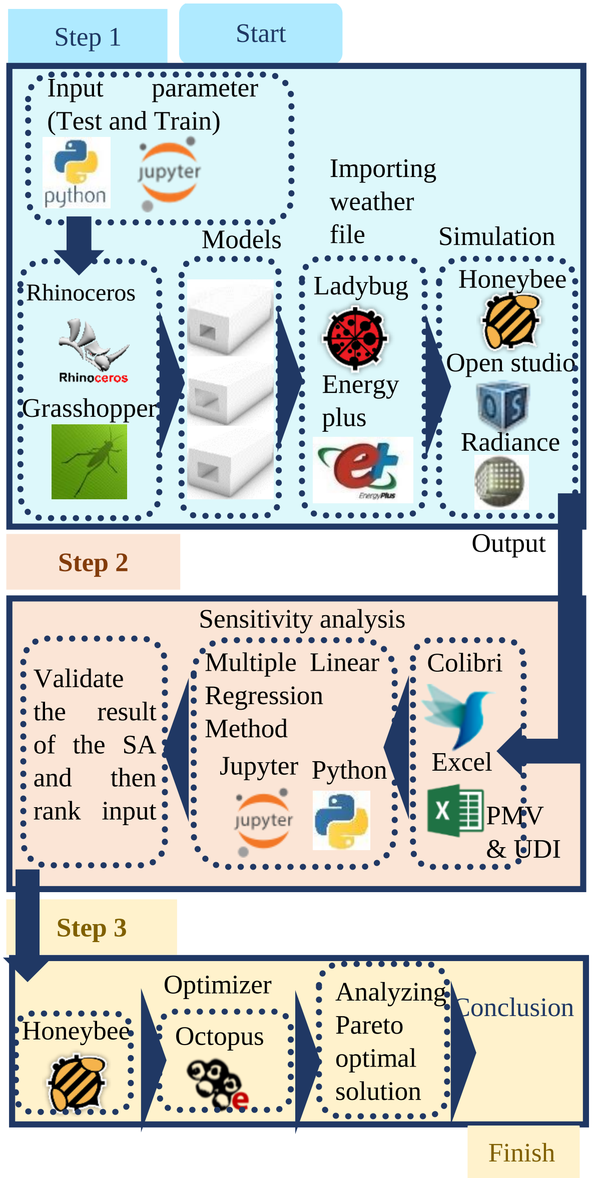

Figure 3. Overall methodology process

First, the geometry model is designed based on the variable parameter. Then SA is carried out. Finally, optimization is carried out based on a simplified variable parameter. Sample size is based on testing and training in Jupiter notebook using Python language. According to the range of each parameter that is between 0-1 the sample size is selected. In this research, all parameter ranges are between 0-1, and therefore there was no need data range standardization. The SA is generally related to the design parameters of building components which are wall (material, insulation) window- to-wall-ratio, windows (window frame thickness and SHGC) and shading (reflectance, depth).

After designing the model, the model was simulated based on the input parameters of honeybee. The daylight index in this research is UDI, which was proposed by [28]. This factor is a dynamic daylight performance. The purpose of it is to determine when daylight levels are useful for the occupant. The suggested range of this index is 2000 lx and 100 lx. it means (<100) lx is too dark and (>2000lx) is too bright [28], [29].

The thermal comfort index in this research is PMV and PPD [30]. The PMV index is the quantitative prediction for the average vote of individuals on a thermal sensation scale that ranges from −3 to +3; where −3 is very cold, 0 is neutral and +3 is very hot. The recommendations range for maintaining a PMV between −0.5 and +0.5. The discomfort hours were not assessed when PPD was higher than 20%. The PMV index is calculated using Eq1 and each component of this index is calculated using Eq(2-6), [31].

$$PMV = \left(0.303^{(e-0.36m)} + 0.028\right) \left[\left(M - W\right) - H - E_c - C_{rec} - E_{rec}\right] \quad (1)$$

$$E = 3.05\times10^{-3}\left(256_{tsk} - 3373 - P_a\right) + E_{sw} \quad (2)$$

$$E = 3.05\times10^{-3}\begin{bmatrix}\left(5733 - 6.9\times 9M - W\right)\\ -P_{(a)}\end{bmatrix} + 0.42\left(M - W - 58.15\right) \quad (3)$$

$$C_{rec} = 0.0014M\left(34 - T_a\right) \quad (4)$$

$$E_{rec} = 1.72\times10^{-5}M\left(5867 - P_a\right) \quad (5)$$

$$H = K_{cl} = \left(t_{sk} - t_{cl}\right) \div I_{cl} \quad (6)$$

Also the PPD index calculates based on (Eq7) [31].

$$PPD = 100 - 95e\begin{pmatrix}-0.03353\times PMV^4\\ -0.2179\times PMV^2\end{pmatrix} \quad (7)$$

This research performed SA using a sampling-based method. SA was used in different fields and performed in different methods. This research is based on Multiple linear regression (MLR) method Eq8 shows that MLR, is about the best-fitting model [27].

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + ... + b_kx_k \quad (8)$$

To calculate the variability of the data, the measure of distance from the mean or description of the data range is often used. Total variability Sum of Squared Total (SST) is a summation of an unexplained variability explained variability. SST is a measure of total variability of a dataset. Sum of Squared Regression (SSR) is a measure explained by variability by your line. Sum of Squared Error (SSE) is a measure of unexplained variability by the regression. The division of SSR on SST is equal to R^2 Eq (9-13) [27].

$$SST = SSE + SSR \quad (9)$$

$$SST = \sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2 \quad (10)$$

$$SSR = \sum_{i=1}^{n}\left(\hat{y}_i - \bar{y}\right)^2 \quad (11)$$

$$SSR = \sum_{i=1}^{n}\left(e_i\right)^2 \quad (12)$$

$$R^2 = \frac{SSR}{SST} \quad (13)$$

Given that the R^2 always increases with increasing the dependent parameter, this is while the new parameter may not have a significant impact, therefore, it is necessary to use the Adjusted R^2, and increasing it means increasing the efficiency of the model. In the other word Adjusted R^2 increases only when the new parameter has a significant impact on the model Eq14, [32].

$$\bar{R}^{2} \prec R^{2} \tag{14}$$

Low R^2 indicates a poor fit of the regression model with the outcome of the building model. The value range of R^2 is between -1.0 and +1.0 [32], [33].

SA was carried out in Jupiter notebook based on MLR. Jupiter notebook. The SA was carried out by coupling python language and honeybee and ladybug. The First simulation result (PPD and UDI 100-2000) is stored in a CSV file by TT Toolbox. Then each set of input variables and simulation results was read from the CSV file and written to the Jupiter notebook in turn by means of python language. The SA consists of two loops: the honeybee plugin performed a full-year simulation in time step and the python performed MLR. At the first, we need to standardize the input parameter to be able to rank them. Then the accuracy of the method was evaluated with F-statistic. The closer F-statistic is to 0, the accuracy of the model is lower and our model is not good Eq15, [32].

$$H_0 = b_1 = b_2 = \ldots = b_k = 0 \tag{15}$$

In the next step, the effective parameter is determined by comparing the R^2 range. Also, due to the time-consuming optimization process and the uncertainty of the desired parameters, it is necessary to perform SA before optimization. While Using SA, the effective parameters can be set in optimization. After all the parameters are obtained from the RSA, the next step is the optimization phase. The parameter obtained from the previous step is plugged into a Multi-Objective Optimization.

Building optimization is a process that is performed by using simulation and based on a stochastic algorithm such as genetic algorithms (GA), particle swarm, and evolutionary [34]. The GA is inspired by the selection process that is based on search. This algorithm can solve non-linear optimization problems and also, they follow global optimum and do not get stuck in local optimum. The most important limitation of GA is the need for many cost functions to achieve the optimum solutions. Building simulation often uses the honeybee plugin and Galapagos engine, Energy Plus, TRNSYS, etc. [35] Fig4.

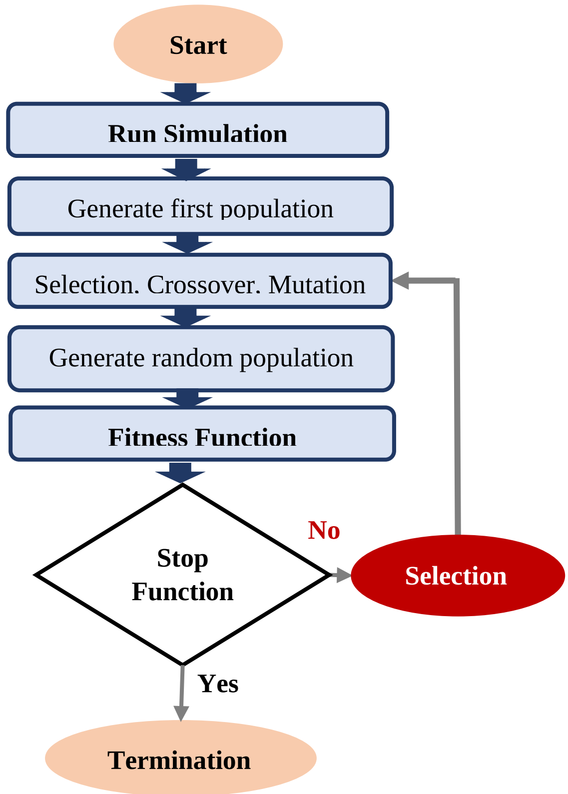

Figure 4. Genetic algorithm process

The evolutionary solver determines the optimum genome that is based on GA. Populations with several individuals create a new generation and when new generations were created the best population is kept until the children get closer to the best value. An individual is a genome [36].

The multi-objective optimization (MOO) is a method to identify a series of thesolution ,not a single solution. The best solution cannot be found based on just one parameter such as energy performance, daylight, or thermal comfort; the best solution should consider all conditions [37]. The optimization process used Octopus and Grasshopper plugin. The design input parameters are connected to GA for the Octopus engine, and the results of daylight and thermal comfort is connected to the fitness input parameter. Building geometry is connected to Grasshopper, and material connected to Honeybee and Ladybug plugin to perform the analysis. The result of each solution in the optimization automatically exports to an Excel file using TT Toolbox [38]. This file is used to create a data plot and find the best solution. In the octopus, Pareto plot can click on each solution and reinstate the solution to find the best solution.

3. Results and Discussion

As mentioned in the methodology the simulation procedure is divided into two parts: the SA and optimization. The result was reported as three sub-subjects. The PMV, PPD (thermal comfort index), and daylighting are considered as objective functions in the one zone. The SA is a process to investigate the objective function through comprehensive research. The simulation is run 11296 times and is generated and executed until it obtains valid values.

The response variables are the average yearly, maximum, and minimum of PMV and PPD. The reason for using the average yearly value is that it changes during the day; in addition, the average value can replace the hourly values. However, checking the average value alone is not enough to check the occupants feeling. Fig5 the range of simulation results.

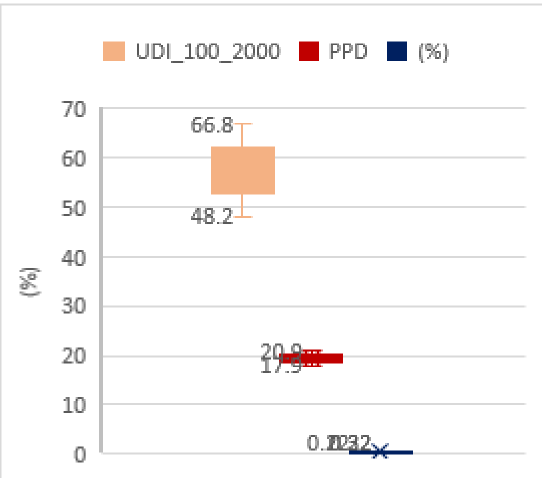

Figure 5. Comparison of the results range of UDI, PPD and PMV for SA

The best fitting model of linear regression equations that describe the PMV, PPD, and UDI values are given by Eq (16-18) respectively.

$$UDI_{ave} = 42.6860 + 5.796e^{-14} \times shadedepth + 3.187e^{-14} \times shadereflectance + 4.263e^{-14} \times SHGC + 43.5976 \times southWWR + 1.137e^{-14} \times windowframethickness + 5.31e^{-13} \times wallR - value \tag{16}$$

$$PMV_{ave} = 0.5914 + 0.5683 \times shadedepth + 0.0030 \times shadereflectance + 3.608e^{-16} \times SHGC + 0.1233 \times southWWR + 1.705e^{-13} \times windowframethickness + 12.4492 \times wallR - value \tag{17}$$

$$PPD_{ave} = 32.0742 + 2.2170 \times shadedepth + 0.0109 \times shadereflectance + 2.309e^{-14} \times SHGC + 0.0799 \times southWWR + 1.705e^{-13} \times windowframethickness + 12.4492 \times wallR - value \tag{18}$$

Based on the six selected design parameter the R^2, Adjusted R^2 coefficients and F-statistic of the UDI (100-2000 Lux), PMV and PPD for each parameter was reported. Table 4 shows this information for the SA.

Table 4. Result comparison of sensitivity analysis between the design parameters

Design Parameter	PMV		
	R^2	Adjusted R^2	F-statistic
Wall R-Value	$5*10^{-3}$	$1*10^{-3}$	6.128
South WWR	0.33	$1*10^{-3}$	661.8
window frame thickness	0	$1*10^{-3}$	2.28e-13
SHGC	0	$1*10^{-3}$	2.28e-13
Shading reflectance	0	$1*10^{-3}$	0.077
Shading depth	0.56	0.56	16.5

Design Parameter	UDI 100-2000(%)		
	R^2	Adjusted R^2	F-statistic
Wall R-Value	0	$1*10^{-3}$	-1.74e-13
South WWR	0.98	0.98	8.11e+04
window frame thickness	0	$1*10^{-3}$	-3.48e-13
SHGC	0	$1*10^{-3}$	0
Shading reflectance	0	$1*10^{-3}$	-1.74e-13
Shading depth	0	$1*10^{-3}$	-1.74e-13

Design Parameter	PPD		
	R^2	Adjusted R^2	F-statistic
Wall R-Value	0.94	0.94	2.17e+04
South WWR	$1*10^{-3}$	0	0.65
window frame thickness	0	$1*10^{-3}$	0
SHGC	0	$1*10^{-3}$	0
Shading reflectance	0	$1*10^{-3}$	$3*10^{-3}$
Shading depth	0.03	0.03	40.47

The result of the model indicates good performance with F-statistic for all parameters, so it means that the predicted model is correct and the data is standard. The Predicted R^2 is in reasonable agreement with the Adjusted-R^2. The value of adjusted R^2 for UDI indicates that more than 98% of the total factor is associated with the south WWR. The value of adjusted R^2 for PPD indicates that more than 94% of the total factor is associated with wall construction. The value of adjusted R^2 for PMV indicates that more than 56% of the total factor is associated with the shading Depth Fig6.

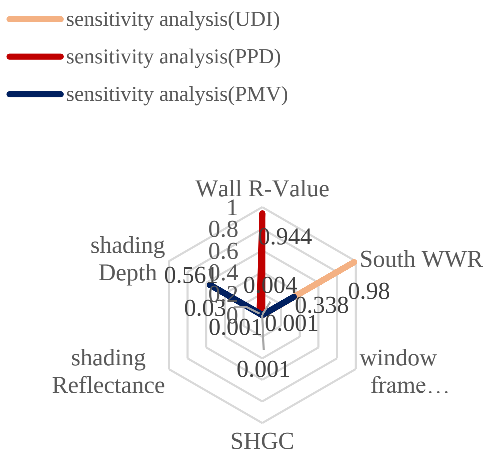

Figure 6. Sensitivity analysis for design parameter on PMV, UDI and PPD

Finally, optimization is carried out by using the obtained MLR. The objective is to maintain these values within the best range. The acceptable range for thermal comfort (PPD index) is less than 20%. The results show that the WWR has the potential to greatly improve building daylight and thermal comfort (PMV index) efficiency, the shading depth has the potential to greatly improve thermal comfort (PMV index) efficiency, and the wall construction R-value has the potential to greatly improve thermal comfort (PPD index) efficiency in the Tehran Table (5 – 7).

Table 5. UDI, PMV, and PPD between different WWRs

Shading depths	UDI	PMV	PPD
0.05	66.18	0.25	18.77
0.09	66.18	0.23	18.28
0.15	66.18	0.21	17.79

Table 6. UDI, PMV and PPD between different Shading depths

WWR	UDI	PMV	PPD
14	48.24	0.25	18.26
26	54.93	0.24	18.28
32	57.05	0.23	17.75
43	60.06	0.23	17.77
52	66.18	0.23	17.75
56	68.86	0.24	18.10

Table 7. UDI, PMV, and PPD between different wall R-values

wall R-value	UDI	PMV	PPD
0.09	66.18	0.25	18.77
0.14	66.18	0.29	19.54
0.19	66.18	0.29	19.09

Pareto plots were developed based on the 600 simulations. Each point shows one design option. Since the best UDI 100-2000 lux is not when the WWR is very large. Fig7 shows that the highest UDI value is achieved when the WWR is more than 50%. The best solution demonstrated the opposite trend of UDI and PPD so the best solution appeared in minimum PPD and maximum UDI. There are 4 variable parameters in this study and the relationship between them may be complicated so interpreting them using Pareto plots lonely is difficult.

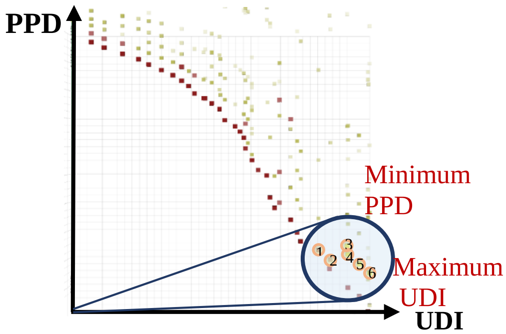

Figure 7. Pareto plot based on UDI and PPD

For showing the best solution for MOO, the region was selected based on maximum UDI and minimum PPD. Each optimal solution is visually compared to the other candidate solution. Finally, 6 best solution candidates for the optimal solution. The Pareto plot is based on UDI and PPD values in the 6 examples, most UDI values are about 63 to 66, most PPD value are18.50 to 18.70 most PMV values are about 0.24 to 0.25 Fig 8 and 9.

We used an office as our simulation space in order to limit our focus to thermal comfort and run simulation based on wide variety of architectural design parameters. Despite some limitation such simulation time, the present study assessed the impact of sensitivity analysis on optimization time. However, we focus on some parameters, but they are important design parameters. Future research could look into more parameters such as sill height, window construction and etc. We also chose to focus our study on thermal comfort, future studies can research visual comfort.

4. Conclusion

In this study, we proposed a comprehensive methodology that can use in different locations. The proposed method is the coupling between a GA optimization tool and SA. A genetic algorithm is used to search the time-to-time output to find the optimal strategy. SA can find the effective parameter. The method for Sais the Multiple Linear Regression. By comparing the magnitude of Adjusted R2 the most significant parameter can be defined. Based on the result of MLR the variable parameters are determined and then simplified for optimization.

The methodology of this research is applied to a simple case to improve the occupant's thermal comfort and daylight. For this purpose, we consider a shading device that is one of the best techniques to reduce the overheating of the building caused by solar heat gain.

From this study the crucial conclusions that can be obtained are as follow:

- The result of SA indicates that the SHGC, shading reflectance, and window frame have no significant effect on the UDI, PPD, and PMV. So, the parameters didn't need to consider as the variable parameters for the optimization process.
- South WWR has a significant effect on the UDI, Wall R-value has significant effect on the PPD and Shading depth, and then south WWR has a significant effect on the PMV.
- Wall R-Value and shading depth for the best solutions of PPD and UDI are not different and that is 0.09 m2k/w
- Using F-Statistics proves that the accuracy of the model is acceptable and leads to the use of standard data and the appropriate percentage range for testing and training.

The standard data for SA help to increase the proposed finally, developing a tool that allows the combined use of, python and honeybee for optimization and SA, would make the application of the proposed method very useful for designers and decision-makers of building. This method can develop for other propose such as optimizing Energy Useful Intensity (EUI), view, etc.

Acknowledgement

No Acknowledgement reports.

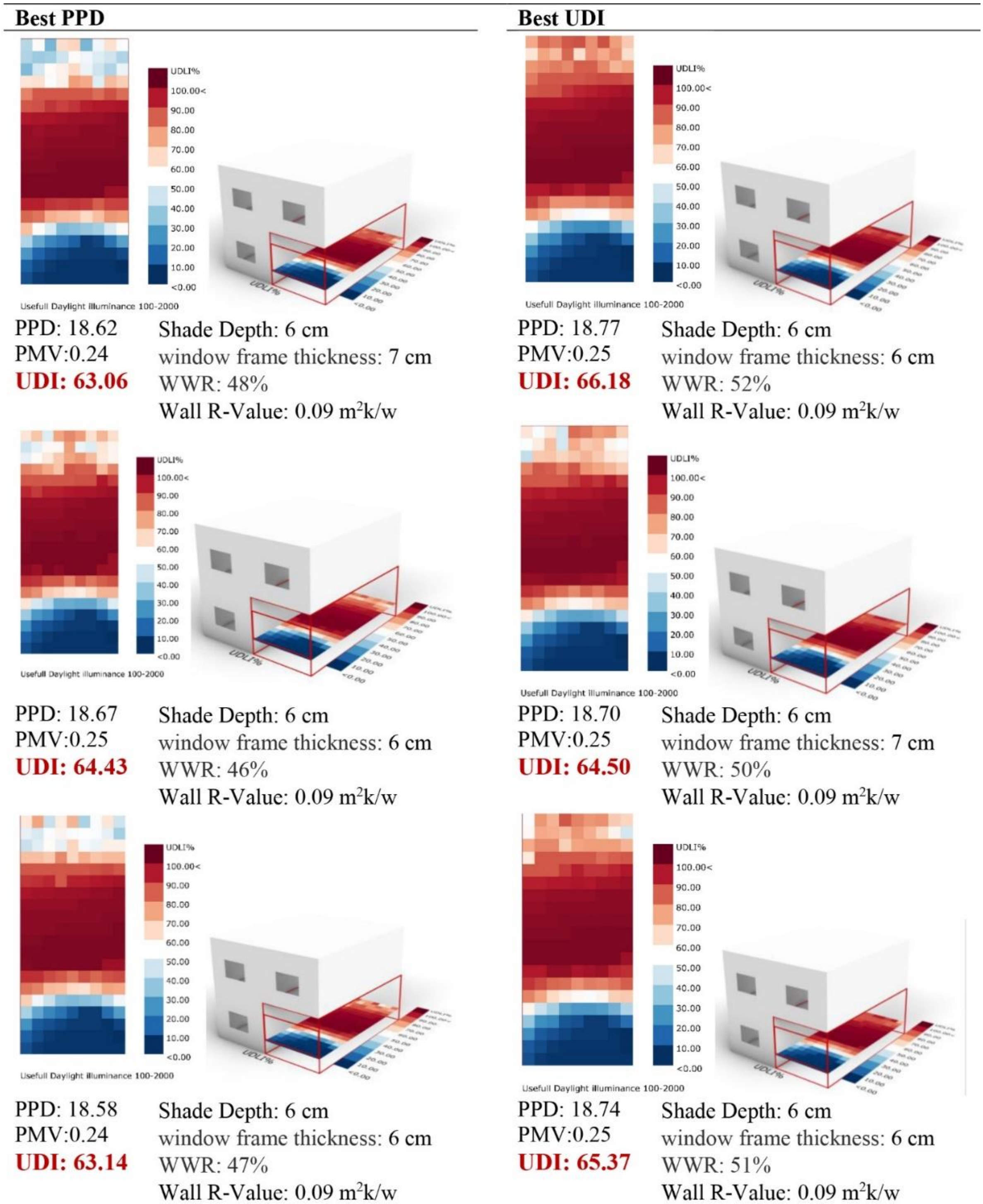

Figure 8. The UDI 100-2000 lux of optimum design solutions in terms of Best UDI and PMV at each solution

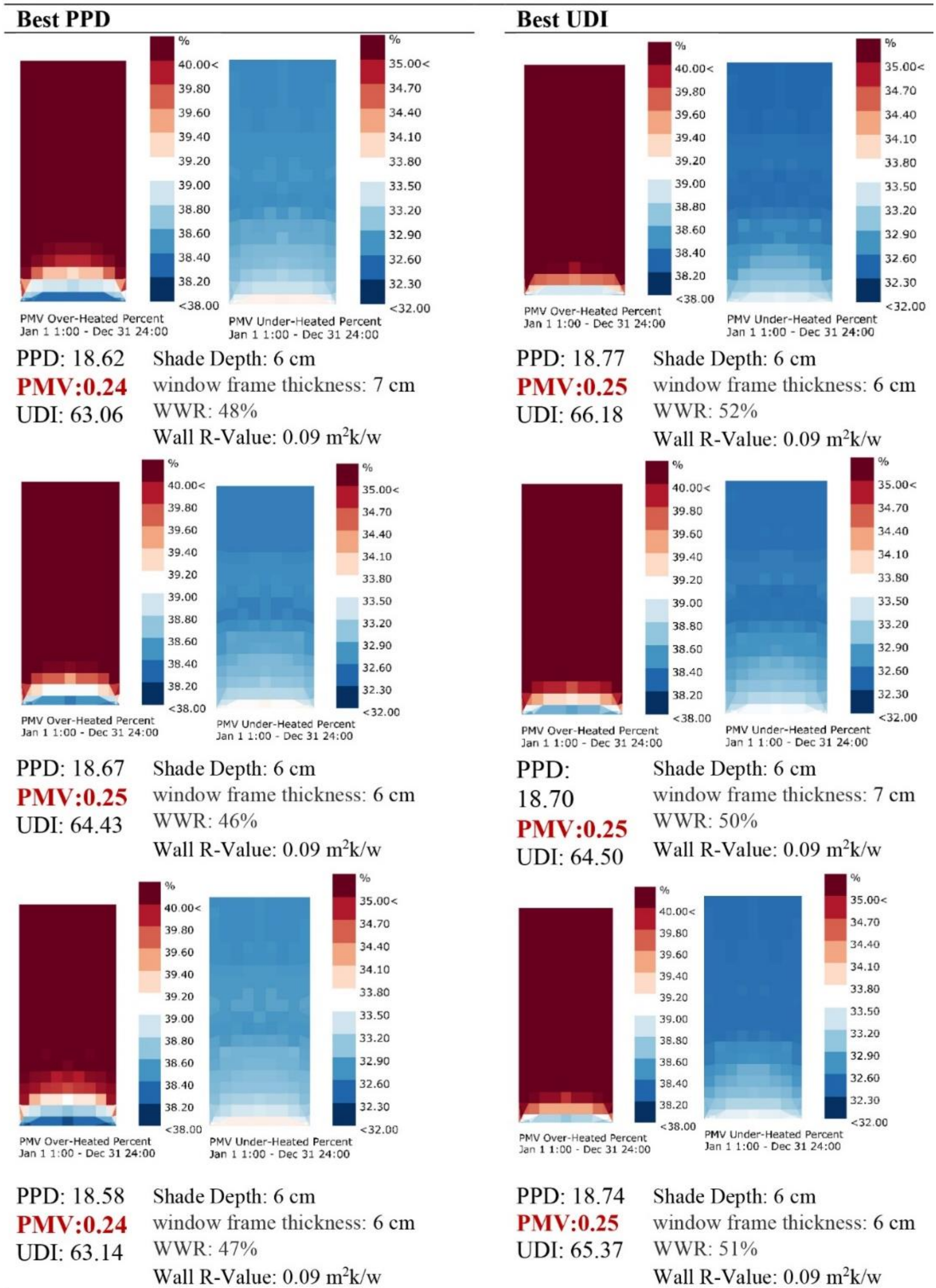

Figure 9. The PMV over heat and under heat of optimum design solutions in terms of Best UDI and PMV at each solution

Nomenclature

WWR	Window to Wall Ratio
VT	Visible Transmittance
SHGC	Solar Heat Gain Coeeficient
MLR	Multiple linear regression
SST	Sum of Squared Total
SSE	Sum of Squared Error
SSR	Sum of Squared Regression
PMV	Predicted Mean Vote
PPD	Percentage of Persons Dissatisfied
SA	Sensitivity analysis
GA	Genetic Algorithms
UDI	Useful Daylight Illuminance
EUI	Energy Useful Intensity
MOO	Multi Objective Optimization
R-Value	Thermal resistance

References

1. Raturi, A.K., Renewables 2019 global status report. 2019.
2. Chiazor, M., The effects of energy efficient design and indoor envirnomental quality in new office buildings. 2009.
3. Amleh, D., A. Halawani, and M.H. Hussein, Simulation-Based Study for Healing environment in intensive care units: enhancing daylight and access to view, optimizing an ICU room in temperate climate, the case study of Palestine. Ain Shams Engineering Journal, 2023. **14**(2): p. 101868.
4. EIA, U., Annual energy review 2011. DOE/EIA, 2011. **384**.
5. Moon, J.W. and S.K. Jung, Development of a thermal control algorithm using artificial neural network models for improved thermal comfort and energy efficiency in accommodation buildings. Applied Thermal Engineering, 2016. **103**: p. 1135-1144.
6. Lodi, C., et al., Improvement of thermal comfort and energy efficiency in historical and monumental buildings by means of localized heating based on non-invasive electric radiant panels. Applied Thermal Engineering, 2017. **126**: p. 276-289.
7. Hawila, A.A.W. and A. Merabtine, A statistical-based optimization method to integrate thermal comfort in the design of low energy consumption building. Journal of Building Engineering, 2021. **33**: p. 101661.
8. Enescu, D., A review of thermal comfort models and indicators for indoor environments. Renewable and Sustainable Energy Reviews, 2017. **79**: p. 1353-1379.
9. ISO, I., 7730: Ergonomics of the thermal environment Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria. Management, 2005. **3**(605): p. e615.
10. Nasrollahzadeh, N., Comprehensive building envelope optimization: Improving energy, daylight, and thermal comfort performance of the dwelling unit. Journal of Building Engineering, 2021. **44**: p. 103418.
11. Ziaee, N. and R. Vakilinezhad, Multi-objective optimization of daylight performance and thermal comfort in classrooms with light-shelves: Case studies in Tehran and Sari, Iran. Energy and Buildings, 2022. **254**: p. 111590.
12. Zhao, J. and Y. Du, Multi-objective optimization design for windows and shading configuration considering energy consumption and thermal comfort: A case study for office building in different climatic regions of China. Solar Energy, 2020. **206**: p. 997-1017.
13. Pagliolico, S.L., et al., Preliminary results on a novel photo-bio-screen as a shading system in a kindergarten: Visible transmittance, visual comfort and energy demand for lighting. Solar Energy, 2019. **185**: p. 41-58.
14. Marzouk, M., M. ElSharkawy, and A. Mahmoud, Optimizing daylight utilization of flat skylights in heritage buildings. Journal of Advanced Research, 2022. **37**: p. 133-145.
15. De Luca, F., A. Sepúlveda, and T. Varjas, Multi-performance optimization of static shading devices for glare, daylight, view and energy consideration. Building and Environment, 2022. **217**: p. 109110.
16. Hensen, J.L. and R. Lamberts, Building performance simulation for sustainable building design and operation. Proceedings of the 60th Anniversary Environmental Engineering Department, Czech Technical University, Prague, 2011: p. 1-8.
17. Mangkuto, R.A., M. Rohmah, and A.D. Asri, Design optimisation for window size, orientation, and wall reflectance with regard to various daylight metrics and lighting energy demand: A case study of buildings in the tropics. Applied energy, 2016. **164**: p. 211-219.
18. Frey, H.C., A. Mokhtari, and T. Danish, Evaluation of selected sensitivity analysis methods based upon applications to two food safety process risk models. Prepared by North Carolina State University for Office of Risk Assessment and Cost-Benefit Analysis, US Department of Agriculture, Washington, DC, 2003.

19. Gagnon, R., L. Gosselin, and S. Decker, Sensitivity analysis of energy performance and thermal comfort throughout building design process. Energy and Buildings, 2018. **164**: p. 278-294.

20. Sanchez, D.G., et al., Application of sensitivity analysis in building energy simulations: Combining first-and second-order elementary effects methods. Energy and Buildings, 2014. **68**: p. 741-750.

21. Kheiri, F., A review on optimization methods applied in energy-efficient building geometry and envelope design. Renewable and Sustainable Energy Reviews, 2018. **92**: p. 897-920.

22. Nguyen, A.T., Sustainable housing in Vietnam: Climate responsive design strategies to optimize thermal comfort. 2013.

23. Roudsari, M.S., M. Pak, and A. Smith. Ladybug: a parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design. in Proceedings of the 13th international IBPSA conference held in Lyon, France Aug. 2013.

24. Reinhart, C.F., J.A. Jakubiec, and D. Ibarra. Definition of a reference office for standardized evaluations of dynamic façade and lighting technologies. in Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26. 2013.

25. Iesna, I., LM-83-12 IES Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE). New York, NY, USA: IESNA Lighting Measurement, 2012.

26. Shahsavari, F., W. Yan, and R. Koosha. A case study for sensitivity-based building energy optimization. in ARCC Conference Repository. 2019.

27. Saltelli, A., et al., Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Computer physics communications, 2010. **181**(2): p. 259-270.

28. Nabil, A. and J. Mardaljevic, Useful daylight illuminance: a new paradigm for assessing daylight in buildings. Lighting Research & Technology, 2005. **37**(1): p. 41-57.

29. Reinhart, M., Rogers.(September 2006). Dynamic Daylight Performance Metrics for Sustainable Building Design. LEUKOS The Journal of the Illuminating Engineering Society of North America. **3**(1).

30. Fanger, P.O., Thermal comfort. Analysis and applications in environmental engineering. Thermal comfort. Analysis and applications in environmental engineering., 1970.

31. Matzarakis, A., Climate, thermal comfort and tourism. Climate change and tourism-assessment and coping strategies, 2007: p. 139-154.

32. Menberg, K., Y. Heo, and R. Choudhary, Sensitivity analysis methods for building energy models: Comparing computational costs and extractable information. Energy and Buildings, 2016. **133**: p. 433-445.

33. Allam, A.S., et al., Estimating the standardized regression coefficients of design variables in daylighting and energy performance of buildings in the face of multicollinearity. Solar Energy, 2020. **211**: p. 1184-1193.

34. Fang, Y. and S. Cho, Design optimization of building geometry and fenestration for daylighting and energy performance. Solar Energy, 2019. **191**: p. 7-18.

35. Magnier, L. and F. Haghighat, Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network. Building and Environment, 2010. **45**(3): p. 739-746.

36. Rutten, D. Evolutionary principles applied to problem solving. in AAG10 conference, Vienna. 2010.

37. De Angelis, E., et al., A Tool for the Optimization of Building Envelope Technologies–Basic Performances against Construction Costs of Exterior Walls. Proceedings of CISBAT 2013, 2013.

38. Deb, K. and M.-o.O.U.E. Algorithms, a n Introduction, Multi-objective evolutionary Optimisation for Product Design an d Manufacturing. 2011, Springer London.