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Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO)

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HIGHLIGHTS

- A methodology is presented for building energy performance optimization.
- EnergyPlus is used as the building energy simulation program.
- Multi-objective particle swarm optimization is used as the optimization approach.
- The method is applied to a single zone case study in four climatic regions of Iran.
- Building specifications are optimized to minimize its annual energy consumption.

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ABSTRACT

This paper proposes an efficient methodology for the simulation-based multi-objective optimization problems, which addresses important limitations for the optimization of the building energy performance. In this work, a mono- and multi-objective particle swarm optimization (MOPSO) algorithm is coupled with EnergyPlus building energy simulation software to find a set of non-dominated solutions to enhance the building energy performance. To evaluate the capability and effectiveness of the approach, the developed method is applied to a single room model, and the effect of building architectural parameters including, the building orientation, the shading overhang specifications, the window size, and the glazing and the wall material properties on the building energy consumption are studied in four major climatic regions of Iran. In the optimization section, mono-criterion and multi-criteria optimization analyses of the annual cooling, heating, and lighting electricity consumption are examined to understand interactions between the objective functions and to minimize the annual total building energy demand. The achieved optimum solutions from the multi-objective optimization process are also reported as Pareto optimal fronts. Finally, the result of multi-criteria minimization is compared with the mono-criterion ones. The results of the triple-objective optimization problem point out that for our typical model, the annual cooling electricity decreases about 19.8–33.3%; while the annual heating and lighting ones increase 1.7–4.8% and 0.5–2.6%, respectively, in comparison to the baseline model for four diverse climatic regions of Iran. In addition, the optimum design leads to 1.6–11.3% diminution of the total annual building electricity demand. The proposed optimization method shows a powerful and useful tool that can save time while searching for the optimal solutions with conflicting objective functions; therefore facilitate decision making in early phases of a building design in order to enhance its energy efficiency.

1. Introduction

Energy is one of the most important resources used by the modern society and is the core of the economic and social activities in the industrialized countries. In recent years, there has been an enormous increase in the global energy demand due to industrial development and population growth. In the context of the European Union efforts to reduce the growing energy expenditure, it is widely recognized that the building sector has an important role, accounting about 40% of the total energy consumption and 36% of

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Nomenclature

COP	coefficient of performance	n	number of decision variables
C_1	cognitive learning factor	Pbest	personal best position
C_2	social learning factor	PMI	particle memory influence
CMI	current motion influence	q	number of equality constraints
$F(\vec{x})$	objective function vector	r	random element
F_{ws}	composite function	S	feasible criterion space
$f_i(x)^{min}$	minimum value of the ith objective function	SI	swarm influence
$f_i(x)^{max}$	maximum value of the ith objective function	t	time
Gbest	global best position	$v_i(t)$	velocity of ith particle
$\vec{g}(\vec{x})$	inequality constraints vector	w	weighted inertia
$\vec{h}(\vec{x})$	equality constraints vector	$x_i(t)$	position of ith particle
k	number of objective functions	$\vec{x}$	decision variables vector
λ_i	weighting coefficient	X	feasible decision space
m	number of inequality constraints		

the carbon dioxide emission [1]. In addition, most of the energy used in buildings and construction sectors is produced from fossil fuels, making them the largest emitter of greenhouse gases on the planet. 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]. As a result, buildings energy efficiency improvement has become an international big deal for designers and researchers given a high potential for building modifications [3] by incorporating whole building energy analyses [4] rather than analyzing a building as a set of disconnected parts [5]. Whole building design can help architects and engineers to determine the amount of cooling, heating, and lighting loads in order to analyze the characteristics and energy performance of buildings. Good energy performance of buildings is generally obtained by selecting more comprehensive and executive decisions to decrease the energy demand. Building designers often use whole building energy simulation programs such as DOE-2, EnergyPlus, ESP-r, eQUEST and TRNSYS to analyze the thermal and energy behaviors of buildings. In order to evaluate the energy performance of a building, many effective and important design parameters must be taken into account. Architectural parameters are very important in reducing the building energy consumption; but are difficult to be tackled because of the complicated and nonlinear interactions of the processes [6]. An approach known as "parametric study" may be used to investigate the building performance. According to this method, the input of each decision variable is changed to understand its effect on the design objective functions while all other building parameters are kept fixed. This technique can be repeated iteratively with other variables. Although studies are a useful method to explore alternative design options and to establish parameter dependencies of the solutions [7], it may be too time consuming and practically impossible due to the large number of combinations. By coupling an appropriate optimization procedure with a whole building energy simulation tool, it is possible to analyze and to optimize buildings characteristics in less time [8].

Over the past years, considerable research works have been directed toward simulation-based optimization of building energy consumption with the overall aim of understanding the most appropriate building parameters and architectural configurations to promote its energy efficiency. Nguyen et al. [9] reviewed the simulation-based optimization methods applied to the building performance analysis and Bandara and Attalage [6] discussed the applicability of the optimization methodologies in the building performance optimization. Brown et al. [10] developed an online building optimization tool to minimize the energy use in a cost effective manner and to evaluate the distributed energy generation alternatives. Chantrelle et al. [11] presented a multi-criteria tool (MultiOpt) based on the NSGA-II genetic algorithm coupled with TRNSYS to optimize the buildings renovation. In a similar work, Tuhus-Dubrow and Krarti [12] developed a genetic algorithm optimization tool coupled with DOE-2 applied to optimize a building shape and envelope features. Saporito et al. [13] performed a multi-parameter study to investigate the heating energy use in the office buildings using a thermal simulation code, named APACHE. In another research, Shan [14] provided a methodology to optimize the building facade with respect to triple objectives of cooling, heating, and lighting electricity demand to achieve the minimum annual energy cost. Kusiak et al. [15] presented a data-driven approach for optimization of a heating, ventilation, and air conditioning (HVAC) system in an office building using a strength multi-objective particle swarm algorithm. In addition, Znouda et al. [16] presented an optimization program that couples genetic algorithm with a simplified tool for building thermal evaluation (CHEOPS) with the purpose of minimizing the buildings energy consumption. Karmellos et al. [17] developed a methodology and a software tool for optimum prioritization of energy efficiency measures based on the primary energy consumption and the initial investment cost criteria in buildings. Moreover, Yu et al. [18] presented a novel multi-objective genetic algorithm model using NSGA-II to optimize the energy efficiency and thermal comfort in buildings. Magnier and Haghighat [19] used TRNSYS simulations, the multi-objective genetic algorithm, and the artificial neural network to optimize the building design. In another work, Wright et al. [20] investigated 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. In addition, Lu et al. [21] presented a comparison study on two design optimization methods for renewable energy systems in buildings, including a single objective genetic algorithm and a multi-objectives non-dominated sorting genetic algorithm (NSGA-II). Recently, Hamdy et al. [22] proposed a modified multi-objective optimization approach based on the genetic algorithm coupled with IDA ICE building performance simulation program to minimize the carbon dioxide equivalent emissions and the investment cost of a two-story house and its HVAC system. Karaguzel et al. [23] integrated the whole building energy simulation program, EnergyPlus, with GenOpt tool to minimize the life cycle cost of a reference commercial office building model.

Echenagucia et al. [24] proposed an integrative approach for the early stages of building design by means of genetic algorithm, with the aim of minimizing the energy need for heating, cooling and lighting. Gossard et al. [25] applied a multi-objective optimization of building envelope using genetic algorithm and artificial neural network to optimize the equivalent thermophysical properties of the external walls in order to improve the building thermal efficiency. Additionally, Murray et al. [26] coupled a degree-days simulation technique with genetic algorithm to optimize the thermal energy efficiency in retrofitting of buildings. Futrell et al. [27] presented a methodology to optimize complex buildings design for daylighting performance using GenOpt optimization tool. Junghans and Darde [28] combined a hybrid single objective genetic algorithm with a modified simulated annealing algorithm to optimize the building energy performance, which can be used by architects and building planners with no knowledge about optimization processes. Yu et al. [18] presented a novel simulation-based improved back-propagation network coupled with multi-objective genetic algorithm (NSAG-II) to optimize the building energy efficiency and the thermal comfort to assist designers in design of green buildings. Newly, Ascione et al. [29] developed a novel optimization procedure for energy performance and thermal comfort of buildings by means of a direct coupling between MATLAB and EnergyPlus. They applied a multi-objective genetic algorithm (NSGA-II), implemented in MATLAB for the thermal design of the building envelope, to minimize the cooling energy demand and the thermal discomfort in two different Mediterranean climates. In another research work, they implemented their method to evaluate the cost-optimal solution in retrofitting a building to optimize the primary energy required by the air-conditioning system and the indoor thermal discomfort [30]. In another study, Kim and Park [31] integrated EnergyPlus with MATLAB program by executing EnergyPlus using m-script file on the MATLAB platform. They used the nonlinear constrained optimization MATLAB toolbox function (FMINCON) to minimize the heating, cooling and lighting energy use in order to obtain the optimal control of blind systems in office buildings. Oh et al. [32] developed a gbXML–IDF converter tool via MATLAB graphical user interface (GUI) platform to transfer Building Information Model (BMI) data to EnergyPlus input file in order to solve a multi-criteria optimal design problem of a BIM-based energy performance simulation model. They considered interior and exterior glazing of window and cavity gas as design variables to minimize the cooling and heating energy consumption and Predicted Mean Vote (PMV) of a building model.

The goal of this study is to purpose a simple and efficient approach for optimization of building energy efficiency. In this paper, a multi-objective particle swarm optimization algorithm (MOPSO) couples with EnergyPlus building energy simulation program by means of an EnergyPlus input file creation tool, jEPlus, to enhance the energy performance of a typical room. After presentation of the coupling strategy, the developed optimization technique is applied to a test case to investigate the effect of building architectural parameters such as the building orientation, the shading overhang specifications, the window size, and the glazing and the wall material characteristics on the building energy performance. Three objective functions of the annual cooling, heating and lighting electricity consumption are considered. Based on the results, a set of optimum architectural configurations are obtained for four major climatic regions of Iran, including cold, mild, warm–dry and warm–humid ones.

2. Methodology

2.1. Multi-objective optimization

The general multi-objective optimization problem is posed mathematically as follows [33]:

$$\begin{aligned}
&\text{Minimize } F(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \ldots f_k(\vec{x})]^T \\
&\text{Subject to}: \begin{cases} \vec{g}(\vec{x}) \leqslant 0 \\ \vec{h}(\vec{x}) = 0 \end{cases} \\
&\vec{x} \in \Re^n, \quad \vec{f}(\vec{x}) \in \Re^k, \quad \vec{g}(\vec{x}) \in \Re^m \text{ and } \vec{h}(\vec{x}) \in \Re^q \\
&X = \{\vec{x} | g_m(\vec{x}) \leqslant 0, \quad m = 1,2,3\ldots m\} \\
&\{h_q(\vec{x}) = 0, \quad q = 1,2,3\ldots q\} \\
&S = \{F(\vec{x}) | \vec{x} \in X\}
\end{aligned} \tag{1}$$

where $\vec{x} \in \Re^n$ is the vector of design variables and n is the number of decision variables. $k \geqslant 2$ is the number of objective functions, and $F(\vec{x}) \in \Re^k$ is their vector in which $f_i(\vec{x}) : \Re^n \to \Re^1$. In addition, m and $\vec{g}(\vec{x})$ are the number of inequality constraints and their vector, respectively. Similarly, q and $\vec{h}(\vec{x})$ are the number of equality constraints and their vector. Finally, X and S are the feasible decision and criterion spaces, respectively.

One of the most popular methods to present multi-objective solutions is proposed by Vilfredo Pareto [34]. A solution is a Pareto or non-dominated solution if there is not any other feasible solution that improves one objective without deteriorating at least another one. Fig. 1 shows a Pareto curve for the minimization of two cost functions, simultaneously. In the multi-objective optimization problems, all points on the Pareto front are potentially an optimum solution. In this respect, selection of the final optimum configuration among the available optimal points requires a process of decision-making. There are many decision-making techniques designed to solve the multi-objective optimization problems, which belong to two general families: the first one, which is known as classical multi-objective optimization method, solves a single objective problem for each Pareto-optimum solution, while the second one searches for all the non-dominated solutions, simultaneously [36,37].

In the decision theory, the weighted sum method (WSM) is the best-known multi-criteria decision making approach [38–42]. The weighted sum strategy converts a multi-objective problem of minimizing a vector of criteria functions into a scalar problem by summing normalized objective functions, multiplied by their weighting coefficients, λ_i. The weighted sum method is formulated as [42,43]:

$$\text{Minimize } F_{ws}(x) = \sum_{i=1}^{k} \lambda_i \frac{f_i(x) - f_i(x)^{\min}}{f_i(x)^{\max} - f_i(x)^{\min}} \tag{2}$$

where $F_{ws}(x)$ is the composite objective function, k is the number of objective functions $f(x)_i$ and $\lambda_i \in [0, 1]$ where $\sum_{i=1}^{k} \lambda_i = 1$. In addition, $f(x)_i^{\min}$ and $f(x)_i^{\max}$ are the minimum and the maximum values of the objective functions, respectively, as they are optimized independently.

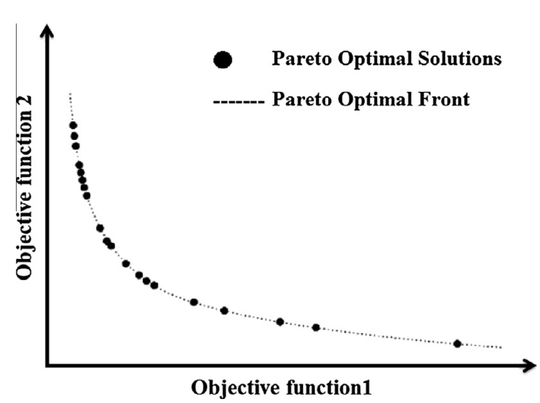

Fig. 1. An example of the Pareto front to minimize two objectives [35].

2.2. Multi-objective particle swarm optimization (MOPSO)

Particle swarm optimization (PSO) algorithm is a population-based stochastic optimization technique developed by Eberhart and Kennedy in 1995 [44]. PSO method is initialized with a group of random particles and then searches for an optima by updating the generations. At each generation, each particle is updated by the following two best values. The first one is the best solution achieved so far. Another one is the best value obtained so far by any particle in the population. This best value is a global one. When a particle takes part of the population as its topological neighbors, the best value is a local best. After finding the two best values, the velocity and the position of a particle may be updated [44,45]. The position of $x_i(t)$ is calculated by adding its velocity, $v_i(t)$ to the current position, i.e.:

$$x_i(t) = x_i(t-1) + v_i(t) \tag{3}$$

where the velocity vector is defined as:

$$v_i(t) = w\ v_i(t-1) + C_1 r_1[\text{Pbest} - x_i(t)] + C_2 r_2[\text{Gbest} - x_i(t)] \tag{4}$$

where w is the inertia weight to control the effect of the particle previous velocity on the current one. C_1 is the cognitive learning factor represents the attraction that a particle has toward its own success; C_2 is the social learning factor represents the particle attraction toward the success of its neighbors. C_1 and C_2 are usually defined as positive constants [45]. In addition, r_1 and $r_2 \in [0, 1]$ are two independent sequences of random numbers, which used to keep away from entrapment on local minimum and to permit the divergence of a small percentage of particles in a larger exploration of the search space [45,46]; Pbest and Gbest are the personal and global best positions. Fig. 2 depicts the velocity and the position updates in the particle swarm optimization algorithm. In the PSO algorithm, the leader that each particle uses to update its position is completely determined once a neighborhood topology is established. However, in the MOPSO one, each particle has a set of different leaders; only one of them can be used to update the particle position. Such set of leaders is stored in an external archive. Finally, the contents of the external archive are reported as the final output of the MOPSO algorithm in the form of Pareto optimal curve [45–51].

2.3. Building energy simulation software

In this research, EnergyPlus simulation program is used to predict the building thermal behavior and energy consumption. EnergyPlus is a whole building energy analysis program developed by the US department of Energy, DOE [52]. It is a stand-alone simulation program without a user-friendly graphical interface, which reads input and writes output as text files. EnergyPlus calculates the cooling and heating loads necessary to maintain the thermal control set points, conditions throughout the secondary HVAC system and coil loads, and the energy consumption of the primary plant equipment. Many of the simulation characteristics, capabilities, and features of EnergyPlus have been inherited from the legacy programs of BLAST and DOE-2 [52].

jEPlus is a building energy simulation manager tool which has been developed by Yi Zhang in 2009 to manage the complex parametric analysis, explore alternative design options, and establish dependencies between design variables using EnergyPlus [53,54]. jEPlus assists building designers to set up the parametric study with an EnergyPlus model and to perform the simulations in a parallel mode.

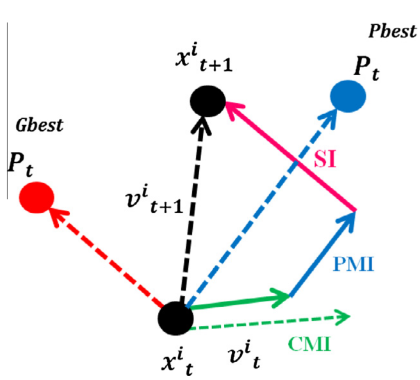

Fig. 2. The updating process of the particle velocity and its position in PSO algorithm.

2.4. Coupling EnergyPlus and MOPSO algorithm

In order to implement the simulation-based optimization problem, a multi objective particle swarm optimization (MOPSO) algorithm code is programmed in MATLAB environment. It should be underlined that the evaluations of objective functions are directly retrieved from EnergyPlus output files. In other words, MATLAB deals with EnergyPlus as a black box function. Therefore, it is necessary to make a communication between EnergyPlus and MATLAB programs. Through an innovation, coupling functions are programmed in MATLAB environment to launch jEPlus tool as an interface with EnergyPlus simulation software. On the command script functions, the values of the decision are replaced in jEPlus software. Afterward, EnergyPlus is used to simulate the annual building energy consumptions. In this way, EnergyPlus can be thoroughly controlled by MATLAB environment and a powerful tool for multi-objective optimization of the building performance can be achieved. The novelty of the coupling approach is to fully control all features of EnergyPlus through MATLAB environment with the help of jEPlus as an interface in order to add the power of MATLAB program to EnergyPlus building simulation software. Coupling MATLAB with EnergyPlus by means of jEPlus solves most of the disadvantages of other existing buildings optimization tools. With the proposed methodology, the power and capabilities of EnergyPlus in building energy simulation can be combined with the power of MATLAB in control and optimization. In this way, not only all metaheuristic optimization algorithms can be implemented for all single and multi-objective optimization problems without any limitation in the selection of objective functions and decision variables (discrete, continuous and mixed-integer ones), but also the multi-criteria optimization of building problems can be solved using both direct and classical multi-objective optimization methods. Fig. 3 shows the optimization framework of this research. Moreover, in Fig. 4, the scheme of MATLAB and EnergyPlus coupling algorithm is demonstrated.

3. A case study

3.1. Description of the building model

In order to evaluate the capability and effectiveness of the proposed optimization approach, the developed method is applied to a single thermal zone test case room in a multi-story building to investigate the effect of architectural design parameters on the room energy performance at different climatic regions of Iran.

Firstly, SketchUp [55] 3D modeling software package is used to define the building geometry and the thermal zone. Fig. 5 shows the architectural schematic view of the baseline room. It should be noted that in the initial building model, only the southern wall of the room is exposed to the sunlight and the outside air. The

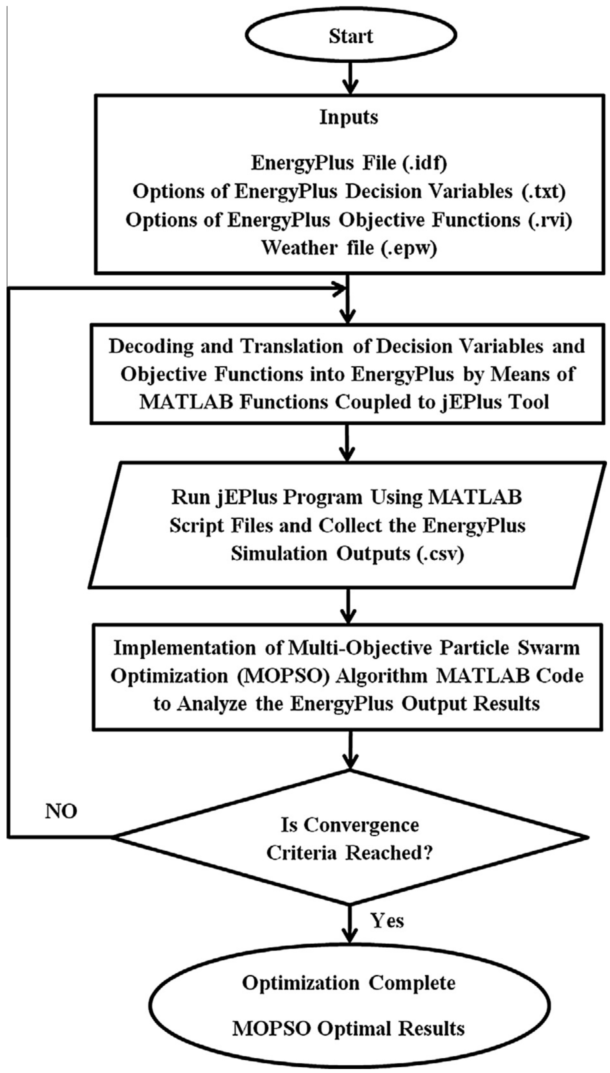

Fig. 3. Flowchart of the purposed simulation-based optimization approach.

model orientation is in degrees with counter clockwise direction. EnergyPlus [56] building energy simulation program is used to model 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.

The length, width, and height of the room are 3 m. It has a double-layer clear glazing window with 13 mm air space equipped with an overhang. The overhang height above the window and its left and right extensions are fixed at zero. No blind is considered for the window. It is assumed that the building is equipped with a packaged terminal heat pump (PTHP) air conditioning system with a COP of 3 in heating mode and a COP of 2.75 in cooling operation. The heating and cooling set point temperatures are 20 °C and 27 °C, respectively, for operating strategy of the zone thermostat control. The room is equipped with 90 W compact fluorescent lamp (CFL) lighting system; and its schedule is set to work twenty-four hours a day. Moreover, the model has a daylighting controller sensor to continuously dim the lighting automatically with the threshold of 500 lux. When illuminance is higher than 500 lux, it is considered high enough not to require artificial lighting, and the lighting system is turned off. To focus on the thermal load due to the room exterior wall, other loads such as occupants and infiltration, does not take into account in this research. Table 1 summarizes the physical characteristics of the baseline case room, which are common in Iran.

3.2. Climatic regions of Iran

Iran is located in the Middle East with an area of about 1,648,000 square kilometers; lies between latitudes 24° and 40°N, and longitudes 44° and 64°E. Iran has a diverse climate, from cold to hot, and from dry to humid. Fig. 6 shows four major climatic regions of Iran, including cold, mild, warm–dry, and warm–humid [57]. In the present paper, Tabriz, Tehran, Kerman and Bandar Abbas have been selected as representative cities for these climatic regions, respectively, whose locations are summarized in Table 2.

3.3. Objective functions and decision variables

In this research, three optimization criteria, including the annual cooling, heating and lighting electricity demand were taken into account to investigate the energy performance of the case study room. The goal is to identify the interactions between the cost functions, and to minimize the annual total building energy demand. The optimization problem consists of seven continues parameters, including the building orientation, the window size, the shading overhang specifications, and the glazing and the wall conductivity. It also contains of five discrete decision variables related to the thermal, solar and visible absorptance properties of wall and the glazing solar and visible transmittance features. In the current work, the values of discrete parameters for the wall and glazing specifications are defined according to the databases provided by EnergyPlus [56] (i.e., ASHRAE materials databases). Dornelles et al. [58] presented average solar absorptance data of painted surfaces with different roughness for solar spectrum range to understand the surfaces spectral behavior in different wavelengths. Thus, in this study, the discrete parameters regarding the absorptance characteristics of the wall are analyzed based on the Dornelles et al. research work. Table 3 shows the list of decision variables used in this study as well as their initial value and range of variation.

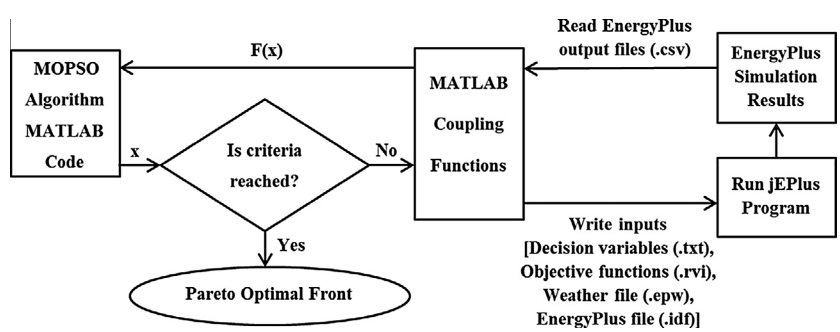

Fig. 4. Coupling method of MATLAB and EnergyPlus by means of jEPlus.

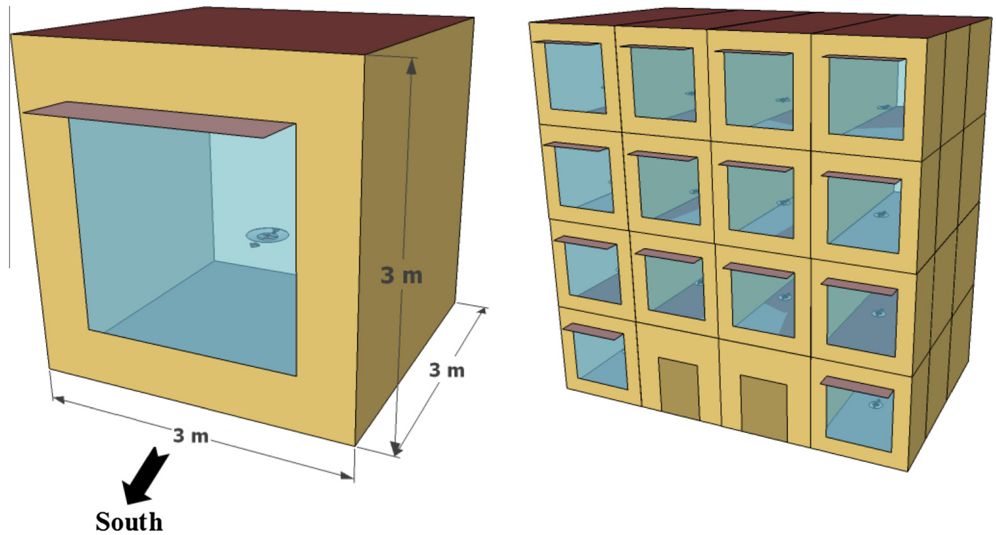

Fig. 5. Schematic view of the EnergyPlus baseline model.

Table 1
Physical properties of the initial test case room.

Component	Property	Value
Wall	Conductivity (W/m K)	0.57
	Thickness (m)	0.2
	Specific heat (J/kg K)	790
	Density (kg/m^3)	1120
Floor/roof	Conductivity (W/m K)	1.11
	Thickness (m)	0.1
	Specific heat (J/kg K)	920
	Density (kg/m^3)	800

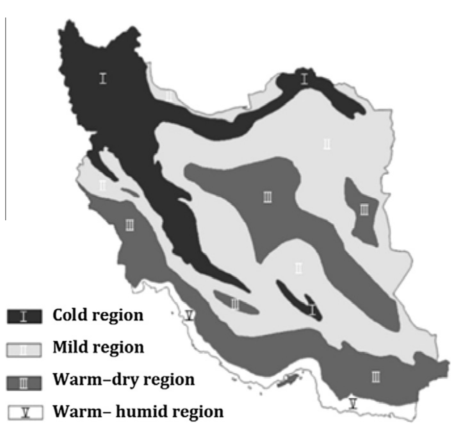

Fig. 6. Climatic regions of Iran [56].

Table 3
Specifications of the decision variables.

Variable name	Unit	Range	Initial value
Building orientation	°	Continues [0,360)	0
Window length	m	Continues (0,3)	2
Window height	m	Continues (0,3)	2
Glazing solar transmittance	–	Discrete	0.775
Glazing visible transmittance	–	Discrete	0.881
Glazing conductivity	W/m K	Continues [0.1,1]	0.9
Wall thermal absorptance	–	Discrete	0.9
Wall solar absorptance	–	Discrete	0.7
Wall visible absorptance	–	Discrete	0.7
Wall conductivity	W/m K	Continues [0.1,1]	0.57
Overhang tilt angle	°	Continues [0,180]	90
Overhang depth	m	Continues (0,0.5]	0.3

3.4. Setting of the particle swarm optimization

In this study, the population size and the maximum generation number of 40 and 25 are used, respectively, and the tolerance is 0.001. In addition, C_1 and C_2 are 2, and the inertia weight of 0.5 with an inertia weight damping rate of 0.99 is chosen. These control parameters of the PSO algorithm have been selected according to the expertise of the previous research works [44–51] and also based on some pre-tests conducted by the authors to get the best trade-off between the computational time and the reliability of the Pareto optimal front. In addition, the evolution of the population continues as long as at least one of the stop criteria is satisfied, i.e. the maximum iteration number is reached or the average change in the spread of the Pareto optimal front becomes lower than the tolerance.

It should be noted that according to the range of variations of decision variables, the number of possible configurations of the building envelope is numerous, while the maximum number of

Table 2
Characteristics of the representative cities.

City	Climate	Latitude (°N)	Longitude (°E)	Elevation (m)
Bandar Abbas	Warm–humid	27.20	56.15	10.00
Kerman	Warm–dry	30.25	56.97	1754
Tehran	Mild	35.68	51.30	1191
Tabriz	Cold	37.80	46.25	1361

Table 4
Comparative analysis of the single objective optimum solutions at Tehran.

Decision variable	Unit	Cooling-based opt. value	Heating-based opt. value	Lighting-based opt. value
Building orientation	°	82	357	87
Window length	m	0.39	2.3	2.99
Window height	m	0.44	2.4	2.99
Glazing solar trans.	–	0.653	0.904	0.904
Glazing visible trans.	–	0.841	0.914	0.914
Glazing conductivity	W/m K	1	0.1	0.79
Wall thermal abs.	–	0.182	0.980	0.750
Wall solar abs.	–	0.194	0.977	0.751
Wall visible abs.	–	0.100	0.967	0.716
Wall conductivity	W/m K	1	0.5	0.22
Overhang tilt angle	°	72	52	62
Overhang depth	m	0.5	0	0

scenarios searched by the PSO algorithm equals to the number of population size multiplied by the number of maximum iteration, which is equal to $40 \times 25 = 1000$. Therefore, the proposed optimization approach leads to decrease the required computational time significantly in comparison to a countless search and therefore, ensures a saving of computational time.

4. Results and discussion

In this section, the results of the purposed method for the simulation-based optimization of the building energy performance are presented. In the first part of the results, two approaches are carried out to deal with the optimization problem at Tehran city located in the mild climate region of Iran. The main goal of this part is to understand the effect of cooling, heating, and lighting on the total electricity consumption and to see how different objective functions can affect the optimum solution. The first approach concerns with the minimization of the annual cooling, heating, and lighting electricity consumption as separate objective functions using single objective PSO algorithm. At the second approach, the bi-objective and triple-objective optimization of the cost functions is evaluated to realize their interactions and obtain all possible optimal and non-dominant solutions, concurrently. In this respect, for the later approach, the MOPSO algorithm is used to extract the Pareto optimal fronts.

In the second part of the results, the weighted sum method (WSM) is applied to select a single optimum solution for final optimum configuration at the different climatic regions of Iran. Finally, based on the results, the effect of room features on the building energy performance is thoroughly discussed at different climatic conditions.

4.1. Single-objective approach

In this section, three objective functions are minimized independently, which leads to a single optimum solution in each case. Table 4 demonstrates the optimum results of the building design parameters for each criterion at Tehran located in the mild climate region of Iran. As presented in Table 4, the mono-criterion optimization results clearly show that the criteria behave contrary to each other.

In the annual cooling-based minimization, the optimization process suggests a building to the west with an orientation angle of 82°, and with the longest possible overhang depth compared to the initial model. In addition, the optimum window size decreased close to 96% not to permit the solar energy to come into the zone through the window to reduce the cooling energy consumption as much as possible. Furthermore, the optimum solar and visible transmittances of glazing are 0.653 and 0.841, respectively, to achieve the least energy from the sun. In the analysis of the absorptances characteristics of the wall material, the optimum thermal, solar, visible absorptances of the wall are 0.182, 0.194 and 0.1, respectively. As a result, in the cooling-based minimization, the most suitable color for the wall is snow white (Dornelles et al. [58], sample no. 50) in order to bring down the cooling electricity demand to the lowest possible amount.

On the other hand, in the analysis of the annual heating minimization, the optimized building is to the south with an orientation angle of 357°, and with no shading overhang over the window. In addition, 38% increase in the window size in comparison to the baseline model, and the optimum glazing conductivity of 0.1 W/m K with the solar and visible transmittance of 0.904 and 0.914, respectively, leads to receive the most energy from the sun through the window. In examining the wall material specifications, the optimum conductivity, and the thermal, solar, and visible absorptance are 0.5, 0.980, 0.977, and 0.967, respectively. As a consequence, in the heating-based minimization, the best choice for the wall color is black (Dornelles et al. [58], sample no. 29) to obtain the most thermal energy from the sun, and therefore to decrease the heating electricity as far as possible.

Eventually, in the lighting-based minimization, the optimization process leads to a building to the west with the orientation angle of 87°, no overhang, with the largest possible window size and a glazing visible transmittance of 0.914 to gain the most daylight from the outside in order to lessen the lighting energy demand. It deserves to be mentioned that the solar transmittance and conductivity of the glazing, as well as, the material properties of the wall have no effect on the lighting electricity consumption, because these factors only influence on the heating and cooling

Table 5
Results of the mono-criterion optimization at Tehran.

Objective function	Baseline value (GJ)	Cooling-based opt.		Heating-based opt.		Lighting-based opt.	
		Value (GJ)	Diff. (%)	Value (GJ)	Diff. (%)	Value (GJ)	Diff. (%)
Annual cooling electricity	3.99	2.82	−29.3	4.7	+17.8	5.94	+48.9
Annual heating electricity	4.02	5.38	+33.6	3.72	−7.7	4.76	+18.4
Annual lighting electricity	1.89	2.37	+25.4	1.92	+1.6	1.86	−1.6
Total annual electricity	9.9	10.56	+6.7	10.34	+4.5	12.56	+26.9

systems. Nevertheless, the optimization process offers a concrete color for the room wall (Dornelles et al. [58], sample no. 53) with the wall conductivity and the thermal, solar, visible absorptance of 0.22, 0.750, 0.751, and 0.716, respectively. In Addition, the solar transmittance and conductivity of the glazing are 0.904 and 0.79, respectively.

Table 5 shows the mono-criterion optimization results, in detail. According to the results, if the annual cooling electricity consumption is minimized, the optimization results demonstrate that the annual cooling electricity consumption decreases about 29.3%, while the annual heating and lighting electricity demands increase 33.6 and 25.4%, respectively in comparison with the baseline model. On the other hand, in the minimization analysis based on the annual heating electricity consumption, the results show that the annual heating electricity consumption decreases 7.7%. In contrast, the annual cooling and lighting electricity consumption increase 17.8 and 1.6%, respectively, compared with the baseline model. As given in Table 5, if the minimization problem is based on the annual lighting electricity consumption, it reduces 1.6% in comparison with the baseline model, which leads to 48.9 and 18.4% increment of the annual cooling and heating electricity consumption, respectively. Consequently, in this approach, two functions increase greatly, in contrast to the third one, which decreases a little. In addition to the aforementioned tips, based on the results, the annual total energy consumption increases 4.5–26.9% compared to the initial model. In this respect, it can be clearly inferred that in the mono-criterion optimization of our typical room model, not only is there no possibility to reduce all three objective functions, simultaneously, but also it leads to increase greatly the annual total energy consumption. Overall, the results of the mono-criterion optimization analysis gave some idea about the interactions between three objective functions. The second approach may give more information regarding these interactions.

4.2. Multi-objective approach

A bi-objective problem occurring in deliberation and determination of the characteristic, operation and performance of the system under study is a trade-off between pairs of the objective functions. In this part, in order to investigate the objective functions interactions, each time two criteria are selected from the objectives functions, e.g. the annual cooling, heating, and lighting electricity consumption. In this case, the optimization process creates an archive of the tested configurations and returns a series of optimum points, which are the Pareto solutions. Figs. 7–9 integrate the bi-objective optimization results of the MOPSO algorithm in the form of Pareto optimal curves, which clearly reveal the conflict between pairs of the objective functions. These optimum points are

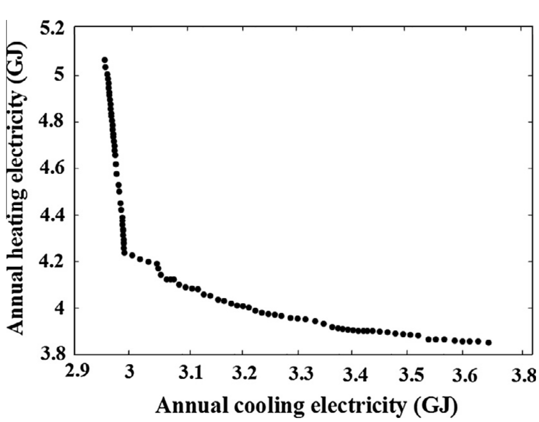

Fig. 7. Pareto front of the bi-objective optimization based on the annual cooling–heating electricity consumption at Tehran.

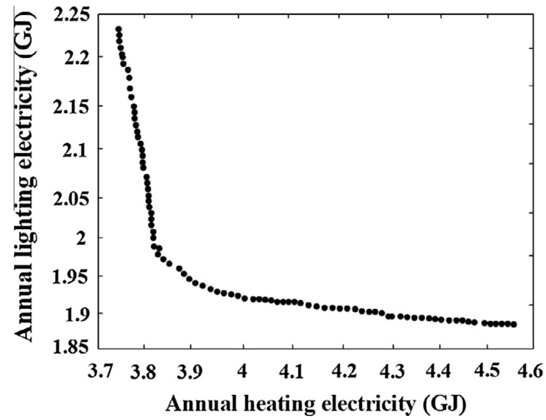

Fig. 8. Pareto front of the bi-objective optimization based on the annual heating–lighting electricity consumption at Tehran.

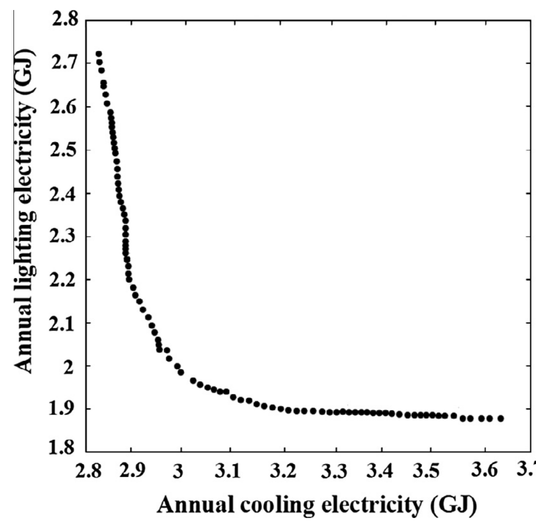

Fig. 9. Pareto front of the bi-objective optimization based on the annual cooling–lighting electricity consumption at Tehran.

ideal points at which both objective functions have their optimum values, independent of the third one. In addition, Fig. 10 shows the optimum results of the triple-objective minimization in the form of three-dimensional Pareto front. As it can be noticed from the figures, as one of the objectives decrease, the other ones increase. In other words, it is impossible to minimize all the objective func-

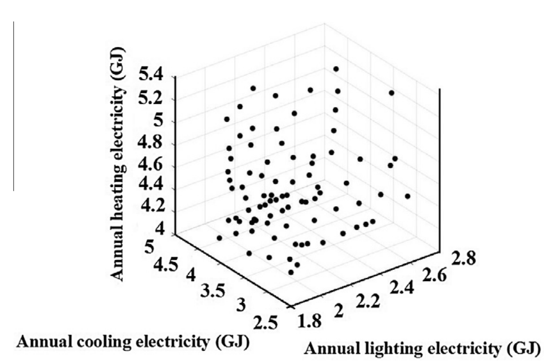

Fig. 10. Pareto front of the triple-objective optimization at Tehran.

Table 6
Optimum design parameters for four climatic regions of Iran.

Decision variable	Unit	Bandar Abbas	Kerman	Tehran	Tabriz
Building orientation	°	278	266	267	270
Window length	m	1.48	1.5	1.6	2
Window height	m	0.68	0.87	0.93	1
Glazing solar trans.	–	0.43	0.6	0.653	0.899
Glazing visible trans.	–	0.77	0.84	0.841	0.913
Glazing conductivity	W/m K	0.13	0.1	0.11	0.11
Wall thermal abs.	–	0.182	0.526	0.269	0.222
Wall solar abs.	–	0.194	0.513	0.288	0.267
Wall visible abs.	–	0.1	0.374	0.244	0.324
Wall conductivity	W/m K	0.1	0.11	0.1	0.12
Overhang tilt angle	°	69	60	63	61
Overhang depth	m	0.41	0.4	0.43	0.39

tions, simultaneously-neither in the bi-objective optimization nor in the triple-objective one.

4.3. Final optimum configuration

Once the optimization is completed and a Pareto-optimum solution set is obtained, the process of decision-making should be performed to determine a single preferred solution. Decision-making depends on many parameters, e.g. the engineering experiences, characteristics and performance of the system, relative importance of the objective functions, and sensitivity of the optimum solutions to the input parameters. As a result, designers and engineers may select the optimum design parameters based on their actual needs and interests. This paper focused on using the weighted sum method to determine a single optimum solution for the triple-objective optimization problem, i.e. to transfer three objectives to a single objective using Eq. (4). As all consumed energy is in the form of electricity, it can be assumed that all objective functions are weighted equally, namely:

$$F_{ws}(x) = \frac{1}{3}\sum_{i=1}^{3}\frac{f_i(x) - f_i(x)^{min}}{f_i(x)^{max} - f_i(x)^{min}} \tag{5}$$

where $f_1(x), f_2(x)$ and $f_3(x)$ are the total annual cooling, heating and lighting electricity consumption, respectively.

Tables 6 and 7 indicate the optimum design parameters and the corresponding objective functions results of triple-objective optimization problem in four major climatic regions of Iran. Optimum building parameters in Table 6 shows that in all climates, facing the room window to the east is the most appropriate orientation to get the most lighting energy from the outside in order to reduce the lighting electrical energy consumption. In addition, the optimum window size gets larger from warm to cold climate to gain more energy from the sun during the cold season. Additionally, the optimum solar and visible transmittance of glazing increase from warm to cold climate regains to obtain more heating energy and daylight from the outside. Moreover, in all climates, the glazing and the wall conductivity are close to the minimum possible values. In the analysis of the optimum absorptance properties of the wall material, the suggested colors for the walls coating are snow white (Dornelles et al. [58], sample no. 50), straw (Dornelles et al. [58], sample no. 27), pearl (Dornelles et al. [58], sample no. 58) and canary yellow (Dornelles et al. [58], sample no. 34) for warm–humid, warm–dry, mild, and cold climates, respectively. In other words, its color becomes darker from warm to cold climate to use more thermal energy from the sun in order to bring down the annual total energy consumption as much as possible. The results of the optimum overhang specifications are somewhat similar in all climate regions, with the shading overhang depth of 0.43–0.39 m and the tilt angle of 60–69°.

The different climatic conditions show a considerable effect on the building energy demands. As seen in Table 7, the optimum cooling energy consumption increases from 1 to 5.43 GJ, and the optimum heating energy consumption decreases from 12 to 2.2 GJ from cold to warm climate. Thus, a building at Tabriz, located in the cold climate, consumes more electricity than a building in other cities mainly due to the excessive heating energy demand. However, the optimum lighting energy demand varies a little between 1.92 and 1.95 GJ in different climates, meaning that it is less affected by the climatic conditions than the other ones. The triple-objective optimization results illustrate for various climatic conditions, the annual cooling electricity consumption reduces 19.8–33.3%, while the annual heating and lighting ones increase 1.7–4.8% and 0.5–2.6%, respectively, compared to the initial room model. As a result, the optimum design leads to 1.6–11.3% decrease of the annual total building electricity demand for four different climate regions of Iran. In addition, the highest change in the cooling energy consumption is at the cold climate with a value of 33.3%, while the heating energy demand has the lowest change of 1.7%. Similarly, the lowest change of the cooling energy demand is at the warm weather conditions with the value of 19.8%, whereas the heating energy consumption has the highest value of 4.8%. In this respect, it can be clearly deduced that the cooling and heating criteria are fully against to each other. Finally, the changes of the annual total energy consumption get smaller

Table 7
Optimum value of the objective functions for four climatic regions of Iran.

City	Objective function	Baseline value (GJ)	Opt. value (GJ)	Diff. (%)
Bandar Abbas	Annual cooling electricity	6.77	5.43	−19.8
	Annual heating electricity	2.1	2.2	+4.8
	Annual lighting electricity	1.89	1.92	+1.6
	Total annual electricity	10.76	9.55	−11.3
Kerman	Annual cooling electricity	2.28	1.66	−27.2
	Annual heating electricity	5.28	5.4	+2.3
	Annual lighting electricity	1.91	1.92	+0.5
	Total annual electricity	9.47	8.98	−5.2
Tehran	Annual cooling electricity	3.99	3.1	−22.3
	Annual heating electricity	4.02	4.4	+9.5
	Annual lighting electricity	1.89	1.93	+2.1
	Total annual electricity	9.9	9.43	−4.8
Tabriz	Annual cooling electricity	1.5	1	−33.3
	Annual heating electricity	11.8	12	+1.7
	Annual lighting electricity	1.9	1.95	+2.6
	Total annual electricity	15.2	14.95	−1.6

from warm to cold climate. Furthermore, in the mono-criterion optimization of our typical model at Tehran, the annual total building electricity demand increased greatly from 4.5 to 26.9% for the different cost functions, while in the triple-criteria minimization problem it decreased 4.8% respect to the basic model. Accordingly, it is inferred that using multi-objective optimization methods may lead to a more desirable and more efficient design than the single-objective ones.

From the above discussion about the multi-criterion optimization approach, it can be concluded that similar to the mono-criterion one, for our typical room model, variation of the annual cooling and heating energy consumption is much more than the lighting one and it is infeasible to minimize all three cost functions, simultaneously. As an overall result, the architectural design parameters as well as the climatic conditions are important and have a noticeable influence on the building energy efficiency, so that the energy consumption can be highly decreased by choosing appropriate building architectural parameters according to the climate.

5. Conclusions

In this article, a powerful approach for the multi-variable optimization of the building energy consumption was introduced. In order to implement the simulation-based optimization, the multi-objective particle swarm optimization (MOPSO) code was programmed in MATLAB environment and coupled with EnergyPlus program through jEPlus parametric simulation manager tool as an EnergyPlus input file creation interface. In the presented optimization problem, the design parameters were the room orientation, the shading overhang specifications, the window size, the glazing and the wall specifications. In addition, three objective functions were taken into account including the annual cooling, heating, and lighting electricity consumption that are entirely nonlinear and coupled. The suggested method was applied to a single room model by taking into account four climatic regions of Iran including warm–humid, warm–dry, mild, and cold. In the optimization part, both mono- and multi-objective optimization analyses were studied with the purpose of realization of the cost function interactions. The results of the mono-criterion optimization problems were compared with the baseline model. In addition, the achieved optimum solutions from the multi-objective optimization problem were reported as Pareto-optimal fronts. The triple-objective optimization results indicated that using the weighted sum method, the annual cooling consumption reduces 19.8–33.3% in comparison to the basic model depends on the climate region. In contrast, the annual heating and lighting electricity consumption increased 1.7–4.8% and 0.5–2.6%, respectively. As a result, the final optimum configuration leads to 1.6–11.3% reduction of the annual total building electricity consumption for four climate regions of Iran. In addition, based on the results, the climate demonstrates a significant effect on the building annual cooling and heating energy consumption, while its effect on the annual lighting electricity demand is negligible. Therefore, it is obvious that architectural design parameters of the building, as well as the climate conditions are important and critical in determining the building energy performance, so that the building energy consumption can be highly reduced by selecting appropriate architectural design parameters in early phases of a building design to improve its energy performance.

The proposed method was used to optimize a single room model, considering the building envelope parameters as decision variables and the building energy demands as the cost functions. However, it is expected to apply the method to a more complex building system, aiming not only to bring down the whole building energy use, but also to optimize other important terms of the building performance such as the thermal comfort, the environmental impacts, the embodied energy, and the investment costs. Therefore, more design parameters may be considered if the goal is extended to cover these objectives in future studies. In addition, robust multi-attributes decision-making methods, such as LINMAP, TOPSIS, and Fuzzy approaches may be used to investigate the performance of the methods.

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