



Office Building Envelope Design Optimization by Modified Competitive Search Algorithm for Energy Saving

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Abstract

Building envelopes for green buildings should be designed with low energy consumption and low construction costs. A modified competitive search algorithm is used for the optimization of the office building design due to the long runtime of simulation tools such as EnergyPlus and TRNSYS. For the minimization of the cost of construction at the needed energy conservation, the envelope configuration, such as window numbers, walls, glass curtain walls, etc., is optimized. Comparing the proposed algorithm with some others, the cost decreased for the optimum design of the building structure at the needed energy load value. The number of iterations is also reduced by the proposed approach. Moreover, the overall area of the window is increased, which has resulted in the natural ventilation being more proper. Since the ratio of the glass curtain wall is increased, it can result that the indoor lighting being better. Per unit area of the envelope, the value of the energy load is smaller and the total cost is lower for the proposed method in comparison with other algorithms, considering that the opening rate of the window is much the same. The total cost decreased by 37.1% in comparison with the initial design. It can be observed that the MCSA is more efficient than the other compared methods in energy saving of the building in this paper.

Keywords: Optimization; Modified competitive search algorithm; Construction cost; Building envelope; Energy conservation.
Received: 25 July 2023; Revised: 27 August 2023; Accepted: 30 August 2023.

Article type: Research article.

1. Introduction

In recent years, buildings have consumed a major portion of energy around the world.^[1,2] In particular, buildings globally account for higher than 40% of the overall energy use.^[3] Although the achieved energy efficiency advantages, it is expected to increase energy consumption in buildings due to population growth.^[4,5] Nevertheless, it is revealed that the

building sector has the potential for the highest energy and economic savings because there are solutions for its improvement that are economically proper and profitable.^[6] Energy conservation actions are increasingly required to be performed in existing buildings because of the low rate of replacement of these buildings (almost 0.07% yearly).^[7] A major amount of energy is consumed in office buildings.^[8] Therefore, it is important for the optimization of the energy use and cost of these building types. The target of designing green buildings is to improve indoor environments with low energy consumption, which has been considerably expanded recently.^[9] Still, there are many thousands of office buildings with green certifications worldwide.^[10] Different parameters affect the energy performance of building envelopes, such as orientation, window shading, area of window and glazing, roof and wall insulations, and weather conditions.^[11,12] That is to say, it is needed to evaluate several combinations of parameters to design green buildings.^[13]

Different research has been carried out in recent decades to optimize buildings.^[14] In Ref. [13], to optimize envelope parameters and the building shape, an optimization method based on simulation was used. An enhanced Manta-Ray Foraging Optimizer coupled with the RIUSKA simulation tool

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was employed to obtain the optimal values of all related variables for the minimization of the energy usage in residential constructions.^[15,16] The applied method has performed completely appropriately compared to the particle swarm optimization method, approaching too close to the optimal in less than 50 percent of the simulations.

In Ref. [17], energy-efficient buildings were reviewed. This paper was aimed at studying building optimization, energy evaluation, and enhancements in energy-efficient buildings. This study includes the effects of various parameters on the buildings' energy use and the ways of minimizing energy usage using various techniques.

In Ref. [18,19], EnergyPlus and TRNSYS have been used effectively, also for HVAC design, due to a cognitive estimation mechanism to decrease the number of the simulation. In Ref. [18], a simulation-assisted control methodology has been used in a high-inertia building. A building simulation model was employed to effectively optimize, both present and future information about the outdoor climatic condition and the state of the building, combining the thermal comfort and the energy consumption indices. In Ref. [19], the authors presented Parametrized Cognitive Adaptive Optimization which has been employed toward the design of both model-based and model-free "plug-and-play" building optimization and control systems, with the lowest human effort necessary to achieve the design.

In Ref. [20], Improved Battle Royal optimizer (IBRO) as the optimization method and the TRNSYS simulation software have been combined for building energy optimization to investigate the influence of the overhangs optimization. Giving the attainments, a development was observed in the comfort level. Moreover, the 4.2% of cooling demand has been reduced for Shanghai.

In Ref. [21], the cost-effective energy-retrofit measures were studied. For the minimization of carbon dioxide emissions and life cycle cost, multi-criteria optimization using a genetic algorithm (GA) has been applied in different types of buildings for 5 various major heating systems by enhancing the building systems and envelope. A multiple-criteria optimization method has been proposed in Ref. [22], to study the energy model of building envelopes. For minimizing the original energy consumption, energy-related global cost, and discomfort hours, GA is coupled with EnergyPlus. The building orientation, radiative characteristics of the plasters, window type, setpoint temperatures, and thermo-physical features of components of the envelope are considered design variables.

Authors in Ref. [23], presented a hierarchy of three-definition of very low energy buildings, nearly zero-energy building, and zero-energy building, as the sequential energy codes of building updated goals to 2050. Six scenarios were provided to investigate the building's energy use between 2025 and 2050. The results indicate an advancement in occurrence time and a reduction in the building's maximum energy use.

In Ref. [24], the optimization design of low-energy buildings was reviewed to provide the results of former studies and to help new researchers and architects. The performance energy consumption and cost were the commonest objective functions. In another review,^[25] the optimizers utilized in the energy-effective geometry and building envelope configuration were discussed. The application of derivative-based and derivative-free techniques has been studied in this paper. For multi-objective optimizations, decision-making techniques have been assumed. Finally, the propositions and limitations for the related future studies were resulted.

To optimize the energy efficiency of the building, different studies have targeted a couple of energy simulation tools with an optimization method.^[26-29] A comprehensive review of these methods presented by Barber and Krarti.^[30] A tailor-made thermal simulation technique was coupled with an optimization method performed in MATLAB in Ref. [31], to implement multiple simulations to achieve the building's optimum configuration. As the optimization technique, a genetic algorithm was employed.

In Ref. [32], a couple of EnergyPlus simulation software and NSGA-II optimization method was applied to attain the optimum result for improving the building energy performance. The effect of several characteristics related to the building architecture like window size, orientation, etc. has been studied. According to the achievements, the yearly cooling energy use was reduced between 55.8% and 76.4% in various studied weather conditions. Nevertheless, an increase of 1 to 4.8% was seen for the annual lighting electricity demand. As the result, using the obtained optimum design, the building's annual total energy consumption was decreased between 23.8% and 42.2%.

In terms of building optimization design, there are some mature software packages, but these take a long time to run and require detailed input of building parameters, which makes it very inconvenient to design a building. Optimizing the design of buildings is relatively easy with some optimization algorithms. Moreover, the interactions between optimizations of energy system design and building envelope were ignored in these techniques. In our manuscript, we recognize the extended simulation times associated with EnergyPlus and TRNSYS. To address this, we've employed a new metaheuristic algorithm, the Modified Competitive Search Algorithm (MCSA), for the optimization of office building designs. This algorithm efficiently balances the goals of minimizing construction costs while achieving energy conservation targets. By optimizing parameters like window numbers, walls, glass curtain walls, and others, we aim to strike a harmonious balance between energy efficiency, cost-effectiveness, and overall sustainability. Still, the application of metaheuristic algorithms to optimize building design is rare. Therefore, the purpose is to present a model of optimization for the office building envelope to conserve energy by a new metaheuristic algorithm, called Modified Competitive Search Algorithm (MCSA). In comparison to other conventional

optimization algorithms also the studied algorithms from the literature, a bigger ratio of glass curtain walls, quicker convergence rate, a bigger overall area of the window, and lesser cost by determined energy load can be achieved through the office building envelope optimization using a modified competitive search algorithm. That is to say, the cost of construction and the energy load of the building per unit area of the envelope can be decreased by the proposed method and consequently, more efficient achievements can be acquired in comparison with other optimization techniques in energy saving of the building. The specific objectives of the presented study have been given in the following:

- Developing a new metaheuristic algorithm, called Modified Competitive Search Algorithm
- Minimizing the construction cost at the needed energy load
- Building envelope optimization to achieve a green building design
- Energy conservation in an office building

2. Materials and methods

In the current study, the modified competitive search algorithm (MCSA) is used to solve the optimization problem of the envelope structure of office buildings. The material of the roof, the number of the windows, material of the glass curtain, the ratio of the glass curtain wall, the window's length and width, the material of window glass, the material of the wall, and the width and length of the sunshade board are considered as the first decision variables. According to the results of optimization, the lesser envelope energy cost (env_C) and the needed value of envelope energy load (env_L) can be achieved simultaneously.^[11,12] For this reason, we can assume that MCSA is an efficient approach to obtain a solution for these types of problems. Under the assumption of ensuring the determined env_L , the building envelope optimization is performed for the minimization of the env_C . Fig. 1 represents the architectural design of the office building.

The types of glass curtain wall material, the material of sunshade board, the material of the roof, the material of the

wall, sunshade board, the material of window glass, and the sunshade board's length, window's length and width, and windows number are the utilized variables in this study. Fig. 2 depicts the three types of sunshade board including grid (T 1), horizontal (T 2), and vertical (T 3), and W_w is the width of the window, W_l is the window length, and Sb_l defines the sunshade board's length. In this study, Shenzhen, Sichuan, and Nanning in China are selected as the case study regions.

The formula of env_C is defined as follows:

$$env_C = A_{wg} \times UC_{wg} + A_{wa} \times UC_{wa} + A_{gc} \times UC_{gc} + A_r \times UC_r + A_{sb} \times UC_{sb} \quad (1)$$

where, A_{wg} , A_{wa} , A_{gc} , A_r , and A_{sb} are respectively the window glass area, wall area, glass curtain area, roof area, and sunshade board area (m^2). UC_{wg} , UC_{wa} , UC_{gc} , UC_r , and UC_{sb} are respectively the window glass unit cost, wall unit cost, glass curtain unit cost, roof unit cost, and sunshade board unit cost (RMB/ m^2).

$$env_L = -20370 + 0.033 \times D_h \times C_{hl} + Y_{ihg} \times 2.010 + 1.079 \times \sum_{j=1}^4 C_{ing_{zj}} \times I_{hj} \quad (2)$$

where, $Y_{ihg} = Y_{ca} \times 13.5$, here, D_h is the yearly degree-hours defined by the monthly average temperature (kh/y). C_{hl} defines the building envelope's heat loss coefficient (W/ m^2K). Y_{ihg} defines the yearly indoor heat gain (Wh/ m^2y). $C_{ing_{zj}}$ denotes the coefficient of insolation gain on z building envelope orientation. I_{hj} is the isolation hours (Wh/ m^2y). Y_{ca} specifies the yearly cooling air-conditioning hours (h).

$$Y_{ca} = 1611 + 118 \times \theta_i - 3.1 \times \theta_i^2 \quad (3)$$

where, $\theta_i = 13.5/C_{hl}$, here, θ_i refers to the increase in the mean temperature of the room (K).

$$C_{hl} = (1.011 + TH_w \times A_{wa} + TH_{gc} \times A_{gc} + TH_r \times A_r) / T_{acf} \quad (4)$$

where, TH_w , TH_{gc} , and TH_r define the wall thermal conductivity, glass curtain thermal conductivity, and roof thermal conductivity (W/ m^2K), respectively. T_{acf} refers to the overall air-conditioning floor areas in the building's perimeter zones (13139.52) (m^2).

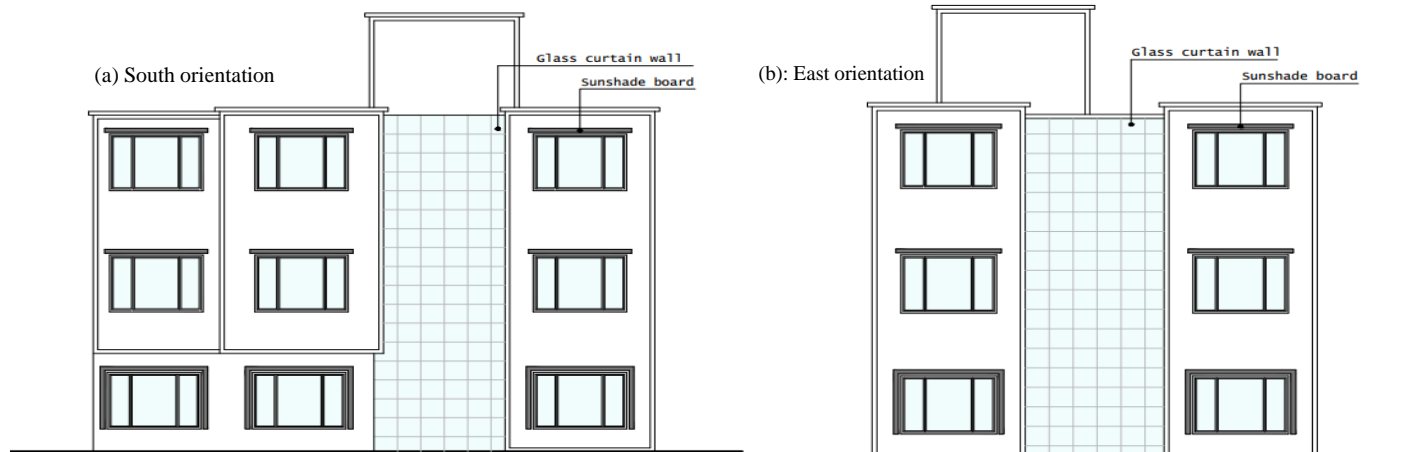


Fig. 1 The architectural design of the office building.

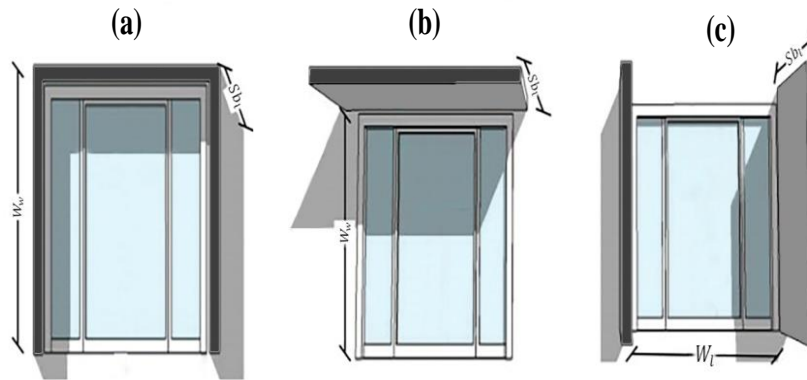


Fig. 2 Three types of sunshade board for windows including (a): Grid, (b): Horizontal, and (c): Vertical.

$$W_{sc} = f(Dr_s, T_{sb}, O) \tag{5}$$

Dr_s is the depth rate of the sunshade (%). T_{sb} defines the type of sunshade board. O refers to the orientation. Orientations I, II, III, and IV denote the north orientation (N), south orientation (S), east orientation (E), and west orientation (W), respectively.

$$C_{ing_{zj}} = (W_{sc} \times \eta \times A_{wg} + 0.035 \times TH_w \times A_{wa} + 0.035 \times TH_{gc} \times A_{gc} + 0.035 \times TH_r \times A_r) / T_{acf} \tag{6}$$

where, W_{sc} is the window's sunshade coefficient.

$$Dr_s = \begin{cases} \frac{S_{b_l}}{W_w} + \frac{S_{b_l}}{W_l} & (G: T 1) \\ \frac{S_{b_l}}{W_w} & (H: T 2) \\ \frac{S_{b_l}}{W_l} & (V: T 3) \end{cases} \tag{7}$$

here, S_{b_l} is the length of the sunshade board (m), W_w defines the window width (m), and W_l denotes the window length (m). G , H , and V refer to the grid, horizontal, and vertical sunshade boards. T 1, T 2, and T 3 are types 1, 2, and 3, respectively.

2.1 Modified Competitive Search Algorithm (MCSA)

2.1.1 The Competitive Search Algorithm (CSA)

The major structure and model of the Competitive Search Algorithm mathematically are defined in this section after the intellectual basis of this algorithm is introduced. Then, the rule of this optimization algorithm is studied.

Intellectual basis; there is a difference between CSA with other algorithms due to that this algorithm is an inspiration for human social activities while the others are inspired by the behaviors of animals and physical laws. A similar process is followed by various competitive programs shown on TV like America's Got Talent and Pop Idol, in which a learning course is taken by participants after being ranked from different aspects to be used in the later step. Finally, after the evaluation of the participants, the optimum one is chosen as the process of optimization.^[33,34] In the beginning stage, it is considered that the program includes various competition scoring standards which are appearance, singing, dancing, weight, and height. Based on a comprehensive test, all competitors are assessed, and then they were ranked based on their scores. According to the given ranks, there will be two general and excellent groups that have been trained for the later

competition step by various techniques. In the end, the champion of the program is chosen after being learned and evaluated sequentially.

The structure and mathematical model of the algorithm; the competitions are defined based on the various rules and their mathematical model has been developed. The rules are including 1) based on several standards the competitors will be evaluated and the points of each competitor are determined subsequently, two general and excellent groups were created based on the points of competitors; 2) competitors learn based on their different abilities. After a while, randomly there will be some changes in the ability of learning. A learning ability threshold is specified by each group, and the robust learning ability is the one with a value higher than this. Moreover, the lesser value is assumed as the normal learning ability; 3) after each course is completed by competitors, in the excellent group, the more different range of learning is related to the powerful learner than the average one. The excellent group includes a greater range of learning, therefore, the range of learning for the next group in the ranking is rather lesser; 4) the learning of the competitors is defined by their capability in the general group such that the ones with higher learning ability aim further on their improvement. However, it is more likely for those with the normal learning ability to be failed by themselves; 5) if the ability of learning of a participant is higher than a determined amount, it can be assumed as reference behavior. According to the capabilities of the competitors, they learn from the excellent one indicators; 6) several competitors are removed from the competition for different causes when each round ends and are substituted by new ones thus the number of competitors is fixed in each round. The indicators of major assessment and the capability of new competitors are defined randomly.

In the simulation of competition, the virtual competitors are accepted for the contest. The competitor's number can be as given below:

$$Y = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \dots & Y_{1,d} \\ Y_{2,1} & Y_{2,2} & \dots & Y_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ Y_{n,1} & Y_{n,2} & \dots & Y_{n,d} \end{bmatrix} \tag{8}$$

here, different indicators assessed for participants of the

competition were denoted by d , in other terms, it then illustrates the problem. The value of fitness of each competitor can be stated as the following formula:

$$F_y = \begin{bmatrix} f([y_{1,1}, y_{1,2}, \dots, y_{1,d}]) \\ f([y_{2,1}, y_{2,2}, \dots, y_{2,d}]) \\ \vdots \\ f([y_{n,1}, y_{n,2}, \dots, y_{n,d}]) \end{bmatrix} \quad (9)$$

here, the participants' number is specified by n , and all row values refer to the fitness value obtained by each competitor. After assessing all competitors in this algorithm, the ranking of their fitness values is determined after each round of the contest. According to the fitness value, two groups of competitors are created including general and excellent. In the excellent group, the maximum-ranked participants with higher strong learning abilities because of the upper limitation will progress lesser than the participants with higher strong learning capabilities with lesser rankings. In the general group, competitors can progress further in upper rankings with higher powerful ability of learning. The updating of index parameters of the excellent competitors (EC) with powerful ability of learning and participants with maximum rankings are as follows:

$$Y_{i,j}^{t+1} = Y_{i,j}^t + A(i) * S_1 * \rho * (u_b^j - l_b^j) \text{ if } A(i) > L_1$$

$$S_1 = (U_B * rand(1) + L_B)\% \quad (10)$$

Nevertheless, the updating of parameters of each index of the excellent competitors with the normal ability of learning and maximum rankings are defined as given below:

$$Y_{i,j}^{t+1} = Y_{i,j}^t + A(i) * S_2 * \rho * (u_b^j - l_b^j) \text{ if } A(i) \leq L_1$$

$$S_2 = (L_B * rand(1))\% \quad (11)$$

here, S_1 and S_2 refer to search limit functions of competitors with powerful ability of learning and general ability of learning, respectively. t defines the number of present iterations. $j = 1,2,3,4 \dots d$ specifies the dimensions' number that Y situated in. The amount of j^{th} evaluation index of the i^{th} competitor is defined by $Y_{i,j}$, in other words, the place information in the j^{th} dimension. U_B and L_B denote the constants; l_b^j and u_b^j respectively refer to the lower and higher bounds of the function in the j^{th} dimensional search limit. The present contestant's learning capability is defined by $A(i)$; ρ specifies the amount randomly achieved using the matrix $[-1, 0, 1]$ to show the competitors' learning direction, i.e., if ρ equals -1 , contestants learn in the opposing direction, if ρ equals 1 , contestants learn in the positive direction, and if ρ equals 0 , contestants will not learn during the current round. L_1 denotes the value of the threshold showing the robustness of learning capability in the excellent group which is related to the matrix $(0, 1)$.

According to Eqs. (10) and (11), only in S_1 and S_2 , the competitors' location update difference in the excellent group is considered. Contestants with the normal ability to learn mostly search in the range $(0\% - L_B\%)$ of the available range for searching for each dimension. Contestants with a powerful ability to learn mostly search between $(L_B\% - U_B\%)$ of the

available range for searching. In this regard, the search extent becomes more inclusive. In the general group, the competitors can investigate based on rule 4 for each evaluation round, and each indicator's update function can be defined as given in the following:

$$Y_{i,j}^{t+1} = \begin{cases} Y_{i,j}^t + \alpha \cdot Q \cdot D & \text{if } A(i) > L_1 \\ Y_{i,j}^t \cdot L_2 \cdot F \cdot A(i) & \text{if } A(i) \leq L_1 \end{cases} \quad (12)$$

$$F = P \cdot o$$

here, α defines the random amount between -1 and 1 , Q denotes a random amount between 0 and 2 , and F specifies a negative factor; L_2 and D refer to the $1 \times d$ matrix, nonetheless, the components in the matrix D equal 1 , and the components in L_2 have been distributed by random with 1 and -1 ; o defines a random factor, while the competitors' location has been renewed, and chosen by random from the matrix $[0.1, 0.2, 0.3, 0.4, 0.5]$; P refers to a standard normal distribution with variance and mean equal 1 and 0 , respectively.

Based on rule 5, the reference behavior is found when the ability of learning becomes higher than a determined amount for any competitor: the competitor can learn from the optimum competitor as stated by their ability of learning, which can be explained by:

$$Y_{i,j}^{t+1} = Y_{i,j}^{t+1} + (Gbest Y_j^t - Y_{i,j}^{t+1}) * A(i) \quad \text{if } A(i) > L_3 \quad (13)$$

here, the index amount in j^{th} dimension of the optimum competitor during i^{th} iteration is specified by $Gbest Y_j^t$; L_3 defines the reference threshold in the range $(0,1)$; $(Gbest Y_j^t - Y_{i,j}^{t+1})$ is the difference between the existing competitor and the optimum competitor. The existing competitor can go nearer to the optimum competitor by multiplying $(Gbest Y_j^t - Y_{i,j}^{t+1})$ times the ability to learn $A(i)$. Using Eq. (10) to (13), the indicators of evaluation of competitors have been learned and renewed. Simultaneously, based on rule 6 several competitors will always exist that cannot continue to the later competition because of different causes after each competition round. Then, a corresponding amount of competitors are included randomly to have a fixed number of competitors, and all indicators of evaluation and abilities of learning are created randomly. According to the abovementioned model, as shown in Fig. 3, the flowchart is used for summarizing the original CSA procedure.

2.1.2 Modified Competitive Search Algorithm (MCSA)

The basic CSA is a new effective metaheuristic to solve the problems of the optimization, but it might suffer some problems such as the wrong random substitution of the worst individual, or premature convergences that are provided by the absence of appropriate exploitation. Consequently, some modifications are presented herein to enhance the algorithm efficiency.^[35] The modifications are including opposite-based learning (OBL) and sine-cosine procedure as the chaotic theory to achieve better efficiency.

To find superior candidate solutions, the OBL evaluates opposite of possible solutions.^[36]

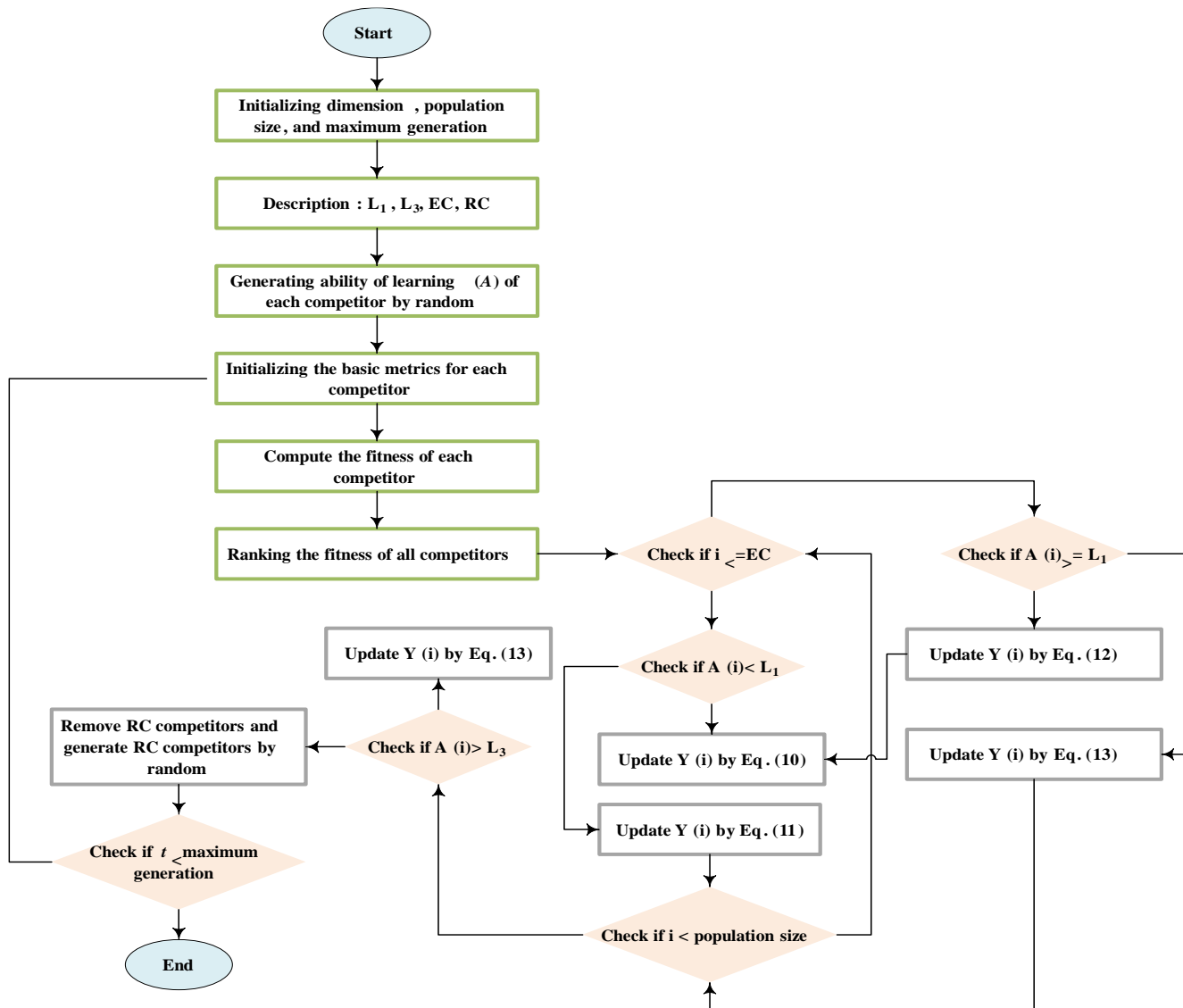


Fig. 3 The flowchart of the original CSA.

In the employed OBL mechanism, adjusting the Jump Rate (JR) controls the likelihood of an opposing population. Following each population update, a stochastic process is employed whereby a random number is generated and subsequently compared to the jump rate, denoted as JR. The following formula generates the opposite population of the present population if the random number is less than JR:

$$x_i^{op} = L_{ui} + L_{bi} - x_i \tag{14}$$

The current population and opposing population get combined and their fitness is evaluated individually. The n solutions with the greatest fitness are then chosen as the new current population.^[36]

In the sine-cosine procedure, the individuals that define the iterations' worst cost, are relatively chosen to be updated and the new location is obtained as given below:

$$Y_{worst}^i = \begin{cases} Y_{worst}^i + a_1 \times \sin(a_2) \times |a_3 \times Y_{best}^i - Y_{worst}^i| & a_4 < 0.5 \\ Y_{worst}^i + a_1 \times \cos(a_2) \times |a_3 \times Y_{best}^i - Y_{worst}^i| & a_4 \geq 0.5 \end{cases} \tag{15}$$

where, a_1, a_2, a_3 and a_4 denote the coefficients that have been achieved by the following formulas:

$$a_1 = \alpha - iter_{curr} \times (\gamma / iter_{max}) \tag{16}$$

$$a_2 = 2\pi \times rand \tag{17}$$

$$a_3 = 2 \times rand \tag{18}$$

$$a_4 = rand \tag{19}$$

here, γ refers to a constant and $iter_{curr}$ and $iter_{max}$ respectively define the current and the highest iterations. Algorithm1 presents the pseudocode and detailed process of MCSA.

<p>Algorithm 1. MCSA pseudocode</p> <p>Initializing n competitors' indicators and determining their parameters.</p> <p>$A = rand(1, n)$</p> <p>while ($t < iter_{max}$)</p> <p>Evaluate competitors' fitness values and rank</p> <p>for $i=1: EC$</p>

```

Use Eqs. (10) and (11) for updating the competitor's
indicators
end for

for i=1+EC: n
    Equation (12) is applied to updating the competitors'
indicators
end for

for i= 1: n
    Equation (13) is applied to update the competitor's
indicators
end for

Eliminate and randomly generate RC competitors
Updating competitor indicators
Generate 40% of the new population by the sine-cosine
procedure based on Eq. (15)
Perform the OBL mechanism based on Eq. (14)
t=1+t
end while
    
```

2.1.3 Algorithm validation

After modeling the suggested MCSA, the efficiency of the technique is better to be evaluated. To analyze the operation of the suggested technique, four standard test functions are applied for validation.^[37,38] These functions are Rosenbrock, Rastrigin, Sphere, and Ackley. Then, the results were put in comparison with some newest algorithms including Ant Lion Optimizer (ALO),^[39] Whale Optimization Algorithm (WOA),^[40] and World Cup Optimization Algorithm (WCOA).^[41] Table 1 states the parameter values of the investigated algorithms.

The optimization algorithms are coded in MATLAB R2016b environment on a laptop with Intel Core™ i5-2410M, 2.30 GHz CPU, and 8 GB RAM. Table 2 defines the applied test functions.

The size of the population and the iterations' highest number for all optimizers are respectively 50 and 200. The algorithms have been independently run 40 times to obtain a proper comparison using the solutions' standard deviation (SD) results. To evaluate the effectiveness of the compared algorithms, their SD and mean values are studied. Table 3 illustrates the results of the comparison of the proposed MCSA and the optimizers.

According to the results obtained in Table 3, in comparison to other algorithms, the proposed MCSA with the lower amount of the mean value gives the maximum accuracy. This better accuracy indicates higher validation of the presented technique with appropriate values. Moreover, the lowest value of the SD shows better reliability of the suggested method than the comparative optimizers. The initial amounts of the decision variables in this paper have been created randomly from their range. If MCSA cannot achieve a more optimum solution after several iterations, as the updated solution, the most optimum solution is chosen for a later iteration. The design parameters have been continuously updated until satisfactory results have been achieved.

Table 1. The parameter value of the investigated optimizers.

Algorithm	Parameter	Value
ALO ^[39]	w	[2, 6]
	No. search agents	50
WOA ^[40]	\vec{a}	2
	\vec{r}	1
WCOA ^[41]	Play off	0.04
	ac	0.3

2.2 Problems of optimization

The northern, southern, eastern, and western walls are optimized wholly in this section without the optimization of the walls in each orientation. Table 4 reports the main data of building and original decision variables.

The range of length and width of the window is set at 1~3 m and the range of the sunshade board length is 1~2 m. The

Table 2. The definition of the applied benchmark functions.

Name	Function	Dim	Range	F_{min}
Rosenbrock	$F_1(z) = \sum_{i=1}^{n-1} [100(z_{i+1} - z_i^2)^2 + (z_i - 1)^2]$	300	[-30,30]	0
Rastrigin	$F_2(z) = \sum_{i=1}^d [z_i^2 - 10 \times \cos(2 \times \pi \times z_i) + 10]$	300	[-5.12,5.12]	0
Sphere	$F_3(z) = \sum_{i=1}^n z_i^2$	300	[-100,100]	0
Ackley	$F_4(z) = -20 \exp(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n z_i^2}) - \exp(\frac{1}{n} \sum_{i=1}^n \cos(2\pi z_i)) + 20 + e$	300	[-32,32]	0

Table 3. The results of the comparison of the proposed MCSA and the algorithms.

Algorithm	Indicator	Rosenbrock	Rastrigin	Sphere	Ackley
ALO ^[39]	Mean	54.717	233.012	563.107	74.123
	SD	24.911	95.009	246.204	57.413
WOA ^[40]	Mean	16.520	144.675	436.198	23.178
	SD	8.145	82.811	202.206	12.235
WCOA ^[41]	Mean	4.315	73.121	364.473	5.652
	SD	3.003	52.031	186.334	2.062
CSA ^[42]	Mean	2.089	7.832	155.663	3.779
	SD	1.971	11.240	112.905	1.543
MCSA	Mean	0.814e-2	1.3512e-5	1.09e-7	2.095e-6
	SD	0.119e-2	0.025e-5	0.968e-7	1.049e-6

Table 4. The main data of building and initial decision variables.

Orientation (z)	$C_{ingzj} \times I_{hj}$
Overall floor area (m ²)	55130.11
Area of the building envelope (m ²)	19010.02
N	8437.20
S	10172.55
E	9926.40
W	6793.70
Roof	14026.50
Y_{ca} (h)	1879.72
C_{hl} (W/m ² K)	6.65
Y_{ihg} (Wh/m ² y)	25454.03
D_h (kh/y)	16098
θ_i (K)	1.99
T_{acf} (m ²)	13140.08
env_C (RMB)	14219399
env_L (kWh/m ² y)	48.95

materials of the glass curtain, wall, roof, and window glass ranged from 1 to 5, 1 to 23, 1 to 19, and 1 to 58, respectively. The numbers define the reference number of the materials. Fig. 4 shows the flowchart of the process of optimization. Increasing the overall window area can lead to increased heat losses, particularly during colder periods. This consideration is indeed crucial when designing energy-efficient buildings, as heat loss through windows can have a significant impact on the overall energy consumption and thermal comfort of the

occupants. In this study, the delicate balance between promoting natural ventilation and minimizing heat losses is recognized. The optimization process seeks to find an optimal trade-off between these competing factors. It's important to note that this optimal trade-off might vary depending on factors such as local climate, building orientation, insulation levels, and occupant behavior. The proposed methodology takes these variables into account to ensure that the increased window area contributes positively to natural ventilation while mitigating potential heat loss drawbacks. In this study, the need to strike a balance between maximizing indoor lighting and minimizing any negative impacts on energy performance and thermal comfort is identified. Our optimization process takes into account factors such as local climate conditions, building orientation, and the use of shading devices to mitigate potential downsides of increased glass area. It's important to emphasize that a holistic approach to design considers various aspects of building performance, and decisions are often influenced by a variety of practical constraints. While an ideal scenario might involve extensive use of glass, real-world considerations such as construction costs, energy efficiency, and occupant comfort play a decisive role in shaping the final design. In this paper, the interplay between building envelope design and HVAC systems has been acknowledge. The optimization process, which primarily focuses on building envelope parameters, assumes a certain baseline HVAC operation for the purpose of comparison and analysis.

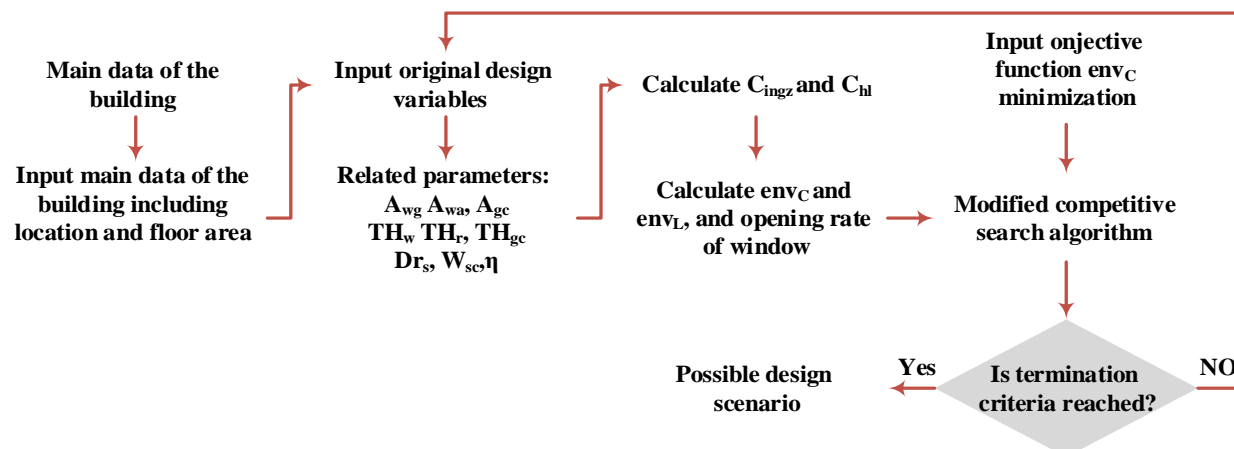


Fig. 4 The detailed optimization process.

3. Design of optimization process by MCSA

The optimization design process in this section is the trial-and-error process. As shown in Fig. 5, the main phases have been described in the following:

- 1) Initialize the algorithm parameters: in this process, the cost function is the env_C function that fits the needed value of the env_L function.
- 2) Set iteration=1.
- 3) The calculation of the population (Pop) is carried out once. As the nature of evaluating the Pop, the probability amplitude matrix is transformed into the binary matrix.
- 4) The cost function env_C at the needed value of env_L is measured, and the best solution (BS) is achieved in the present Pop.
- 5) Carry out a comparison of BS with the optimum best solution of all former Pops. If BS is better than the conventional optimum solution (OS), BS and its matching individual BS_i substitute the OS and its matching individual OS_i as the updated OS and OS_i . If not, the OS and OS_i stay the same.
- 6) Iteration = iteration+1, repeat 1-6. When iteration>maximum iteration, the termination criteria are reached.
- 7) Output the OS and OS_i .

3.1 Results of MCSA

The optimization experiment is made to the architectural design depicted in Fig. 1. MCSA optimization process curve in comparison to CSA, GA, PSO, and NSGA-II is depicted in Fig. 6.

It is observed that the best optimum results are obtained after 200 iterations, *i.e.*, the minimum env_C is achieved at this point, which is equal to 10375281.5 RMB at the needed value

of env_L equal to 45.7692 kWh/m²y. Table 5 reports the best optimum variables' values.

4. Comparative assessment

4.1 Comparative results of the MCSA and other optimization algorithms

A comparison and analysis of the results of the optimization of MCSA and several optimization algorithms are carried out, which is reported in Table 6.

Based on the performed comparison, it is observed that when the MCSA is applied to solve the optimization problem, the env_C is lower in comparison to other optimization algorithms by choosing the proper type of material and fairly allocating the occupied area by the glass curtain wall, walls, and windows at the requirement of env_L . The convergence speed is also faster. The larger overall area of the window of MCSA indicates that the natural ventilation is more proper. It

Table 5. The best optimum variables' values by MCSA.

Variable	value
T_{sb}	2
The overall area of the window (A_w)(m ²)	429.9
Number of windows (W_n)	105
The ratio of the glass curtain wall (R_{gcw})	0.31
UC_r	5
UC_{sb}	3
UC_{wa}	3
UC_{wg}	1
UC_{gc}	3
W_w	2.65
W_l	1.53
Sb_l	1.10
env_C (RMB)	10375281.5
env_L (kWh/m ² y)	45.7692

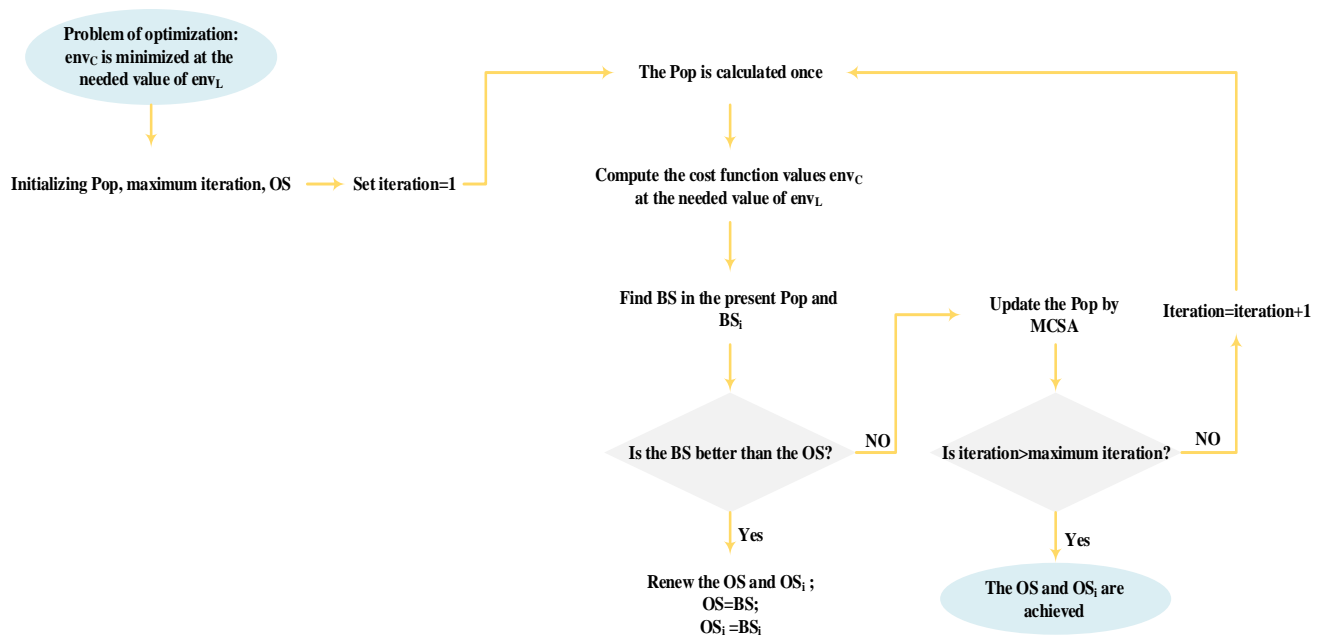


Fig. 5 Design of optimization process by MCSA.

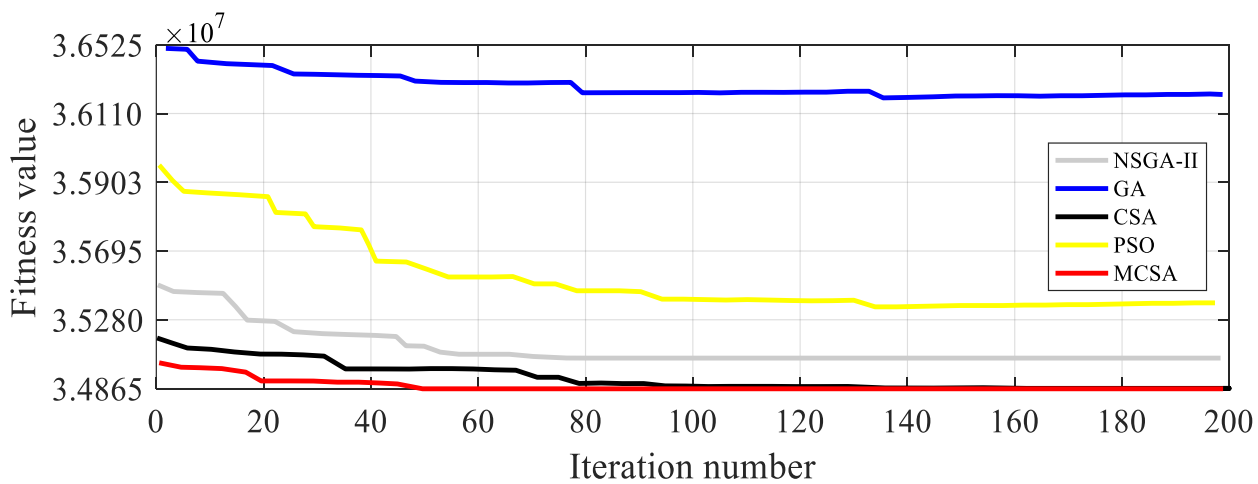


Fig. 6 The MCSA optimization process curve in comparison to CSA, GA, PSO, and NSGA-II.

Table 6. The optimization results of MCSA and other optimization algorithms.

Variable	PSO	GA	NSGA-II	CSA	MCSA
A_w	415.9	375.3	410.7	427.5	429.9
W_n	121	150	108	110	105
$R_{g_{cw}}$	0.30	0.29	0.28	0.28	0.31
UC_r	14	11	12	7	5
UC_{sb}	4	21	15	6	3
UC_{wa}	6	10	13	4	3
UC_{wg}	31	26	17	5	1
UC_{gc}	5	1	4	2	3
W_w	2.15	1.58	1.90	2.30	2.65
W_l	1.56	1.58	1.55	1.54	1.53
Sb_l	1.20	1.05	1.25	1.15	1.10
env_c	11593144	10877211	10611275	104928	1037528
	.1	.4	.6	35	1.5
T_{sb}	2	3	3	2	2
$Iter^*$	134	137	80	77	48

(*Iter: iteration number for convergence)

can be the result that the indoor lighting is more appropriate due to the increased value of the $R_{g_{cw}}$ by MCSA. Moreover, the decreased value of the iteration number for convergence shows a higher rate of convergence. The overall cost decreased by 37.1% in comparison with the initial design.

To compare, the energy load and cost of the building are normalized for all algorithms to achieve env_L and env_C per unit area of envelope concerning all comparative methods. Table 7 reports the results of the comparison.

As can be observed from Table 7, env_L is smaller and env_C is lower per unit area of the envelope for the proposed method in comparison with other algorithms, considering that the opening rate of the window is much the same. It can be the result that the MCSA is more efficient than the other compared methods in energy saving of the building herein.

Table 7. The comparison results of the presented MCSA with some other methods.

Variable	PSO	GA	NSGA-II	CSA	MCSA
env_L per unit area	0.0014	0.0018	0.0015	0.0010	0.0005
env_C per unit area	268.54	155.82	217.11	165.275	139.9218
The opening rate of the window	-	15.91%	10.07%	-	10.11%

5. Conclusions

A green or sustainable building is one that is resource-efficient, environmentally responsible, healthier with lower pollution, and has applicable space for occupants during its life-cycle of a building. Saving energy and decreasing costs are significant aspects of designing a green building. For the optimization of the building design, an optimization algorithm has been used in this paper due to the fact that simulation software such as EnergyPlus and TRNSYS require detailed input of parameters related to the building, and running them is a time-consuming process. Herein, a new metaheuristic optimizer called the Modified Competitive Search Algorithm (MCSA) was used as the optimum design technique for the office building envelope. To lessen the cost of construction at the needed energy conservation, window numbers, walls, glass curtain walls, etc. were optimized. A comparison of the proposed algorithm with some others from the literature was carried out. The cost is reduced by MCSA for the optimum design of the building structure at the needed energy load value. The number of iterations was decreased based on the proposed method. Moreover, the overall area of the window was increased, which resulted in better natural ventilation. Since the ratio of the glass curtain wall was increased, it could be concluded that the indoor lighting was better. Per unit area of the envelope, the value of the energy load was smaller and the total cost was lower for the proposed method in comparison with other

algorithms, considering that the opening rate of the window is much the same. According to the achieved results, the total cost decreased by 37.1% in comparison with the initial design. It can be the result that the MCSA is more efficient than the other compared methods in energy saving of the building herein. Although this study is defined by the results of a particular design, it can be used in other building designs. For future works, the presented approach can be applied to other building designs, various building types, and also other weather conditions.

Acknowledgement

This study was supported by Thammasat Postdoctoral Fellowship. Also, this work was supported by the Thailand Science Research and Innovation Fundamental Fund fiscal year 2023.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

References

- [1] G. Aghajani, N. Ghadimi, Multi-objective energy management in a micro-grid, *Energy Reports*, 2018, **4**, 218-225, doi: 10.1016/j.egy.2017.10.002.
- [2] X. Shi, Z. Tian, W. Chen, B. Si, X. Jin, A review on building energy efficient design optimization from the perspective of architects, *Renewable and Sustainable Energy Reviews*, 2016, **65**, 872-884, doi: 10.1016/j.rser.2016.07.050.
- [3] Y. Himeur, K. Ghanem, A. Alsalemi, F. Bensaali, A. Amira, Artificial intelligence-based anomaly detection of energy consumption in buildings: a review, current trends and new perspectives, *Applied Energy*, 2021, **287**, 116601, doi: 10.1016/j.apenergy.2021.116601.
- [4] Wei, Cai, Optimal bidding and offering strategies of compressed air energy storage: a hybrid robust-stochastic approach, *Renewable Energy*, 2019, **143**, 1-8, doi: 10.1016/j.renene.2019.05.008.
- [5] Zhi, Yuan, A new technique for optimal estimation of the circuit-based PEMFCs using developed Sunflower Optimization Algorithm, *Energy Reports*, 2020, **6**, 662-671, doi: 10.1016/j.egy.2020.03.010.
- [6] Bo, Liu, Multi-objective optimization for thermal comfort enhancement and greenhouse gas emission reduction in residential buildings applying retrofitting measures by an Enhanced Water Strider Optimization Algorithm: a case study, *Energy Reports*, 2021, **7**, 1915-1929, doi: 10.1016/j.egy.2021.03.044.
- [7] F. Amirifard, S. A. Sharif, F. Nasiri, Application of passive measures for energy conservation in buildings - a review, *Advances in Building Energy Research*, 2019, **13**, 282-315, doi: 10.1080/17512549.2018.1488617.
- [8] Melika, Hamian, A framework to expedite joint energy-reserve payment cost minimization using a custom-designed method based on Mixed Integer Genetic Algorithm, *Engineering Applications of Artificial Intelligence*, 2018, **72**, 203-212, doi: 10.1016/j.engappai.2018.03.022.
- [9] C. Z. Tian, Building energy optimization tools and their applicability in architectural conceptual design stage, *Energy Procedia*, 2015, **78**, 2572-2577, doi: 10.1016/j.egypro.2015.11.288.
- [10] Yang, Geng, Indoor environmental quality of green office buildings in China: large-scale and long-term measurement, *Building and Environment*, 2019, **150**, 266-280, doi: 10.1016/j.buildenv.2019.01.014.
- [11] Binghui, Si, Ineffectiveness of optimization algorithms in building energy optimization and possible causes, *Renewable Energy*, 2019, **134**, 1295-1306, doi: 10.1016/j.renene.2018.09.057.
- [12] Binghui, Si, Performance indices and evaluation of algorithms in building energy efficient design optimization, *Energy*, 2016, **114**, 100-112, doi: 10.1016/j.energy.2016.07.114.
- [13] H. Xian, Li, Energy performance optimisation of building envelope retrofit through integrated orthogonal arrays with data envelopment analysis, *Renewable Energy*, 2020, **149**, 1414-1423, doi: 10.1016/j.renene.2019.10.143.
- [14] H. Zhong, J. Wang, H. Jia, Y. Mu, S. Lv, Vector field-based support vector regression for building energy consumption prediction, *Applied Energy*, 2019, **242**, 403-414, doi: 10.1016/j.apenergy.2019.03.078.
- [15] J. Liu, C. Chen, Z. Liu, K. Jermsittiparsert, N. Ghadimi, An IGDT-based risk-involved optimal bidding strategy for hydrogen storage-based intelligent parking lot of electric vehicles, *Journal of Energy Storage*, 2020, **27**, 101057, doi: 10.1016/j.est.2019.101057.
- [16] Dongmin, Yu, RETRACTED: Energy management of wind-PV-storage-grid based large electricity consumer using robust optimization technique, *Journal of Energy Storage*, 2020, **27**, 101054, doi: 10.1016/j.est.2019.101054.
- [17] H. Samanta, R. Maity, S. Laha, P. K. Talapatra, A review on energy-efficient building. *Advances in Air Conditioning and Refrigeration*. Singapore: Springer Singapore, 2020: 257-268, doi: 10.1007/978-981-15-6360-7_23.
- [18] I. T. Michailidis, S. Baldi, M. F. Pichler, E. B. Kosmatopoulos, J. R. Santiago, Proactive control for solar energy exploitation: a German high-inertia building case study, *Applied Energy*, 2015, **155**, 409-420, doi: 10.1016/j.apenergy.2015.06.033.
- [19] S. Baldi, I. Michailidis, C. Ravanis, E. B. Kosmatopoulos, Model-based and model-free "plug-and-play" building energy efficient control, *Applied Energy*, 2015, **154**, 829-841, doi: 10.1016/j.apenergy.2015.05.081.
- [20] C. Luo, L. He, S. Huang, B. Huang, C. Yang, L. Du, An improved bald eagle algorithm based on Tent map and Levy flight for color satellite image segmentation, *Signal, Image and Video Processing*, 2023, **17**, 2005-2013, doi: 10.1007/s11760-022-02413-x.

- [21] J. Hirvonen, J. Jokisalo, J. Heljo, R. Kosonen, Towards the EU emission targets of 2050: cost-effective emission reduction in Finnish detached houses, *Energies*, 2019, **12**, 4395, doi: 10.3390/en12224395.
- [22] Fabrizio, Ascione, Building envelope design: multi-objective optimization to minimize energy consumption, global cost and thermal discomfort. Application to different Italian climatic zones, *Energy*, 2019, **174**, 359-374, doi: 10.1016/j.energy.2019.02.182.
- [23] X. Yang, S. Zhang, W. Xu, Impact of zero energy buildings on medium-to-long term building energy consumption in China, *Energy Policy*, 2019, **129**, 574-586, doi: 10.1016/j.enpol.2019.02.025.
- [24] S. Longo, F. Montana, E. R. Sanseverino, A review on optimization and cost-optimal methodologies in low-energy buildings design and environmental considerations, *Sustainable Cities and Society*, 2019, **45**, 87-104, doi: 10.1016/j.scs.2018.11.027.
- [25] F. Kheiri, A review on optimization methods applied in energy-efficient building geometry and envelope design, *Renewable and Sustainable Energy Reviews*, 2018, **92**, 897-920, doi: 10.1016/j.rser.2018.04.080.
- [26] C. Waibel, T. Wortmann, R. Evins, J. Carmeliet, Building energy optimization: an extensive benchmark of global search algorithms, *Energy and Buildings*, 2019, **187**, 218-240, doi: 10.1016/j.enbuild.2019.01.048.
- [27] X. Yuan, M. Ali Karbasforousha, R. B. Y. Syah, M. Khajehzadeh, S. Keawsawasvong, M. L. Nehdi, An effective metaheuristic approach for building energy optimization problems, *Buildings*, 2022, **13**, 80, doi: 10.3390/buildings13010080.
- [28] V. Monetti, E. Davin, E. Fabrizio, P. André, M. Filippi, Calibration of building energy simulation models based on optimization: a case study, *Energy Procedia*, 2015, **78**, 2971-2976, doi: 10.1016/j.egypro.2015.11.693.
- [29] Taehoon, Hong, Automatic calibration model of a building energy simulation using optimization algorithm, *Energy Procedia*, 2017, **105**, 3698-3704, doi: 10.1016/j.egypro.2017.03.855.
- [30] K. A. Barber, M. Krarti, A review of optimization based tools for design and control of building energy systems, *Renewable and Sustainable Energy Reviews*, 2022, **160**, 112359, doi: 10.1016/j.rser.2022.112359.
- [31] Sadik, Yigit, A simulation-based optimization method for designing energy efficient buildings, *Energy and Buildings*, 2018, **178**, 216-227, doi: 10.1016/j.enbuild.2018.08.045.
- [32] Navid, Delgarm, A novel approach for the simulation-based optimization of the buildings energy consumption using NSGA-II: case study in Iran, *Energy and Buildings*, 2016, **127**, 552-560, doi: 10.1016/j.enbuild.2016.05.052.
- [33] N. Razmjoooy, M. Ramezani, N. Ghadimi, Imperialist competitive algorithm-based optimization of neuro-fuzzy system parameters for automatic red-eye removal, *International Journal of Fuzzy Systems*, 2017, **19**, 1144-1156, doi: 10.1007/s40815-017-0305-2.
- [34] A. Noori, M. J. Shahbazadeh, M. Eslami, Designing of wide-area damping controller for stability improvement in a large-scale power system in presence of wind farms and SMES compensator, *International Journal of Electrical Power & Energy Systems*, 2020, **119**, 105936, doi: 10.1016/j.ijepes.2020.105936.
- [35] M. Khajehzadeh, M. R. Taha, M. Eslami, A new hybrid firefly algorithm for foundation optimization, *National Academy Science Letters*, 2013, **36**, 279-288, doi: 10.1007/s40009-013-0129-z.
- [36] J. Xu, S. Xu, L. Zhang, C. Zhou, Z. Han, A particle swarm optimization algorithm based on diversity-driven fusion of opposing phase selection strategies, *Complex & Intelligent Systems*, 2023, 1-33, doi: 10.1007/s40747-023-01069-5.
- [37] D. Yu, Y. Wang, H. Liu, K. Jermsittiparsert, N. Razmjoooy, System identification of PEM fuel cells using an improved Elman neural network and a new hybrid optimization algorithm, *Energy Reports*, 2019, **5**, 1365-1374, doi: 10.1016/j.egypro.2019.09.039.
- [38] M. Khajehzadeh, M. R. Taha, M. Eslami, Opposition-based firefly algorithm for earth slope stability evaluation, *China Ocean Engineering*, 2014, **28**, 713-724, doi: 10.1007/s13344-014-0055-y.
- [39] M. Mani, O. Bozorg-Haddad, X. Chu, Ant lion optimizer (ALO) algorithm. *Advanced Optimization by Nature-Inspired Algorithms*. Singapore: Springer Singapore, 2017: 105-116, doi: 10.1007/978-981-10-5221-7_11.
- [40] S. Mirjalili, A. Lewis, The whale optimization algorithm, *Advances in Engineering Software*, 2016, **95**, 51-67, doi: 10.1016/j.advengsoft.2016.01.008.
- [41] N. Razmjoooy, M. Khalilpour, M. Ramezani, A new metaheuristic optimization algorithm inspired by FIFA world cup competitions: theory and its application in PID designing for AVR system, *Journal of Control, Automation and Electrical Systems*, 2016, **27**, 419-440, doi: 10.1007/s40313-016-0242-6.
- [42] Y. Xu, H. Liu, S. Xie, L. Xi, M. Lu, Competitive search algorithm: a new method for stochastic optimization, *Applied Intelligence*, 2022, **52**, 12131-12154, doi: 10.1007/s10489-021-03133-4.

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