Simulation-Based Optimization of Smart Building Energy Using Artificial Neural Network

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Abstract

The present study aims to investigate the influence of the window size, the glazing properties and the shading overhang specifications on the energy consumption in smart buildings located in Alexandria, Egypt taking in account thermal and visual comfort. In this study, single objective and multi-objective optimizations are carried out on four objective functions, namely annual cooling, annual heating, annual lighting and annual total energy consumption using genetic algorithm. The simulations are performed using EnergyPlus through Openstudio to generate database that used to train an artificial neural network for the four objective functions. Results indicate the most significant factors are window wall ratio, glazing solar transmittance and glazing visible transmittance. Furthermore the increasing of window wall ratio and glazing solar transmittance produces an increase in cooling energy consumption and a decrease in heating energy consumption in addition window wall ratio and glazing visible transmittance have a high positive impact on lighting consumption in both cities. The multi objective optimization study is a powerful and useful tool that can save time while searching for the optimal solutions with conflicting objective functions.

Keywords: Surrogate-Based Optimization, Openstudio, Matlab, Artificial Neural Network, Energy Consumption.

Introduction

Nomenclature

ANN	Artificial Neural Network	**LHS**	Latin Hypercube Sampling Plan
CFL	Compact Fluorescent Lamp	**MOGA**	Multi Objective Genetic Algorithm
DoE	Design of experiments	**OD**	Overhang Depth
GST	Glazing Solar Transmittance	**OT**	Overhang Tilt Angle
GVT	Glazing Visible Transmittance	**PTHP**	Packaged Terminal Heat Pump
HVAC	Heating, Ventilation and Air Condition	**RBF**	Radial Basis Function
IDHVAC	Integrated Daylighting and HVAC	**WWR**	Window Wall Ratio

Energy is one of the secrets of life on this planet. The humanity realized the importance of energy and its function in the continuity of life. With the rise of welfare of life the building energy consumption increased extraordinary energy became the basic pivot for the most conflicts in the last decades. Moreover the pollution that results from energy consumption and its negative impact on environment and climate. Therefore these problems have attracted more attention in the field of energy saving and investigating the effective ways to decrease energy consumption.

Buildings have played an important role in energy consumption. Furthermore buildings have a large impact on environment by increasing greenhouse gas emissions. Whereas Egyptian electricity holding company reported that the total generated energy was 189.5 TWh in year 2016/2017 [1]. Where the building sector (commercial and residential buildings) consumes about 54% of the total energy consumption. Figure (1) shows the total energy consumption by purpose. Figure (2) illustrates the average growth rate of energy consumption for the industrial purposes increased at a rate of 0.8% for the period from 2012/2013 till 2016/2017, while the average growth rate of sold energy for the residential purposes still fixed at 42.3% for the period from 2012/2013 till 2016/2017 [1].

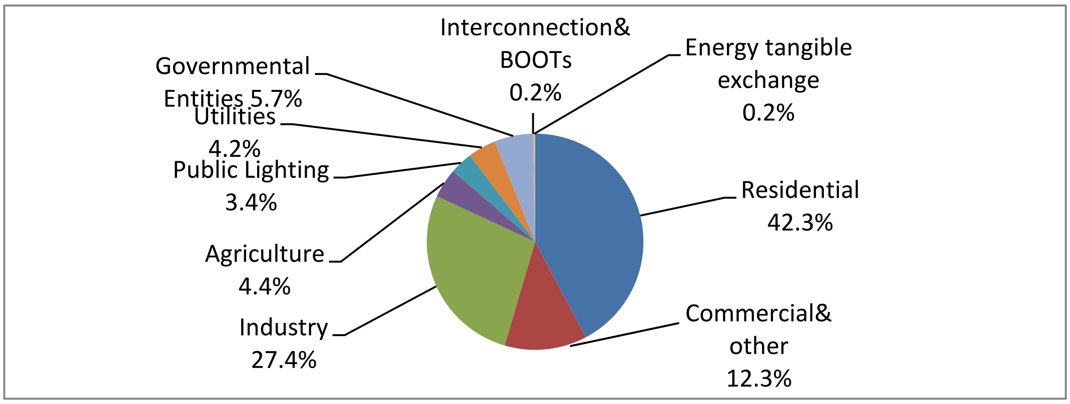


Figure (1): Total electricity consumption by purpose [1]

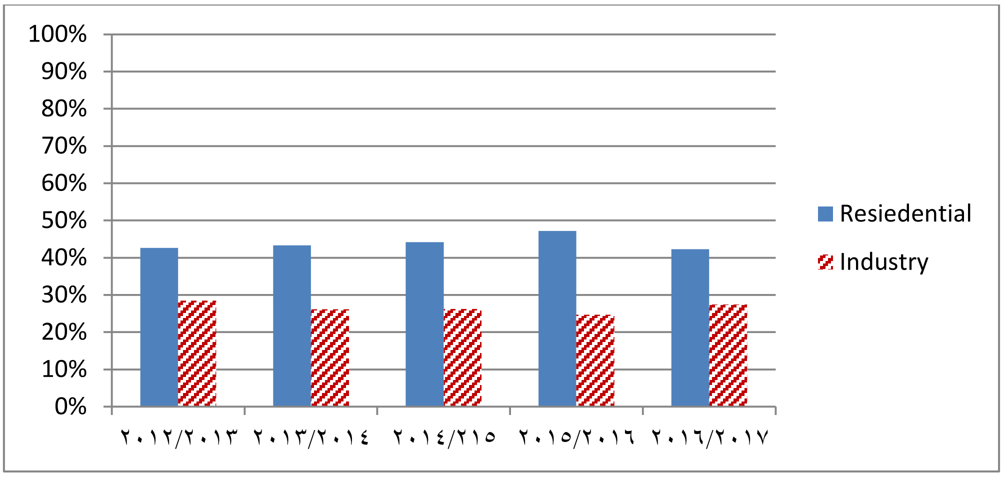


Figure (2): The average growth rate of electricity consumption for the residential and industrial purposes [1]

According to the U.S. energy information administration, energy consumption in buildings is dominated almost 57% by heating, ventilation and air conditioning (HVAC), and lighting [2]. Over the past years, many studies have been published on the factors that influence that energy consumption and human comfort levels. Lee et al. [3] presented a parametric sensitivity analysis for the impact of different types and properties of window systems in a building envelope on energy consumption for five Asian cities and the various performance properties of window systems that can lead to energy saving buildings. Samaan et al. [4] provided heuristic optimization of cooling loads and daylighting levels in deep halls of Egyptian universities by testing various alternatives of design parameters and found that optimizing windows shading of overhangs and louvers, low-transmittance characteristics of glazing, and ventilation system would provide from 26% to 31% reduction in the cooling loads compared to base case. Kim et al. [5] developed an integrated meta-model for a daylighting, heating, ventilating, and air conditioning (IDHVAC) system was developed to predict building energy performance by artificial lighting regression models and artificial neural network (ANN) models with a database that was generated using the EnergyPlus model. Wright and Loosemore [6] presented the application of a multi-objective genetic algorithm search method in the identification of the optimum payoff characteristic between the energy cost of a building and the occupant thermal discomfort and found the MOGA was able to find the optimum pay-off characteristic between the daily energy cost and zone thermal comfort, but that the characteristic between the capital cost and energy cost was sub-optimal. Therefore Elbeltagi et al [7] developed a strategy to visualize parametric energy analysis in context of residential building in New Cairo, Egypt coupled with parametric analysis and energy modeling (Rhino (3D graphics), Grasshopper (parametric modeling)). They stated that such strategy helps architects and decision makers to see which design parameters would lead to more efficient designs prior to modeling the whole building simulation in a comfortable format, discover integrated solutions, and test design alternatives to make data-based decisions. Khoroshiltseva et al [8] provided a multi-objective optimization study based on Harmony search and Pareto front approaches to identify the set of optimal shading devices. The multi-objective approach was used to determine the shading devices to allow for thermal and lighting comfort for inhabitants. Scanferla and Motuziene [9] presented a parametric analysis for the a different properties of glazing for high rise office building in Italy and Lithuania using DesignBuilder and found in the coldest climate the main problem is the huge surface of relatively high glass U-value compared with standard walls, while in the warmer one the main efforts need to be done to avoid the summer overheating caused by incoming solar radiation.

The present study aims to achieve sustainability goals in smart building. The study focuses on multi objective optimization based on five design variables, namely the window wall ratio, the glazing visible transmittance, glazing solar transmittance, the overhang tilt angle and overhang depth. A surrogate based optimization study has been conducted using artificial neural network with a database that was generated using the EnergyPlus model.

Methodology

In the following the methodology followed in this is explained

1.1 Development building model

A base case office space is located in Alexandria climatic region (31.2°N latitude; 29.59°E longitude). The weather data used in this simulation is extracted from the international weather files for energy calculations 2.0 (ETMY) for the city of Alexandria, Egypt [10].The building geometry is modelled by SketchUp 3D modelling software package [11]. The office dimensions are (4.0 m×4.0 m×4.0 m). Only the northern external wall has external window and all opaque building components of the reference office are considered as adiabatic, with the exception of a wall that includes a window as shown in Fig. (3).

With the advance in computing technology, computer simulation and modelling has been widely used for providing accurate and detailed appraisal of building energy performance [4]. The thermo-physical properties of the building envelope, shading overhang system, artificial lighting and its room controller daylight sensor, and HVAC system and its zone thermostat can be modelled by EnergyPlus [12] building energy simulation program.

The base case office has external walls consisting of 3 layers (cement plaster, concrete block, and cement plaster). A double clear glazed, air filled, window is chosen in this study. The thickness of glazing layer is 3 mm while the thickness of the air layer is 13 mm equipped with overhang. No window blind is used for the window. It is assumed that the building is equipped with a packaged terminal heat pump (PTHP) air conditioning system. The room is equipped with compact fluorescent lamp (CFL) lighting system. Moreover, the model has a daylighting controller sensor to dim the lighting automatically with the threshold of 500 Lux (46.45 FC). All those parameters are kept fixed through optimization are summarized in Table 1.

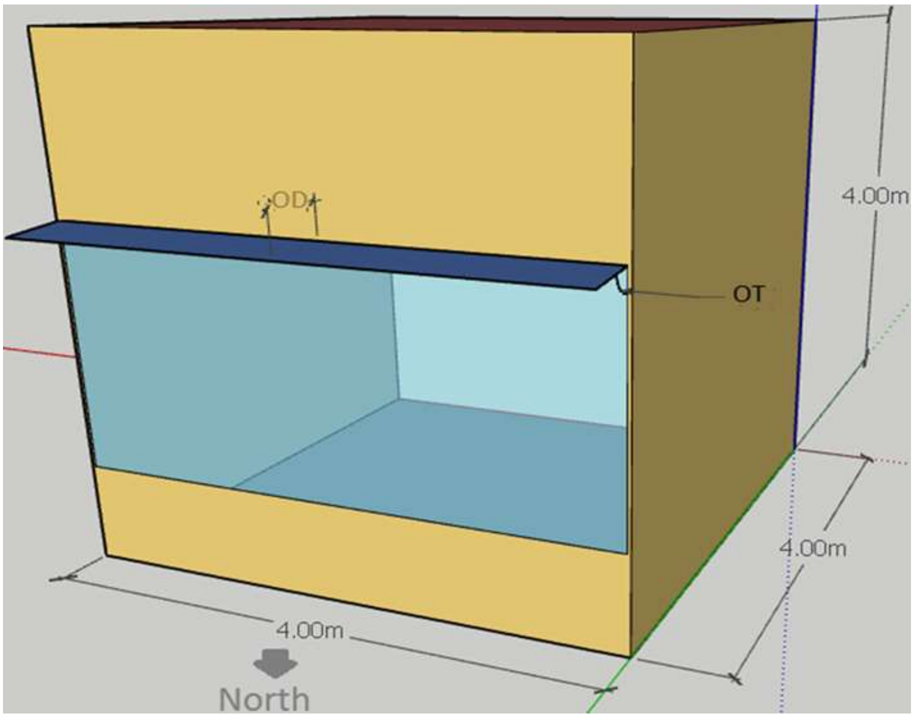


Figure (3): Schematic of the used office room

Table 1: Fixed parameters for building model

Section	Parameter	value	
Site	Orientation	North (0 deg.)	
Wall specifications		Cement plaster	Concrete block
	Thickness (m)	0.02	0.2
	Roughness	Smooth	Med. Rough
	Conductivity (W\m K)	0.727	0.571
	Density (kg\m^3)	1602	609
	specific heat (J\kg K)	840	840
	thermal absorptance	0.9	0.9
	solar absorptance	0.4	0.5
	visible absorptance	0.4	0.5
Glazing specifications	Front side solar reflectance	0.075	
	Back side solar reflectance	0	
	Front side visible reflectance	0.081	
	Back side visible reflectance	0	
	Infrared transmittance	0	
	Front side infrared hemispherical emissivity	0.84	
	Back side infrared hemispherical emissivity	0.84	
Schedule	Working days	Weekly days except Friday	
	Working hours	07:00 – 19:00	
HVAC	Cooling set-point	21 °C (Working hours) & 15.6 °C (off hours)	
	Heating set-point	24 °C (Working hours) & 26.7 °C (off hours)	
	Ventilation flow rate	0.00944 m^3/s person	
	Air changes per hour	1/h	
Thermal loads	Occupancy density	1 person (Working hours)	
	Artificial lighting system	10.7W/m^2(Working hours) & 0 (off hours)	
	Equipment	6.9 W/m^2(Working hours) & 0.69 (off hours)	
	Infiltration flow rate	0.075 L/s-m^2 (Working hours) & 0.3 (off hours)	

Table 2: Design variables for building model

Design variable	Unit	Baseline	Range
Window wall ratio(WWR)	-	0.5	(0,1)
Glazing solar transmittance(GST)	-	0.5	(0,1)
Glazing visible transmittance(GVT)	-	0.5	(0,1)
overhang tilt angle(OT)	degree	90	(0,180)
overhang depth(OD)	m	0.25	[0,0.5]

1.2 Objective functions and design variables

This study aims to investigate the influence of five design variables (window wall ratio, glazing visible transmittance, glazing solar transmittance, overhang tilt angle and overhang depth) on the energy performance in our case study. Where the previous founds [3-4] show the importance of building window in heat gain or heat loss of buildings that has a great effect on cooling and heating consumption. Furthermore it has another important effect on lighting consumption by allowing entrance of natural light into buildings. Table 2 shows the list of design variables used in this study within the range of variation. The optimization problem consists of four objective functions (annual cooling consumption, annual heating consumption, annual lighting consumption and annual electricity consumption). The goal is to minimize the four objective functions and study the interactions between the cost functions.

1.3 Description of the numerical simulations and validation

1.3.1 Development surrogate model based optimization

As shown in Fig. (4), a surrogate model was developed to optimize the design variables, using a genetic algorithm. The first stage is creating the sampling plan and conducting the simulations. The second stage is building the artificial neural network model by using the database generated by the EnergyPlus model in training model and test model. The third stage is the optimization process by minimizing the energy consumption in building in terms of the design input variables, while satisfying the constraints for indoor thermal and visual comfort. All calculations were conducted using an in-house Matlab code.

1.3.2 Design of experiment

Design of experiments (DoE) is a statistical approach to study the effect of several factors on a certain process using a limited number of experiments [13]. The latin hypercube sampling plan (LHS) is one of the most widely used plans. The training dataset for five design variables as listed in Table (3) which exhibits a uniformly distributed points in the domain as shown in Fig. (5).

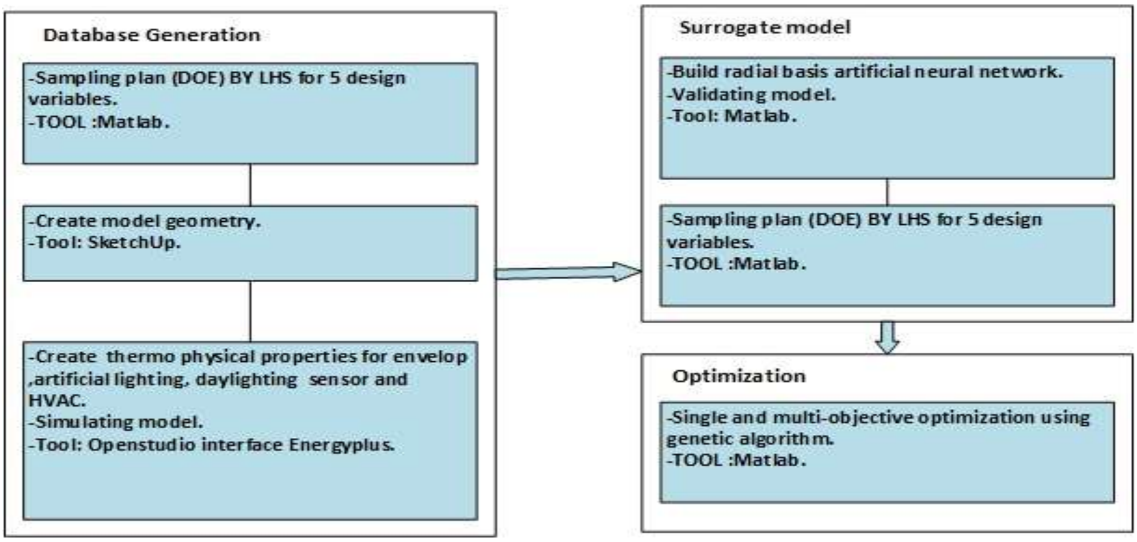


Figure (4): A flowchart of the surrogate-based optimization approach

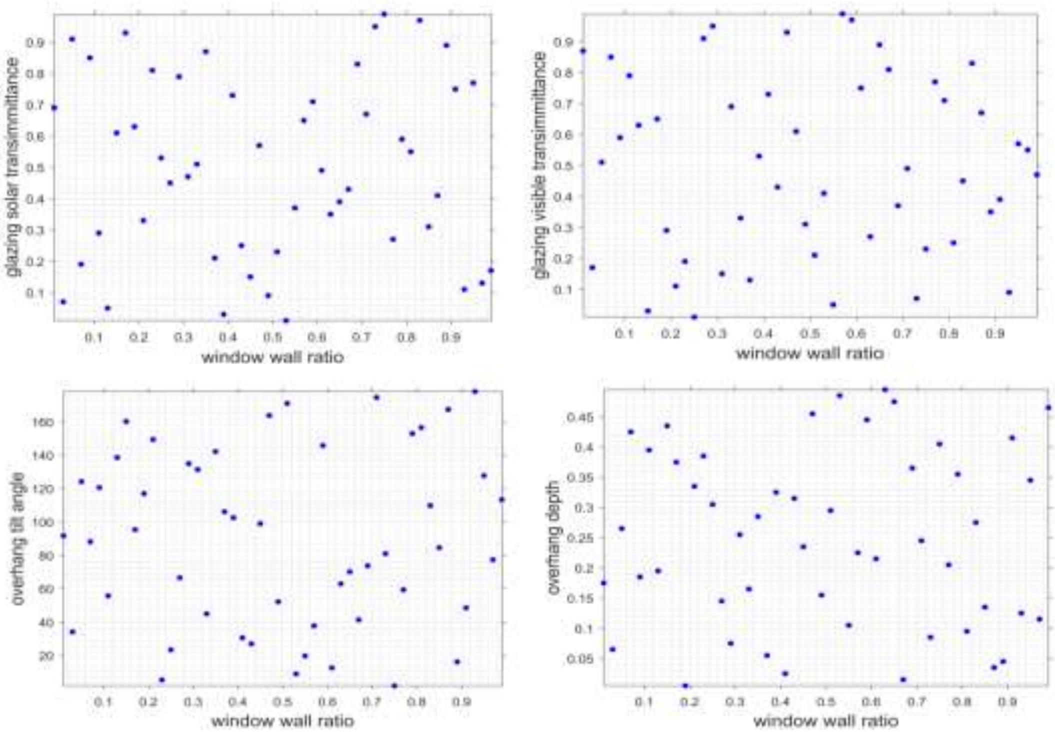


Figure (5): Latin hypercube sampling plan

1.3.3 Artificial neural network building

Radial basis function (RBF) artificial neural networks are composed of three functionally distinct layers. The input layer is simply a set of sensory units. The second layer is a hidden layer of sufficient dimension which performs a non-linear transformation of the input space to a hidden-unit space. The third and final layer performs a linear transformation from the hidden-unit space to the output space [14]. The (RBF) transfer function is included in MATLAB. The newrb function was used in building neural network. It is called in the following way:

net = newrb (P, T, goal, spread, MN, DF)

where P and T are matrices of input parameters and target values as illustrated in Table 3, spread is the radius of the basis function and it default spread value is one, goal is the specified mean squared error and its value $1e^{-4}$, MN is the maximum number of neurons, DF is the number of neurons to add between displays. Figure (6) presents a qualitative estimation of the accuracy of the fitted artificial neural network.

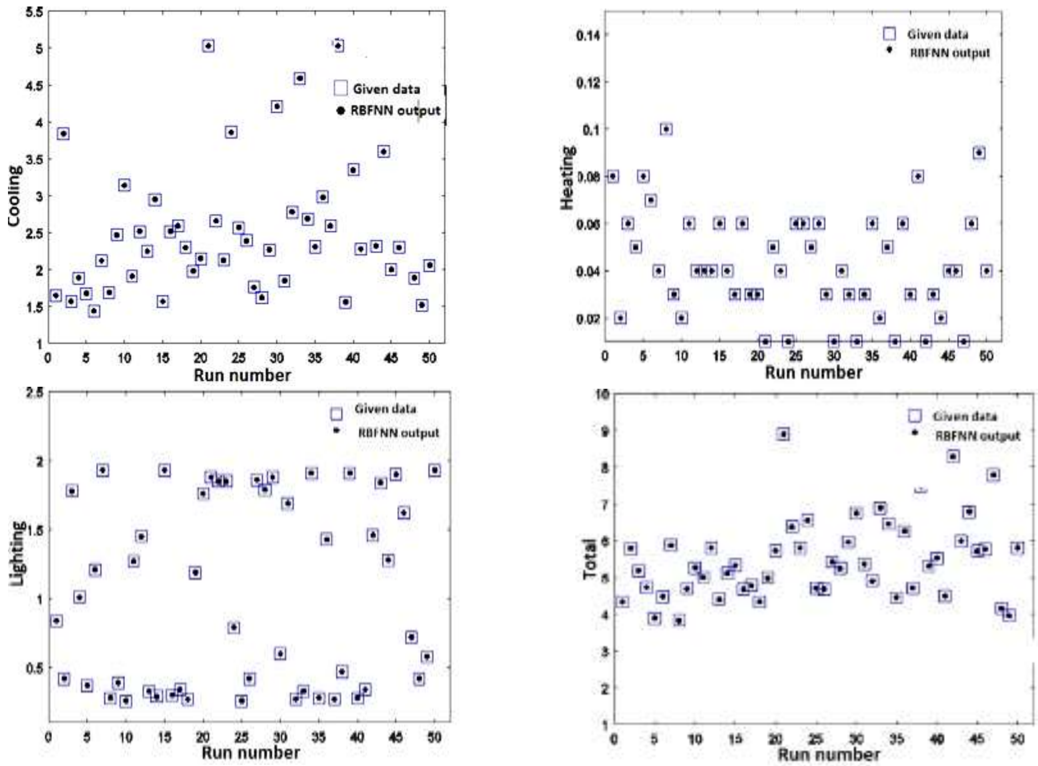


Figure (6) Agreement between the given data and ANN prediction

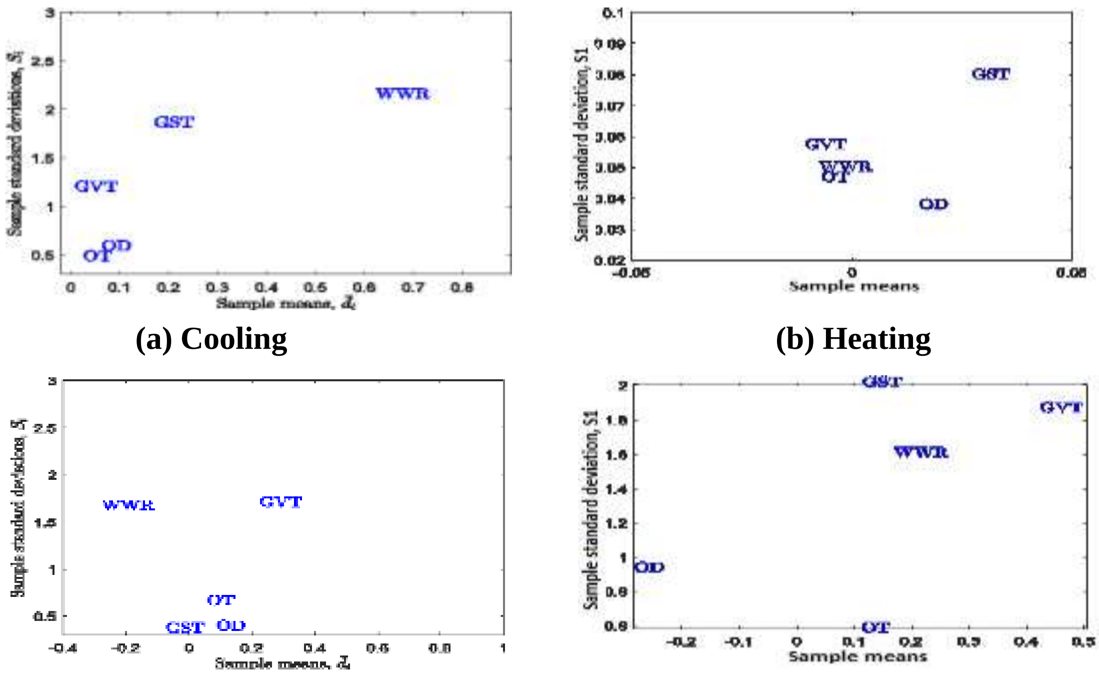
Table 3: Training database for the surrogate model

Results from DOE					Energyplus Simulations			
WWR	GST	GVT	OT	OD	cooling	heating	lighting	total
0.53	0.01	0.41	9	0.485	1.65	0.08	0.84	4.34
0.71	0.67	0.49	174.6	0.245	3.84	0.02	0.42	5.79
0.07	0.19	0.85	88.2	0.425	1.57	0.06	1.78	5.19
0.43	0.25	0.43	27	0.315	1.89	0.05	1.01	4.73
0.27	0.45	0.91	66.6	0.145	1.68	0.08	0.37	3.9
0.13	0.05	0.63	138.6	0.195	1.44	0.07	1.21	4.48
0.25	0.53	0.01	23.4	0.305	2.12	0.04	1.93	5.88
0.45	0.15	0.93	99	0.235	1.69	0.1	0.28	3.83
0.47	0.57	0.61	163.8	0.455	2.47	0.03	0.39	4.7
0.59	0.71	0.97	145.8	0.445	3.14	0.02	0.26	5.27
0.49	0.09	0.31	52.2	0.155	1.91	0.06	1.27	5.01
0.63	0.35	0.27	63	0.495	2.52	0.04	1.45	5.81
0.29	0.79	0.95	135	0.075	2.25	0.04	0.33	4.41
0.87	0.41	0.67	167.4	0.035	2.95	0.04	0.29	5.12
0.03	0.07	0.17	34.2	0.065	1.57	0.06	1.93	5.34
0.61	0.49	0.75	12.6	0.215	2.52	0.04	0.3	4.68
0.41	0.73	0.73	30.6	0.025	2.59	0.03	0.34	4.78
0.65	0.39	0.89	70.2	0.475	2.3	0.06	0.27	4.34
0.17	0.93	0.65	95.4	0.375	1.98	0.03	1.19	4.99
0.19	0.63	0.29	117	0.005	2.15	0.03	1.76	5.73
0.73	0.95	0.07	81	0.085	5.03	0.01	1.88	8.9
0.93	0.11	0.09	178.2	0.125	2.66	0.05	1.85	6.38
0.37	0.21	0.13	106.2	0.055	2.13	0.04	1.85	5.81
0.69	0.83	0.37	73.8	0.365	3.86	0.01	0.79	6.56
0.85	0.31	0.83	84.6	0.135	2.57	0.06	0.26	4.71
0.99	0.17	0.47	113.4	0.465	2.39	0.06	0.42	4.69
0.05	0.91	0.51	124.2	0.265	1.76	0.05	1.86	5.43
0.11	0.29	0.79	55.8	0.395	1.62	0.06	1.79	5.25
0.23	0.81	0.19	5.4	0.385	2.27	0.03	1.88	5.97
0.91	0.75	0.39	48.6	0.415	4.21	0.01	0.6	6.75
0.09	0.85	0.59	120.6	0.185	1.85	0.04	1.69	5.36
0.57	0.65	0.99	37.8	0.225	2.78	0.03	0.27	4.91
0.95	0.77	0.57	127.8	0.345	4.59	0.01	0.33	6.89
0.55	0.37	0.05	19.8	0.105	2.69	0.03	1.91	6.46
0.77	0.27	0.77	59.4	0.205	2.31	0.06	0.28	4.46
0.35	0.87	0.33	142.2	0.285	2.98	0.02	1.43	6.26
0.67	0.43	0.81	41.4	0.015	2.59	0.05	0.27	4.72
0.83	0.97	0.45	109.8	0.275	5.03	0.01	0.47	7.48
0.01	0.69	0.87	91.8	0.175	1.56	0.06	1.91	5.31
0.79	0.59	0.71	153	0.355	3.35	0.03	0.28	5.53
0.97	0.13	0.55	77.4	0.115	2.28	0.08	0.34	4.5
0.75	0.99	0.23	1.8	0.405	4.86	0.01	1.46	8.29
0.31	0.47	0.15	131.4	0.255	2.32	0.03	1.84	5.99
0.81	0.55	0.25	156.6	0.095	3.6	0.02	1.28	6.79
0.21	0.33	0.11	149.4	0.335	2	0.04	1.9	5.72
0.51	0.23	0.21	171	0.295	2.3	0.04	1.62	5.77
0.89	0.89	0.35	16.2	0.045	5.08	0.01	0.72	7.79
0.33	0.51	0.69	45	0.165	1.89	0.06	0.42	4.16
0.39	0.03	0.53	102.6	0.325	1.52	0.09	0.58	3.96
0.15	0.61	0.03	160.2	0.435	2.06	0.04	1.93	5.81

Results and discussion

1.4 Screening of parameters

It is the importance to minimize the number of parameters that influence the objective function; Screening process was conducted using Morris's method. Morris's method aims to estimate the parameters of the distribution of elementary effects associated with each variable, the principle being that a large measure of central tendency indicates a variable with an important influence on the objective function across the design space and a large measure of spread indicates a variable involved in interactions and/or in terms of which f is nonlinear [15]. Figure (7) illustrates the impact of design variables on the objective function. It is clear that the window wall ratio (WWR) has the largest negative impact on the annual cooling energy consumption whereas the glazing solar transmittance (GST) and the glazing visible transmittance (GVT) are less significant and involved interactions whereas the overhang tilt (OT) and the overhang depth (OD) have negligible effect. But for the annual heating energy consumption, GST have the largest tendency furthermore GVT, GST and WWR have less significant tendency and having negative effect but OD has the lowest positive impact. For annual lighting energy consumption GVT and WWR having the largest impact and involved interactions and OT, GST and OD are less importance. For annual total energy consumption the most significant factor is GST furthermore the negative effect of increasing WWR and GVT on annual total energy consumption whereas OD have less importance and positive trend and OT have negligible effect.



(a) Cooling **(b) Heating**

(c) Lighting **(d) Total**

Figure (7) Elementary effect distribution

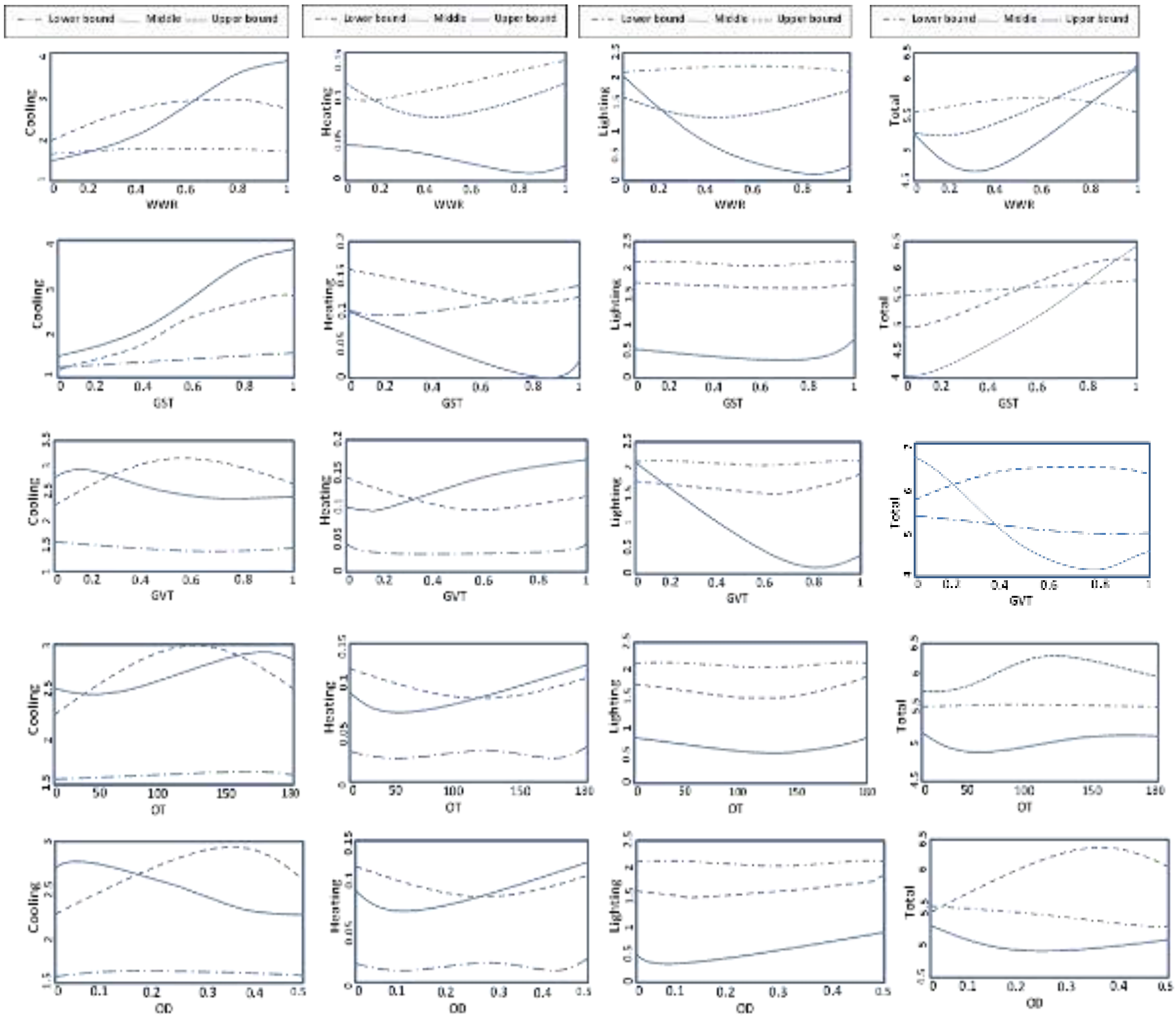


Figure (8) Main effect plots

1.4.1 Effect of single parameter

Figure (8) presents the effect of varying each parameter within keeping the other parameters at their (1) maximum values, (2) middle values and (3) minimum values (cf. Table 2). For instance, the effect of changing WWR on the annual cooling energy consumption when the other parameters have minimum values, the annual cooling energy consumption has approximately a fixed value but when the other parameters are kept at middle values, the annual cooling energy consumption increases from 0.5 to 3.85. While keeping them at maximum values the annual cooling energy consumption increases from 2 to 2.5. Moreover, the effect of changing WWR on the annual heating energy consumption when the other parameters have minimum values, the annual heating energy consumption increases slightly from 0.1 GJ to 0.14 GJ but when the other parameters are kept at middle values, the annual heating energy consumption decreases from 0.05 GJ to 0.001 GJ. While keeping them at maximum values the annual heating energy consumption decreases within the increasing of WWR till 0.4 then increase. In addition the annual lighting consumption still fixed at lower bounds but within the increasing of WWR the lighting consumption decreases to 0.1 at middle bounds while at the maximum bounds the lighting consumption decreases from 1.6 to 1.2 and then increases to the same value. Finally, the effect of changing WWR on annual total energy consumption when the other parameters have minimum values, the annual total energy consumption has approximately a fixed value but when the other parameters are kept at middle values, the annual total energy consumption decreases from 5.2 GJ to 4.6 GJ then increases to 6 GJ. While keeping them at maximum values the annual total energy consumption increases from 5 GJ to 6 GJ. The GST changing increases the annual cooling and total consumption at middle values within contrary to annual heating consumption while it hasn't any impact on annual lighting consumption whereas, GVT has the great impact on annual lighting consumption at middle values. It is obvious that the varying parameters within keeping the other parameters at their minimum values haven't enough influence on the objective functions. This can be referred to the interaction between the design variables.

1.5 Optimization geometry

There are many definitions for optimization. The simplest definition is “the art of making things the best.” Interestingly, many people do not like that definition as it may not be reasonable, or even possible, to do something in the very best possible way. In practice, doing something as well as possible within practical constraints is very desirable [16]. Furthermore the mathematical definition is the process of maximizing and/or minimizing one or more objectives without violating specified design constraints, by regulating a set of variable parameters that influence both the objectives and the design constraints [7]. Three optimization studies have been conducted; the first is single objective optimization, the second is two- objective optimization, the last is multi-objective optimization. There are many used algorithms for the optimization of building energy design, the most frequently used algorithms are annealing, tabu search, ant colony, differential evolution, particle swarm and genetic algorithms (GAs) [17] . Throughout this paper a genetic algorithm (GA) is used for conducting the three optimization studies. Figure (9) presents a flow chart for the genetic algorithm process.

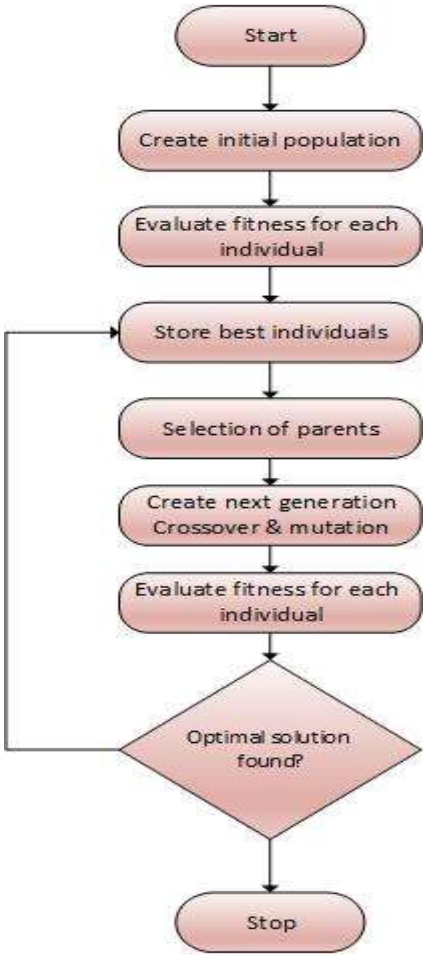


Figure (9) Flow chart for the genetic algorithms technique

1.5.1 Single-objective approach

This technique is used to minimize the four objective functions independently. Table 4 lists the used settings for optimization studies using Matlab 2017a. Table 5 lists the optimized values of the design variables for the best values of the four objective functions. The optimized dataset demonstrates that the criteria behave contrary to each other. It can be seen that the lowest possible value for the annual cooling energy consumption is 1.208 GJ takes place by selecting the optimum value of window wall ratio as 0.001, the optimum values of glazing solar and visible transmittance are 0.272 and 0.817 respectively and the optimum values of overhang tilt angle and depth are 54.551 and 0.096 respectively. On the other hand the lowest possible value for the annual heating energy consumption is 0.026 GJ takes place by selecting the optimum value of window wall ratio is 0.713, the optimum values of glazing solar and visible transmittance are 0.798 and 0.379 respectively and the optimum values of overhang tilt angle and depth are 56.229 and 0.109 respectively. In addition the annual lighting energy of the optimization model is 0.483 GJ takes place by selecting the optimum value of window wall ratio is 0.568, the optimum values of glazing solar and visible transmittance are 0.587 and 0.810 respectively and the optimum values of overhang tilt angle and depth are 111.177 and 0.119 respectively. Eventually, the optimum design values that used to minimize the annual total energy consumption to 3.6197 GJ are 0.372 (window wall ratio), 0.301 (glazing solar transmittance), 0.856 (glazing visible transmittance), 87.27 (overhang tilt angle) and 0.11(overhang depth).

These results revealed that increasing the window wall ratio will increase the cooling consumption and thus the total consumption but it will decrease the heating and the lighting consumption. On the other hand, the increasing of GVT has an obvious positive impact on the lighting consumption and the increasing of GST has an obvious positive impact on the heating consumption and negative impact on the cooling consumption.

Table 4: Genetic setting for single objective optimization

Population type	Double vector
Population size:	200
Elite count	2
Crossover fraction:	0.8 (default)
Crossover operation:	Intermediate crossover
Selection operation:	Tournament (tournament size equals 4)
Mutation operation:	Adaptive Feasible
Hybrid function	Pattern search
Maximum number of generations	1000

Table 5: Results of the single objective optimization

Objective	WWR	GST	GVT	OT	OD	Value(GJ)
Annual cooling	0.001	0.272	0.817	54.551	0.096	1.20757
Annual heating	0.713	0.798	0.379	56.229	0.109	0.0263146
Annual lighting	0.568	0.587	0.810	111.177	0.119	0.482798
Total annual	0.372	0.301	0.856	87.27	0.11	3.6197

Table 6: Genetic setting for multi objective optimization

Population type	Double vector
Population size:	200
Crowding distance fraction	0.35
Crossover fraction:	0.8 (default)
Crossover operation:	Intermediate crossover
Selection operation:	Tournament (tournament size equals 2)
Maximum number of generations	1000

Table 7: Pareto front points using MOGA

No.	WWR	GST	GVT	OT	OD	Cooling(GJ)	Heating(GJ)	Lighting(GJ)	Total(GJ)
1	0.365	0.326	0.875	83.168	0.096	1.734	0.085	0.046	3.625
2	0.002	0.224	0.839	53.197	0.120	1.214	0.120	1.562	4.539
3	0.188	0.179	0.918	48.388	0.082	1.315	0.131	0.955	4.012
4	0.055	0.324	0.905	42.261	0.433	1.693	0.071	2.158	5.641
5	0.032	0.268	0.783	51.217	0.196	1.269	0.103	1.642	4.717
6	0.048	0.405	0.901	41.987	0.461	1.751	0.069	2.189	5.712
7	0.230	0.313	0.845	60.485	0.121	1.419	0.102	0.587	3.822
8	0.089	0.486	0.579	53.348	0.123	1.399	0.075	1.451	4.660
9	0.643	0.749	0.304	74.766	0.173	4.499	0.015	0.924	7.428
10	0.524	0.538	0.288	88.95	0.102	3.286	0.0005	1.159	6.401
11	0.081	0.294	0.780	55.214	0.121	1.244	0.108	1.254	4.292
12	0.361	0.387	0.812	80.781	0.100	1.822	0.070	0.010	3.675
13	0.780	0.911	0.128	79.35	0.105	5.287	0.00002	1.593	8.910
14	0.413	0.563	0.655	80.435	0.115	2.450	0.024	0.001	4.358
15	0.333	0.340	0.860	65.915	0.108	1.645	0.090	0.187	3.666
16	0.453	0.754	0.383	62.918	0.170	3.388	0.0009	0.934	6.260
17	0.688	0.778	0.507	57.916	0.141	4.567	0.022	0.123	6.730
18	0.740	0.906	0.149	79.055	0.143	5.242	0.003	1.516	8.788
19	0.044	0.352	0.712	53.271	0.121	1.244	0.100	1.464	4.503
20	0.775	0.909	0.133	79.106	0.107	5.294	0.001	1.574	8.901

1.5.2 Multi-objective approach

The Pareto front concept is applied and a bi-objective optimization is performed by running genetic algorithm using Matlab 2017a in order to determine building energy performance by a trade-off between pairs of the objective functions. Figure (10) illustrates the Pareto optimal curve between the annual cooling energy consumption and the annual heating energy consumption. It is clear that any improvement in one objective will result in the worsening of at least one other objective. In addition the multi-objective optimization study has been conducted using the settings given in Table 6. Table 7 lists the Pareto optimal point for the four objective functions. Therefore, Fig. (11) shows the optimum results for the four objective minimization in the form of three-dimensional Pareto fronts. Once the optimization is completed and a Pareto-optimum solution set is obtained, the multi-criteria decision-making is required, which is affected by the importance that is given to each objective function. Decision making depends on stakeholders' needs and wills. In this study, the most remarkable objective function to emerge from the quart-objective optimization study is the annual total energy consumption because this study focuses on minimization energy consumption generally. So the annual total energy consumption represents a valuable alternative to energy optimization in smart building. From Table 8, the case 1 has the lowest value for the annual total energy consumption, which is 3.625 GJ. Furthermore the optimum design values for case 1 are WWR is 0.365, GST is 0.326, GVT is 0.875, OT is 83.168 and OD is 0.096 m.

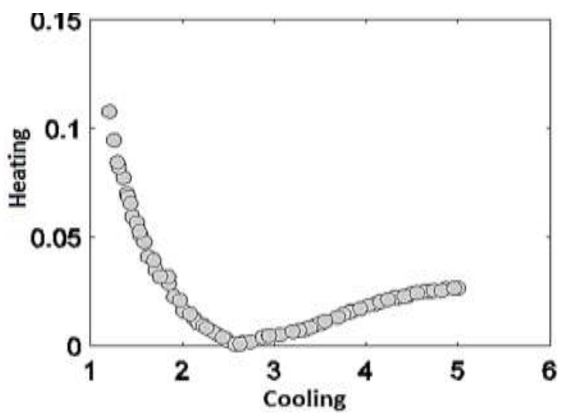


Figure (10) Pareto front for the bi-objective optimization

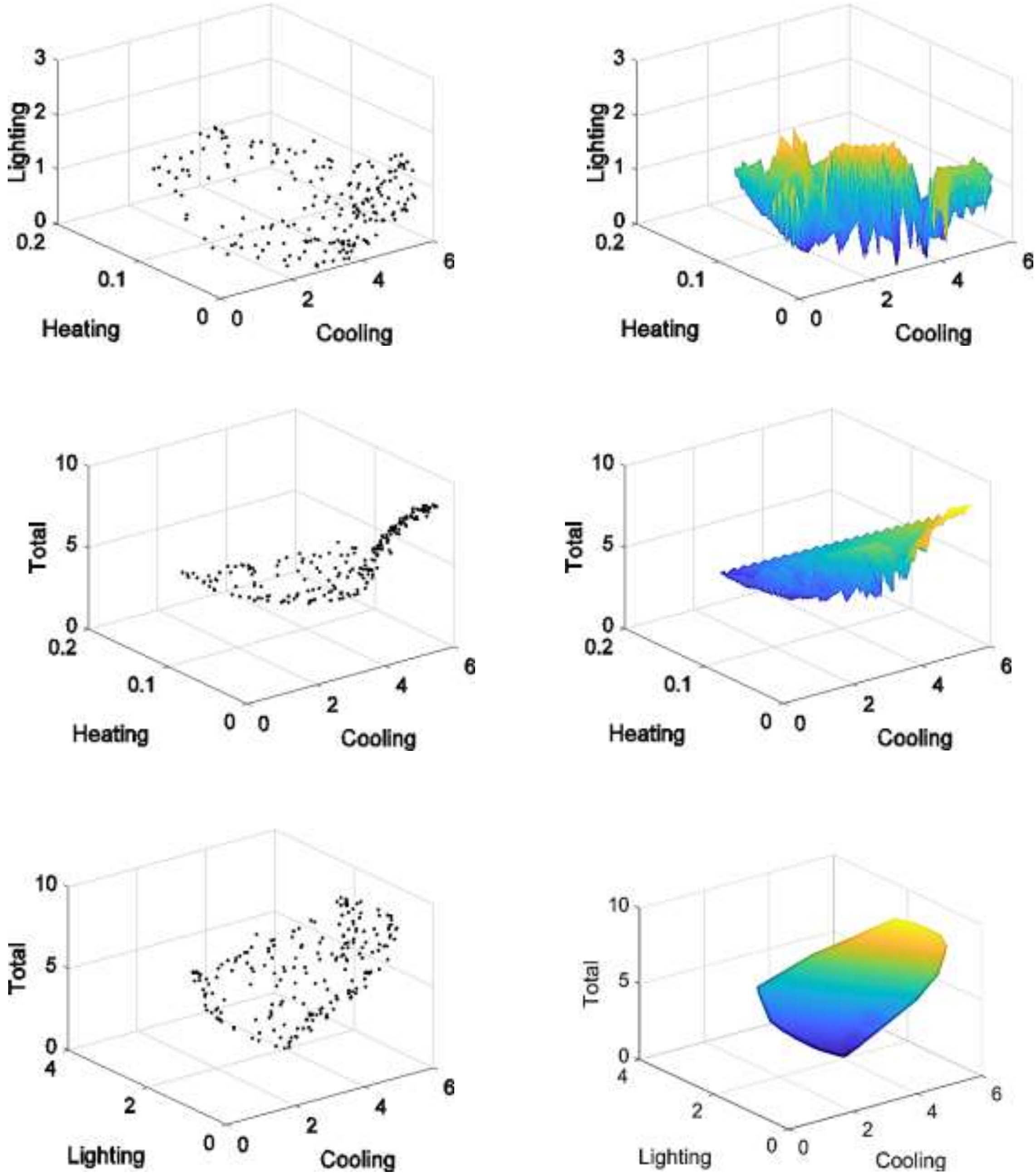


Figure (11) Pareto fronts of the triple-objective optimization

Conclusions

The present study investigated the impact of the size and the properties of glazing for windows and overhang tilt and depth on the building energy consumption in the city of Alexandria, Egypt. Sampling plan is created by Latin hyper cube using Matlab and simulated using EnergyPlus through Openstudio (building energy modeling). A surrogate model is created by building an artificial neural network using Matlab. The artificial neural network was applied in the optimization study using genetic algorithms. Single objective and multi-objective optimization were applied on four objective functions those are annual heating, annual cooling, annual lighting and annual total consumption. The obtained results can be summarized as follows:

- The most significant factors on building energy consumption are the window wall ratio, the glazing solar transmittance and the glazing visible transmittance.
- WWR and GST have a high negative impact on the cooling consumption and the opposite with heating consumption. In addition WWR and GVT have a high positive impact on lighting consumption.
- The four objective functions have interactions and a trade-off between pairs of the objective functions. So the multi-objective optimization approach was applied.
- The annual total consumption function presents the major function in minimization energy consumption in this study. For minimum total consumption value, the optimum design values are WWR is 0.365, GST is 0.326, GVT is 0.875, OT is 83.168 and OD is 0.096 m.
- The multi-criteria decision-making depends on designers' needs and wills to select the Pareto front design points that are resulted from the multi-objective optimization study.

Future studies on energy optimization of smart buildings might extend building integrated photovoltaic (BIPV) that uses photovoltaic materials instead of conventional building materials such as roof, glazing and façade to exploit panels interfaces for electricity generation at the same time to minimize the cooling loads taking in consideration the architectural esthetic elements.

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