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A NOVEL DESIGN-BASED OPTIMIZATION SOLUTION FOR BUILDING BY SENSITIVITY ANALYSIS

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A NOVEL DESIGN-BASED OPTIMIZATION SOLUTION FOR BUILDING BY SENSITIVITY ANALYSIS

Abstract

The important objective of a building must be to provide a comfortable environment for people. Heating, ventilation and air conditioning (HVAC) systems provide a comfortable environment, but they are using high energy consumption, therefore, designing an energy-efficient building that balances energy performance and thermal comfort is necessary. To achieve this subject is important to choose the effective parameters for energy performance. This research aim is 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 hours and thermal comfort hour based on test and training on Jupiter Notebook (Anaconda3). The sensitivity analysis uses a multiple linear regression (MLR) method. Secondly, optimization is based on a genetic algorithm (GA) with the effective parameters to optimize the daylight and thermal comfort performance. For this, we developed a parametric model using the Grasshopper plugin for Rhino and then use Honeybee and Ladybug plugins to simulate thermal comfort and daylight, at the end use the Octopus engine to find an optimization solution. The result of this paper is essential as a preliminary analysis for shading devices, window-to-wall ratios, and wall construction optimization in the open-plan office.

Keywords

Thermal comfort, designerly approach to daylighting, multi-objective optimization, sensitivity analysis.

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ABSTRACT

The important objective of a building must be to provide a comfortable environment for people. Heating, ventilation, and air conditioning (HVAC) systems provide a comfortable environment, but they are using high energy consumption, therefore, designing an energy-efficient building that balances energy performance and thermal comfort is necessary. To achieve this subject is important to choose the effective parameters for energy performance. This research aim is to produce a methodology for multi-objective optimization of daylight and thermal comfort 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 hours and thermal comfort hour based on test and training on Jupiter Notebook (Anaconda3). The sensitivity analysis uses a multiple linear regression (MLR) method. Secondly, optimization is based on a genetic algorithm (GA) with the effective parameters to optimize the daylight and thermal comfort performance. For this, we developed a parametric model using the Grasshopper plugin for Rhino and then use Honeybee and Ladybug plugins to simulate thermal comfort and daylight, at the end use the Octopus engine to find an optimization solution. The result of this paper is essential as a preliminary analysis for shading devices, window-to-wall ratios, and wall construction optimization in the open-plan office.

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ملخص

يجب أن يكون الهدف الأهم للمبنى هو توفير بيئة مريحة للناس. توفر أنظمة التهوية والتدفئة وتكييف الهواء بيئة مريحة ولكنها تستخدم استهلاكًا عاليًا للطاقة، وبالتالي فإن تصميم مبنى موفر للطاقة يوازن بين أداء الطاقة والراحة الحرارية أمر ضروري. لتحقيق هذا الغرض من المهم اختيار المتغيرات الفعالة لأداء الطاقة. يهدف هذا البحث إلى إنتاج منهجية للتحسين متعدد الأهداف للإضاءة الطبيعية والراحة الحرارية من أجل دراسة تأثير مواد الجدار وتظليل لمبنى المكاتب (اختيار طهران كموقع أساسي). تم تطوير محاكاة المبنى والتحقق من صحتها من خلال مقارنة ساعات النهار المتوقعة وساعة الراحة الحرارية بناءً على الاختبار والتدريب على Jupiter Notebook (Anaconda3). تم استخدام تحليل الحساسية عن طريق طريقة الانحدار الخطي المتعدد (MLR). ثانيًا، يعتمد التحسين على الخوارزمية الجينية (GA) مع المتغيرات الفعالة لتحسين أداء الإضاءة الطبيعية والراحة الحرارية. لهذا، قمنا بتطوير نموذج بارامترى باستخدام البرنامج المساعد Grasshopper لـ Rhino ثم استخدم مكونات Honeybee و Ladybug لمحاكاة الراحة الحرارية وضوء النهار، ثم في النهاية استخدم محرك Octopus لإيجاد حل أمثل. تعتبر نتيجة هذه الورقة ضرورية كتحليل أولي لأجهزة التظليل، ونسب النافذة إلى الجدار، وتحسين بناء الجدار في فراغات المكاتب المفتوحة.

الكلمات المفتاحية: الراحة الحرارية، توجه تصميمى للإضاءة الطبيعية، تحسين متعدد الأهداف، تحليل حساسية.

1. INTRODUCTION

Increasing the environmental challenges can lead to global warming, the energy efficiency of buildings has an effective role in architectural design. Today global approaches want to reduce energy consumption to achieve a sustainable environment (Raturi, 2019). 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 environments. (Chiazor, 2009), (Yoon, 2008). Good buildings have thermal and lighting comfort conditions in places because they have a fundamental impact on building performance (US Department of Energy, 2011), However many researcher foci on thermal comfort and daylight but unfortunately, many researchers proposed the theoretical results that are not useful for buildings (Moon, 2016), (Lodi, et al., 2017). A place that has thermal comfort are 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 (Hawila, 2021), (Enescu, 2017). 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. (ISO, 2005), (Enescu, 2017).

The important purpose of proper design is to improve energy and daylight. On the other hand, building optimization is one of the cost-effective solutions to increase building performance. (Rajagopalan, 2015). Windows performance overall heat transfer is usually about five times greater than other building components, but designer usual use a high window-to-wall ratio in their project (Lau et.al, 2016). The experiments and research indicate that measure of U-value, Solare Heat Gain Coeeficient (SHGC), visible transmit (VT), glass, double-layer glass and window size could increase thermal comfort (Zhao, 2020), (Pagliolico, et al., 2019). Solar shading devices have a perform considerable advantage in the Confrontation with solar radiation (Goia, et al., 2013), (Freewan, 2014).

Due to relatively little knowledge about optimization and uncertainties of design parameters, designers the default values should confidante 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 SA before optimization (Hensen, 2011).

- Sensitivity analysis in building

Sensitivity analysis (SA) is the statistical method that can calculate the relationship between input and output parameters. (Mangkuto et al., 2016). Statistical methods examine the effect of these parameters by examining many output parameters relative to the input parameter (Frey, et al., 2003). SA has a significant effect on understanding building simulation. SA's purpose is to predict the performance of design parameters, also a research on these parameters is useful to achieve the optimal building (Gagnon, et al., 2018), (Sanchez, et al., 2014).

- Optimization Methodology

In recent years optimization algorithms have much attention to solving the optimization problems in building design. Optimization is a 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 (Kheiri, 2018), (Nguyen, 2013).

1.1. Aim and Motivation

This research bridges 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 usual 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. (Roudsari, et al., 2013) (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 and python ability. The variable parameter in this study is wall construction (R-Value), 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.

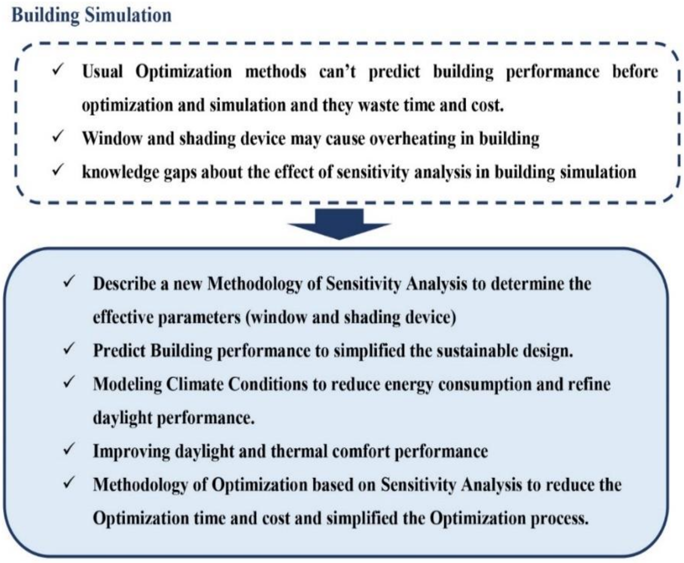

Fig.1: Strategy of research aim.

2. METHODOLOGY

2.1. Software

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 (Roudsari, et al., 2013).

2.2. Model Description and Materials

The building is located at Tehran. The office is occupied daily from 8 AM to 6 PM. The base case building represents the typology of the Reinhart office (Reinhart, 2013). The selected office is located on the ground floor with a total area of 29.52m² (Fig2).

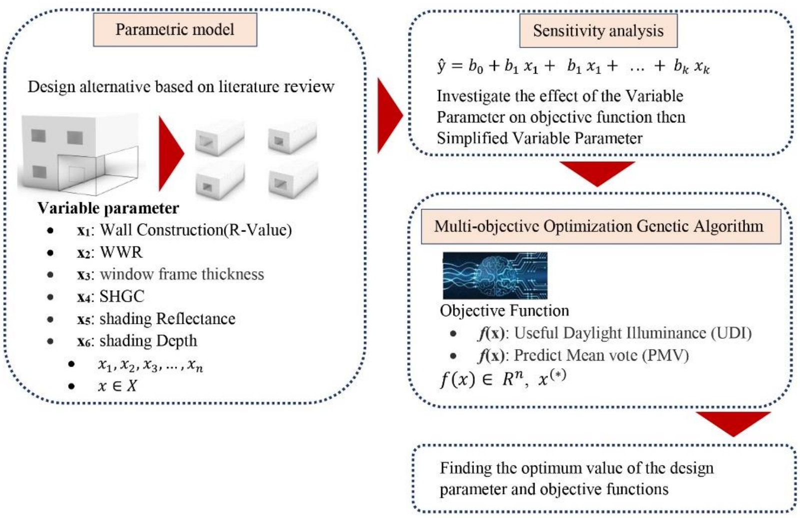

Fig.2: Case study design process.

The shading system position is above the window that is 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 ($W/m^2 \cdot K$)	Concrete brick
Roof ($W/m^2 \cdot K$)	Concrete 0.10
Exterior window ($W/m^2 \cdot K$)	Double glazing Window
Floor ($W/m^2 \cdot K$)	Concrete 11.76

The number of people per area (occupant density) is 0.06 (people/m2). The Lighting density is 2.235 (W/m2). 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 (Iesna, 2012).

It is generally considered that if the indoor illuminance were above 500 lx the indoor lighting requirements can provide. The range of design parameters selected by test and train. 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

2.3. Solving Simulation Process

Considering the objective of this research is the MOO of daylight and thermal comfort so this objective can maximize the PMV and Useful Daylight Illuminance (UDI) and optimize the energy and daylight was performance. The research framework performed in three main steps Fig3. And at the first designed the geometry model, based on the variable parameter then perform the SA, at the end performed the optimization based on a simplified variable parameter. Sample size taken by test and train on Jupiter notebook based on Python language. According to the range of each parameter that is between 0-1 the sample size is selected. In this research, all parameter range is between 0-1 so we don't need to standardize the data range. The SA is generally related to the design parameters of building components they are wall (material, insulation) window- to-wall-ratio, windows (window frame thickness and SHGC) and shading (reflectance, depth).

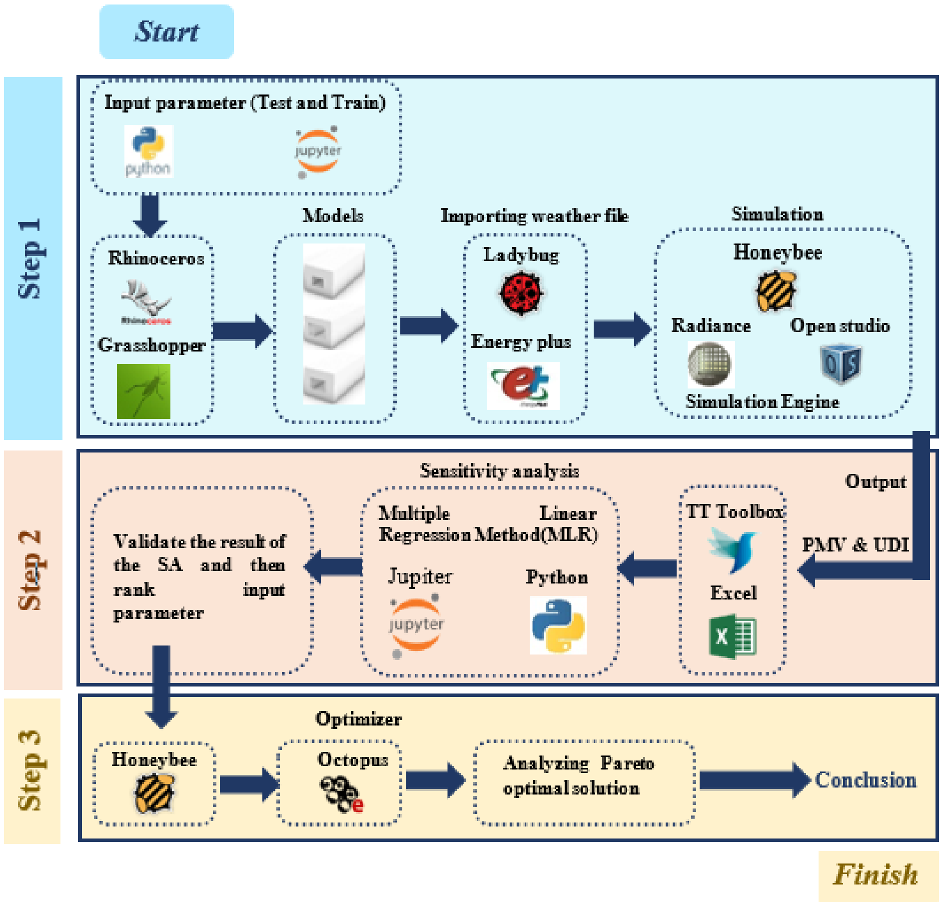

Fig.3: Overall methodology process

2.4. Sensitivity Analysis

After designing the model, the model was simulated based on the input parameters of a honeybee. The daylight index in this research is UDI. Which was proposed by (Nabil, 2005). 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 (Nabil, 2005), (Reinhart et.al, 2006).

The thermal comfort index in this research is PMV and PPD (Fanger, 1970). 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 calculate based on Eq1 and each component of this index is calculated based on Eq (2-6).

$$PMV = (0.303^{e-0.036m} + 0.028)\,[(M - W) - H - E_C - C_{rec} - E_{rec}] \quad (1)$$

$$E = 3.05 * 10^{-3}\,(256_{tsk} - 3373 - P_a) + E_{sw} \quad (2)$$

$$E_c = 3.05 * 10^{-3}\,[(5733 - 6.99 * 9M - W) - P_a] + 0.42\,(M - W - 58.15) \quad (3)$$

$$C_{rec} = 0.0014M\,(34 - T_a) \tag{4}$$

$$E_{rec} = 1.72 * 10^{-5}\,M(5867 - P_a) \tag{5}$$

$$H = K_{cl} = t_{sk} - t_{cl} / I_{cl} \tag{6}$$

Also the PPD index calculate based on (Eq7) (Matzarakis, et al., 2007).

$$PPD = 100 - 95e\,(-0.03353 * PMV^4 - 0.2179 * PMV^2) \tag{7}$$

This research performed SA using a sampling-based method. SA was used in different fields and performed in different methods. This research performed based on MLR method Eq8 show the MLR, is about the best fitting model.

$$\hat{y} = b_0 + b_1\,x_1 + b_1\,x_1 + \ldots + b_k\,x_k \tag{8}$$

To calculate the variability of the data often use the measure of distance from the mean or description of the data range. Total variability (SST) is a summation of and unexplained variability explained variability. SST is a measure total variability of a dataset. SSR is a measure explained by variability by your line. SSE is a measure of unexplained variability by the regression. The division of SSR on SST is equal to R2 Eq (9-13).

$$SST = SSE + SSR \tag{9}$$

$$SST = \textstyle\sum_{i=1}^{n}(y_i - \bar{y})^2 \tag{10}$$

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

$$SSR = \textstyle\sum_{i=1}^{n} {e_i}^2 \tag{12}$$

$$R^2 = \frac{SSR}{SST} \tag{13}$$

Given that the R2 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 R2, and increasing it means increasing the efficiency of the model. In the other word Adjusted R2 increases only when the new parameter has a significant impact in the model Eq14.

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

Low R2 indicates a poor fit of the regression model with the outcome of the building model. The value range of R2 is between -1.0 and +1.0 (Menberg, et al., 2016), (Allam, et al., 2020).

SA performed on Jupiter notebook based on MLR. Jupiter notebook. The SA was performed by the coupling of 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.

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

In the next step, the effective parameter is determined with compare the R2 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 (MOO).

2.5. 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. (Fang, 2019). 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 (Reynold, 2018). The most important limitation of GA is to need for many cost functions to achieve the optimum solutions. Building simulation often uses the honeybee plugin and Galapagos engine, Energy Plus, TRNSYS, etc. (Magnier, 2010) (Fig4).

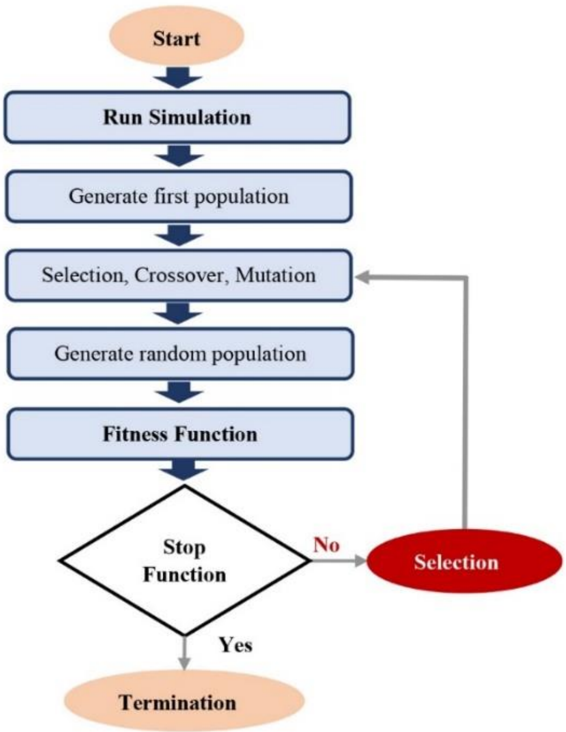

Fig.4: Genetic algorithm process.

The evolutionary solver determines the optimum genome that is based on GA. Population with several individuals creates 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. (Rutten, 2010).

The multi-objective optimization (MOO) is a method to identify a series of solutions, not a single solution. The best solution can't find based on just one parameter such as energy performance, daylight, or thermal comfort, the best solution should consider all conditions (De Angelis, et al., 2013). The optimization process used Octopus a 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 (Deb, 2011). This file is used to create a data plot and find the best solotion. 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.

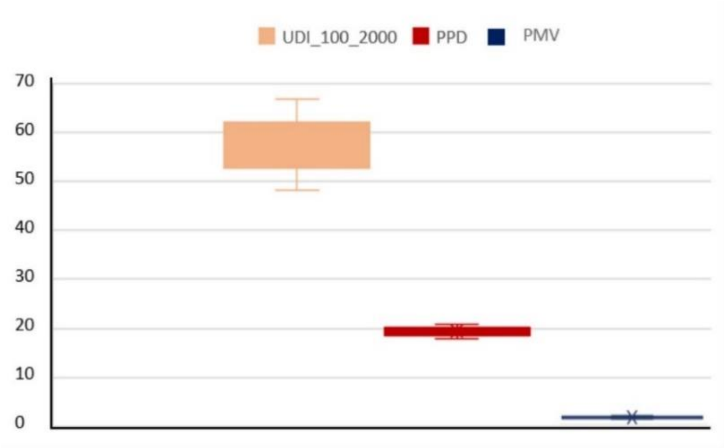

Fig.5: Comparison of the results range of UDI, PPD, and PMV for SA

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

$$UDI_{ave} = 42.6860 + 5.796\ e^{-14} * shade\ depth + 3.187\ e^{-14} * shade\ reflectance + 4.263\ e^{-14} * SHGC + 43.5976 * south\ WWR + 1.137\ e^{-13} * window\ frame\ thickness + 5.31\ e^{-13} * wall\ R - value \tag{16}$$

$$PMV_{ave} = 0.5914 + 0.5683 * shade\ depth + 0.0030 * shade\ reflectance + 3.608\ e^{-16} * SHGC + 0.1233 * south\ WWR + 1.332\ e^{-15} * window\ frame\ thickness + 0.0524 * wall\ R - value \tag{17}$$

$$PPD_{ave} = 32.0742 + 2.2170 * shade\ depth + 0.0109 * shade\ reflectance + 2.309\ e^{-14}\ SHGC + 0.0799 * south\ WWR + 1.705\ e^{-13} window\ frame\ thickness + 12.4492\ wall\ R - value \tag{18}$$

Based on the six selected design parameter the R2, Adjusted R2 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	UDI 100-2000(%)			PPD			PMV		
	R^2	Adjusted R^2	F-statistic	R^2	Adjusted R^2	F-statistic	R^2	Adjusted R^2	F-statistic
Wall R-Value	0	$1*10^{-3}$	-1.74e-13	0.94	0.94	2.17e+04	$5*10^{-3}$	$1*10^{-3}$	6.128
South WWR	0.98	0.98	8.11e+04	$1*10^{-3}$	0	0.65	0.33	$1*10^{-3}$	661.8
window frame thickness	0	$1*10^{-3}$	-3.48e-13	0	$1*10^{-3}$	0	0	$1*10^{-3}$	2.28e-13
SHGC	0	$1*10^{-3}$	0	0	$1*10^{-3}$	0	0	$1*10^{-3}$	2.28e-13
Shading reflectance	0	$1*10^{-3}$	-1.74e-13	0	$1*10^{-3}$	$3*10^{-3}$	0	$1*10^{-3}$	0.077
Shading depth	0	$1*10^{-3}$	-1.74e-13	0.03	0.03	40.47	0.56	0.56	16.5

The result of the model indicates good performance with F-statistic for all parameter, 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 the 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).

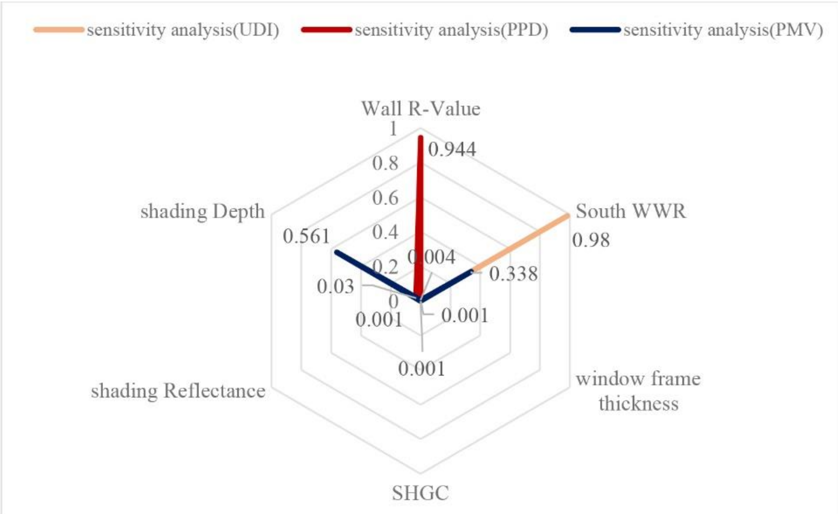

Fig.5: Sensitivity analysis for design parameter on PMV, UDI and PPD.

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 WWR

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 6. UDI, PMV and PPD between different shading depths

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 7: UDI, PMV and PPD between different wall R-value

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 show 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 hard.

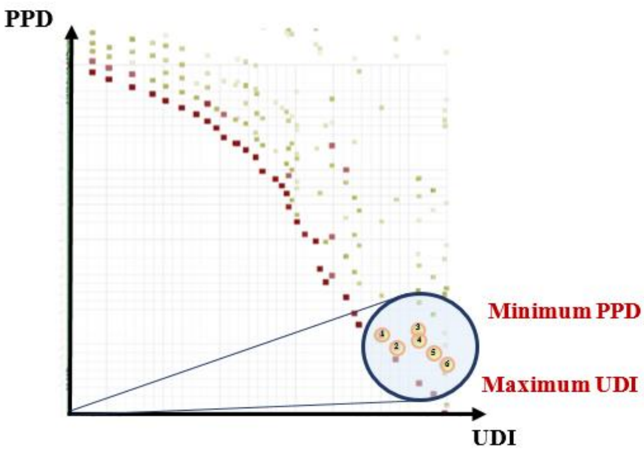

Fig.6: Pareto plot based on UDI and PPD

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.

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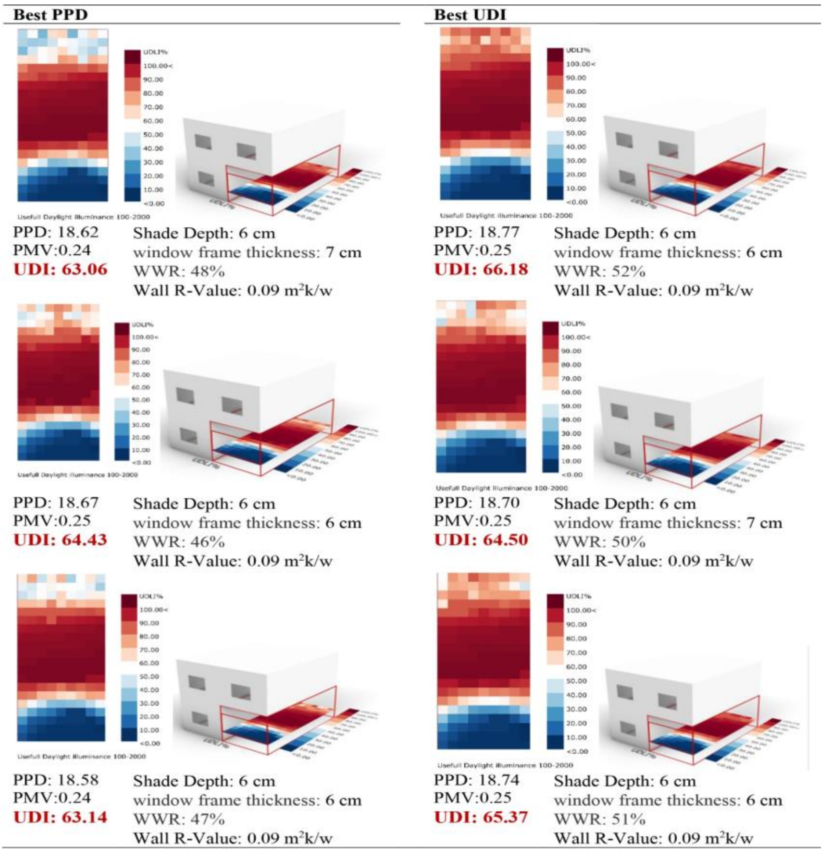

Fig.7: The UDI 100-2000 lux of optimum design solutions in terms of Best UDI and PMV at each solution

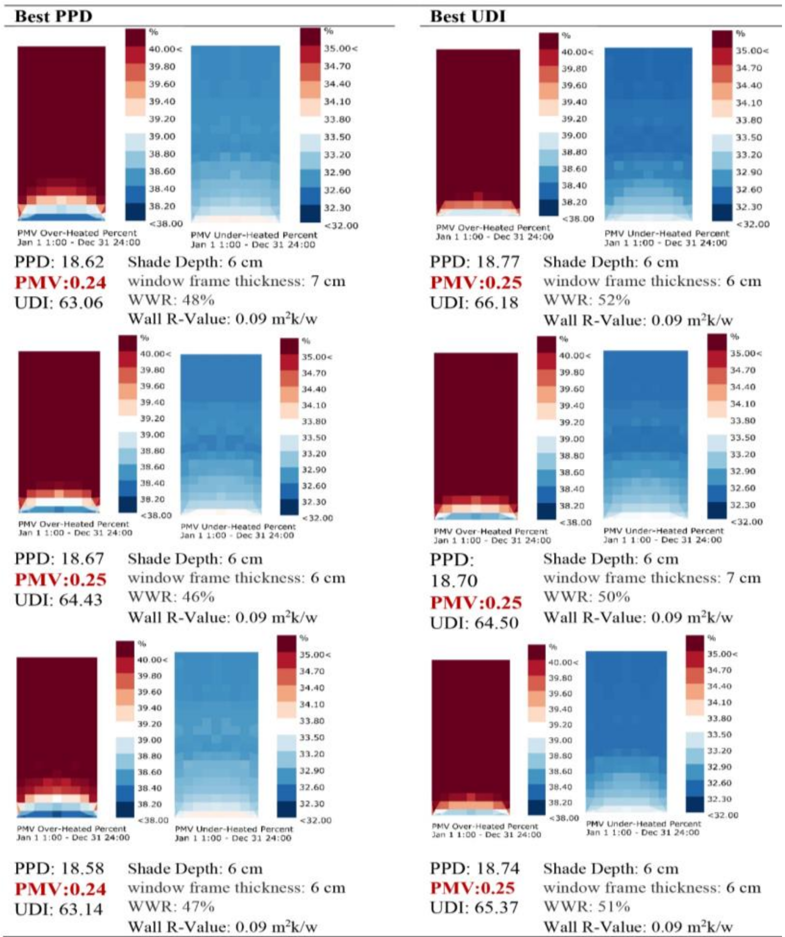

Fig.8: The PMV overheat and under heat of optimum design solutions in terms of Best UDI and PMV at each solution.

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 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 EUI, view, etc.

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