Contents list available at CBIORE journal website

International Journal of Renewable Energy Development

Journal homepage: https://ijred.cbiore.id

Research Article

Multi-objective decision optimization design for building energy-saving retrofitting design based on improved grasshopper optimization algorithm

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Abstract. With the national emphasis on building energy efficiency planning, energy efficiency optimization in existing buildings requires renovation measures based on multi-objective factors. In order to get the optimal solution in the multi-objective decision-making of renovation, the study proposes a class of improved grasshopper optimization algorithms. The process employs a systematic methodology to identify an optimal energy renovation method, taking into account the specific characteristics of the building environment. It then classifies and formulates the energy reduction substitution items for building renovation, and finally, it synchronizes the cost of the renovation project as a measure for decision-making. The elite inverse strategy approach enhances the grasshopper optimization algorithm to facilitate the multi-objective decision-making process associated with building renovation measures. The results showed that the improved grasshopper optimization algorithm could achieve a decision accuracy of 98.8% for the test samples, which was 5.5% higher than the accuracy of the particle swarm optimization algorithm. Repeated run tests of the research algorithm for multi-objective decision making yielded a mean decision fitness value of 2.34×10^4 and a data extreme value of 0.38×10^4. Compared to other algorithms improved grasshopper optimization algorithm converged in a lower range of fitness values, which indicated that the algorithm worked well for multi-objective optimization and the model repeatability was good. The research algorithm was used to decide the energy efficient renovation planning of the building and the power consumption of the renovated power supply system was reduced by 23.7%-49.6%. This indicates that the renovated building has better energy efficiency and can provide a reliable technical direction for decision-making optimization of building energy efficiency renovation.

Keywords: Building energy efficiency planning; Multi-objective decision making; Meta-heuristic approach; Elite inverse strategy approach; Grasshopper optimization algorithm; New energy sources.

Received: 17th July 2024; Revised: 26th August 2024; Accepted: 18th September 2024; Available online: 30th September 2024

1. Introduction

With the rapid development of the construction industry, some of the old buildings are no longer in line with today's industry development concept (Han *et al.*, 2023). Currently, the construction industry is being transformed towards energy sustainability, so energy-saving optimization and renovation measures are taken for earlier buildings (Deng *et al.*, 2022). At the same time, the rationality of the energy structure of existing buildings is poor. Furthermore, with the energy consumption of human activities, it will cause a large amount of greenhouse gas emissions, leading to further deterioration of climate problems (Zheng *et al.*, 2022). However, optimized renovation involves multiple aspects such as the resettlement of the original occupants, the selection of the optimized renovation area, the calculation of the renovation cost, and the prediction of the renovation effect (Nikas *et al.*, 2022). To facilitate the coordination of multiple objective factors in the process of building renovation, the early linear programming method is employed to partition the calculation of multiple factors and coordinate the overall optimal strategy after the completion of the local solution separately (Vijayan *et al.*, 2022). However, this method is susceptible to difficulties in the resolution of complex data types (Khan *et al.*, 2023). Therefore, the solution is introduced into the multi-objective intelligent optimization algorithm (Elsheikh *et al.*, 2023). The Pareto optimization method compares the global optimal solution through mathematical operations on multiple objective functions. However, the calculation needs to prioritize the confirmation of global extreme values (Martín-Ortega *et al.*, 2024). Intelligent algorithms continue to develop vector evaluation genetic algorithms and random weight genetic algorithms (Zhang *et al.*, 2022). Vector evaluation genetic algorithm generates local optimal solutions of sub-populations by prioritizing computation, and then forms new sub-populations to obtain the global optimal solution after cycling in a cross-mutation manner (Brahami *et al.*, 2022). The stochastic weighted genetic algorithm, on the other hand, accomplishes the global evaluation of the optimal solution by accumulating data information during the search process. However, the above

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algorithms are inadequate for structured multi-objective decision making (MODM).

Currently there are proposals to rectify the high energy consumption part of old buildings, but the actual building rectification program involves many influencing factors. To solve this challenge, researchers have studied MODM programs. Wang et al. proposed a decision-making renovation method based on a four party evolutionary game model for energy-saving renovation of old residential buildings. The process took different groups as decision branches, explored suitable execution methods through the evolution of stable strategies in the model, and combined auxiliary solutions to achieve the goal of building energy-saving optimization. The research results indicated that the proposed method could effectively improve the energy-saving renovation progress of buildings (Wang *et al.*, 2024). Balezentis et al. proposed energy-saving methods for replacing renewable energy sources in household buildings to address energy conservation issues. The process took measures such as building energy renovation, replacement of renewable energy technologies, and replacement of energy-saving appliances as decision-making options. Moreover, it implemented renovation measures in combination with the willingness of households to renovate. The research results indicatedthat the proposed method achieved the energy-saving goals of buildings within the range of residents' willingness (Balezentis *et al.*, 2024). Bhuyan et al. proposed a research method based on frame balancing for the multi-objective optimization problem of data privacy. The method calculated the surrogate value of the cost of maintaining user privacy steps in real time by setting a bijective framework of user requirements and optimization cost, and balanced the relationship between the two to obtain the optimal solution by computational methods such as Gaussian distribution. The results demonstrated that the proposed method effectively protects user privacy while measuring the cost (Bhuyan *et al.*, 2022). Liu et al. proposed a research method based on hesitant fuzzy entropy algorithm for the multi-objective problem of micro EDM machining. The method evaluated the suitability of the process factors through numerical testing of the machining parameters, and decided the actual thread of machining based on the numerical range of the suitability. The results demonstrated that the proposed method decided a better quality machining process (Liu *et al.*, 2024). Zheng et al. proposed a research method based on the combination of physical and data systems for the operational MODM problem of smart steel mills. The method determined the decision-making priority through network hierarchy assignment. Moreover, the final operation mode was determined by unit operation sub-line evaluation strategy. The results indicated that the decision making of the proposed method optimized the operational effectiveness of the steel plant (Zheng *et al.*, 2022).

Yildiz et al. proposed a research model based on grasshopper optimization algorithm (GOA) for practical engineering problems. The model proposed a multi-category approach through domain exploration and completed feasibility test based on simulated decisions. The results indicated that the proposed method had a better optimization effect for structural coordination of engineering problems (Yildiz *et al.*, 2022). Reddy and Bojja proposed a GOA based research model for visual tracking problem. The method transformed the actual decision variables through differential evolutionary approach and performed vision tracking with the help of capture capability of the algorithm. The results indicated that the proposed method could effectively carry out the real time tracking behavior of vision (Reddy & Bojja, 2022). Deng and Liu adopted a GOA based research model for the numerical optimization problem of engineering. The method accomplished multiple numerical attempts through intelligent self-adjustment of search technique to improve the model inertia weights with butterfly optimization algorithm. The results showed that the proposed method had significant optimization effect on engineering problems (Deng & Liu, 2023). Badr et al. proposed a new variant of GOA based research method for the optimization problem of management side reform of power grids. The method defined the parameters through grouping mechanism, and the defined parameters were tested in comparison of variants and standard. The results were used to optimize the operation model. The outcomes indicated that the proposed method had a better effect on the management side reform of the power grid (Badr *et al.*, 2023). Hosseini et al. proposed a model based on GOA with gene expression algorithms for the decision-making problem of blasting mining programs. The model established a relational equation by detecting the dust diffusion of blasting and the real environmental problems to control the harmful factors of blasting by training simulation. The results demonstrated that the proposed method has a more accurate guidance effect for mining blasting (Hosseini *et al.*, 2022).

In summary, the current research methods for MODM optimization are prone to be constrained by local optimal solutions during the exploration process. Therefore, the study proposes a GOA with an improved population exploration range for energy efficiency renovation decision-making in buildings. The algorithm innovatively introduces an elite inverse learning strategy into GOA, which enables the promotion of energy-efficient retrofit strategies by coordinating conflicts between retrofit projects. The use of chaotic sequence mechanism enhances the motion activity of the initial population of the algorithm and provides more coordinated directions for studying algorithmic decisions. Moreover, it optimizes the energy structure and climate environment of the building through retrofit measures, with a view to establishing effective theoretical support for multifunctional building models in building retrofit.

2. Method

In this chapter, the renovation value is calculated by analyzing the building energy efficiency methods. The value of the renovation generation is calculated based on the cost of the renovation measure. The energy efficiency is calculated by comparing the energy consumption of the retrofit item with that of the original item. The MODM of the energy efficiency retrofit is performed with the improved GOA. Finally, the GOA is optimized using the elite inverse learning strategy.

2.1 Modeling of multi-objective renovation measures based on building energy efficiency

As the pace of modernization continues to move forward, buildings have become a common landscape in people's lives (Xiao *et al.*, 2023). In the current development of the construction industry, it is necessary to consider not only the intrinsic properties of the building itself, but also the energy-saving and environmental protection of buildings (Usman & Abdullah, 2023). For the completed building, it is also need to ensure that people use the basis of energy-saving transformation (Verma *et al.*, 2023). The target point of energy-saving renovation is mainly divided into two aspects, user experience and energy consumption degradation (Ren *et al.*, 2023). Based on these two goals can be sub-categorized according to the building structure and energy, the specific energy classification items are shown in Fig. 1.

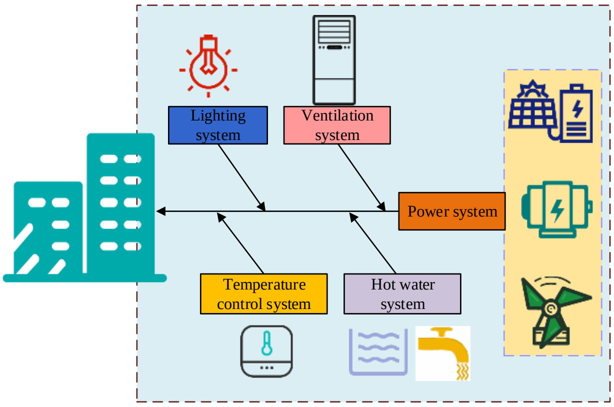


Fig.1 Classification of building energy systems

Fig. 1 shows the conventional energy system of the building, including the ventilation system, lighting system, temperature control system, hot water system and power supply system. The main functions of the building rely on the power system to provide security. Therefore, the energy conservation can be carried out through both open-source and cost-saving. Environmentally friendly new energy is currently an effective method for building energy conservation (Wang *et al.*, 2024), which can simultaneously balance environmental protection and energy conservation with electricity demand (Goyal, 2022). The study replaces part of the building's power supply demand with new energy, and the specific process is shown in Fig. 2.

Fig. 2 shows the energy supply process incorporating two types of new energy methods, wind power and solar power. Solar power is used during daytime hours. Wind power supply is used as a back-up supplemental energy supply, taking into account the size and duration of the wind (Kiss & Szalay, 2023). The energy-saving modification of the building can also be done by changing the facilities of the building (Lin & Yang, 2022). For example, replacing the power of non-essential appliances with low power ones (Liu *et al.*, 2023). Therefore, the overall renovation measures for designing the building for energy efficiency are shown in Fig. 3.

Fig. 3 shows the transformation program divided into broad direction and refined classification. Pre-screening is performed with broad direction and screening classification is performed with single-item categorization. Based on the specific categorization, a renovation initiative is proposed, and the

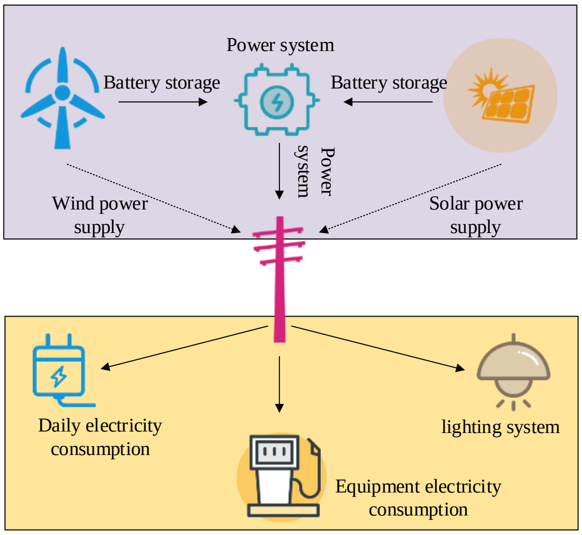


Fig.2 New energy utilization in buildings

renovation initiative is expressed as a single-item decision to participate in the design of the program. Consider the scope of decision-making based on the designed renovation items. Consider the energy rating with the equipment based on necessity (Noorzai *et al.*, 2023). The set of decision variables to summarize the overall is shown in Equation (1).

$$x = (x_1^1, \dots, x_{k1}^1, \dots, x_1^n, \dots x_{kn}^n) \tag{1}$$

In Equation (1), x denotes as the decision set. n denotes the total number of remodeling items. i represents the i-th transformation item variable k denotes the corresponding renovation measure, and x_{kn}^i denotes the replacement of the original i measure with the k change measure. Considering that there is a renovation cost exceeding the energy-saving budget in the actual renovation, the restriction term is set as shown in Equation (2).

$$\sum_{k=1}^{ki} x_k^i \le Q_i \tag{2}$$

In Equation (2), k_i represents the number of other options for the renovation measure. Q_i represents the number of final executable projects for the renovation item i number. The remaining renovation items that can be performed can be calculated based on the qualifying circumstances of the condition, as shown in Equation (3).

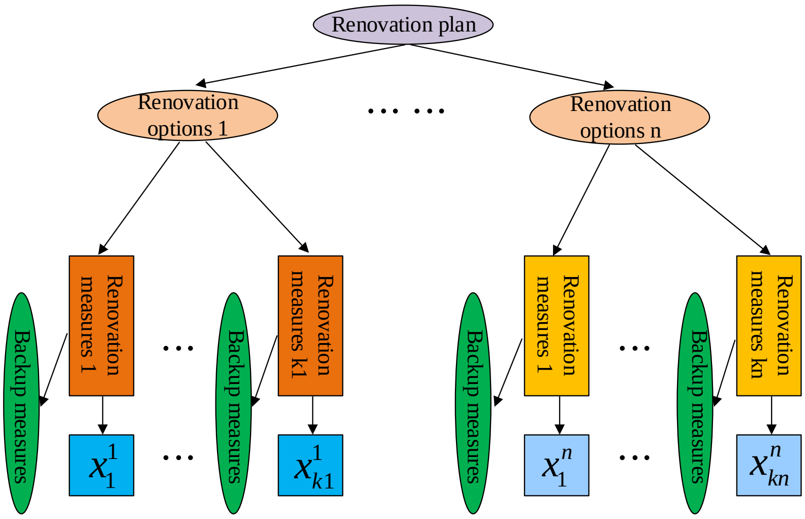


Fig.3 Classification of renovation measures

$$x_r^i = Q_i - \sum_{k=1}^{ki} x_k^i \tag{3}$$

In Equation (3), x_r^i denotes the number of unmodified items in the i position of the remodeling project. Counting the current implementation or changes to the renovation program yields the overall number of unrenovated items in the program, and the set of unrenovated items is represented in Equation (4).

$$x_r = (x_r^1, x_r^2, \ldots, x_r^n) \tag{4}$$

To assess the effectiveness of the building's remodeling program more intuitively, the set of statistical original and remodeling items is expressed as Equation (5).

$$\begin{cases} x(t_m) = (x_1^1(t_m), \ldots, x_{k1}^1(t_m), \ldots, x_1^n(t_m) \ldots, x_{kn}^n(t_m)) \\ x_r(t_m) = (x_r^1(t_m), x_r^2(t_m), \ldots, x_r^n(t_m)) \end{cases} \tag{5}$$

In Equation (5), t_m denotes the current point in time. m is the value taken at the time point. $m=0,1,2,\ldots,T$, S denote the maintenance frequency under the time period. The change process of appliance population under the two groups is shown in Equation (6).

$$\begin{cases} x(t_{m+1}) = G(x(t_m), u(t_m), t_m) \\ x_r(t_{m+1}) = G(x_r(t_m), u_r(t_m), t_m) \end{cases} \tag{6}$$

In Equation (6), G denotes the population change function for the program. $u(t_m)$ denotes the repair process function. The population change of non-repairable appliances in the process is calculated as shown in Equation (7).

$$G_k^i(x_k^i(t_{m+1})) = \mu_k^i v_k^i \frac{x_k^i(t_m)^2}{x_k^i(t_0)} - \mu_k^i x_k^i(t_m) + x_k^i(t_m) + u_k^i(t_m) \tag{7}$$

In Equation (7), $G_k^i(x_k^i t_{m+1})$ denotes the population change function for the appliance. (t_{m-1}, t_m) denotes the set time period period. $\mu_k^i(t_m)$ denotes the number of repairs during the time period. μ_k^i and v_k^i denote the two adjustment parameters of the function, respectively.The constant failure probability algorithm is introduced for the types of appliances that can be restored by repair. The calculation is shown in Equation (8).

$$G_k^i(x_k^i(t_{m+1})) = (1 - \frac{1}{\theta_k^i}) x_k^i(t_m) + u_k^i(t_m) \tag{8}$$

In Equation (8), θ_k^i represents the calculated mean failure period of the appliance. The purpose of energy-saving and cost saving in the renovation process are divergent (Farghali *et al.*, 2023), so the relationship between multiple objectives needs to be measured to arrive at an optimal solution (Han *et al.*, 2023).

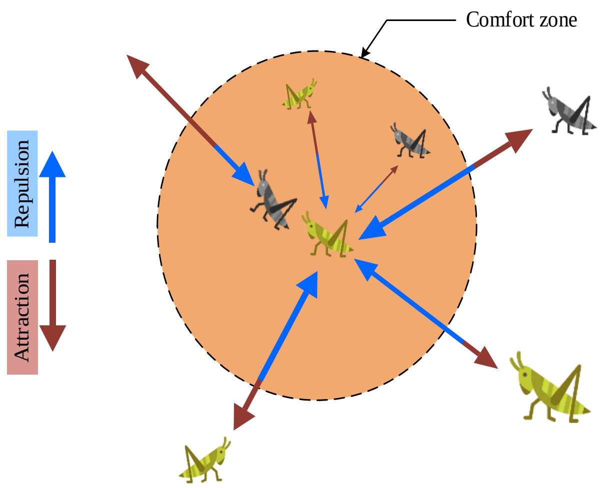


Fig.4 Grasshopper optimization algorithm

2.2 Optimization of building energy efficiency renovation decision based on GOA

With the progress of social development, engineers began to consider the energy-saving and environmental protection of buildings (Sharma & Kumar, 2022). In the energy-saving renovation problem of buildings, the study must reach the energy-saving purpose but also must pay attention to the cost of renovation and the user's willingness (Xu & Juan, 2022), so the specific implementation plan needs to be optimized in a number of objectives in the decision-making to optimize a suitable path (Decorte *et al.*, 2023). Therefore, the study introduces the improved GOA to optimize the building energy-saving renovation problem. The specific algorithm works as shown in Fig. 4.

In Fig. 4, the algorithm uses the grasshopper traveling position as a decision point and sets multiple decision directions as survival or consumption factors during grasshopper movement. The relationship between the single strategy and the suitable range is measured to simulate the grasshopper behavior to decide the optimization method (Zhang *et al.*, 2023). The research method represents the set of grasshopper populations as shown in Equation (9).

$$X = \{X_i\}.\, i = 1,2,3, \ldots, N \tag{9}$$

In Equation (9), X serves as the set grasshopper population set. N represents the number of individual grasshoppers in the population. The random number generation is used to set the grasshopper individual coordinate points, and the dimension space is the search range of grasshoppers (Ma *et al.*, 2023). The rule of random number generation is shown in Equation (10).

$$X_{id} = l_d + rand(u_d - l_d) \tag{10}$$

Equation (10), X_{id} denotes a random number in d-dimensional space. *rand* denotes the random function. u_d denotes the upper bound of the dimension space. I_d denotes the lower bound of the dimension space. The values of the process parameters are updated and adjusted by iteratively varying the exploration expenditure and mining revenue of the exploring grasshopper, after a two-stage dynamic relationship equilibrium. The formula for parameter updating is Equation (11).

$$c = c_{\max} - (t\frac{c_{\max} - c_{\min}}{L}) \tag{11}$$

In Equation (11), c represents the process parameters. t represents the current iteration round. $c_{\min}$ represents the lower limit of the parameter. $c_{\max}$ represents the upper limit of the parameter. L represents the total number of iteration rounds of the algorithm. The process calculates the interaction behavior between individuals with the gravity function. When the value of the gravity function is 0, the individuals are in the comfort zone. The position information of the population is deduced by calculating the behavior between individuals. The update of the position is expressed through Equation (12).

$$X_i(t+1) = c\left\{\sum_{\substack{j=1 \\ j\neq i}}^{N} c\frac{u-1}{2} S(|X_j - X_i|)\frac{X_j - X_i}{d_{ij}}\right\} + T \tag{12}$$

In Equation (12), X_i denotes the current position of the i-th individual. X_j denotes the current position of the j-th individual. u denotes the upper boundary of the exploration range. l denotes the lower boundary of the exploration range. S_i denotes the force between individuals of the population. d_{ij} represents the Euclidean distance between individuals. T represents the optimal individual value. The optimal individual under the next

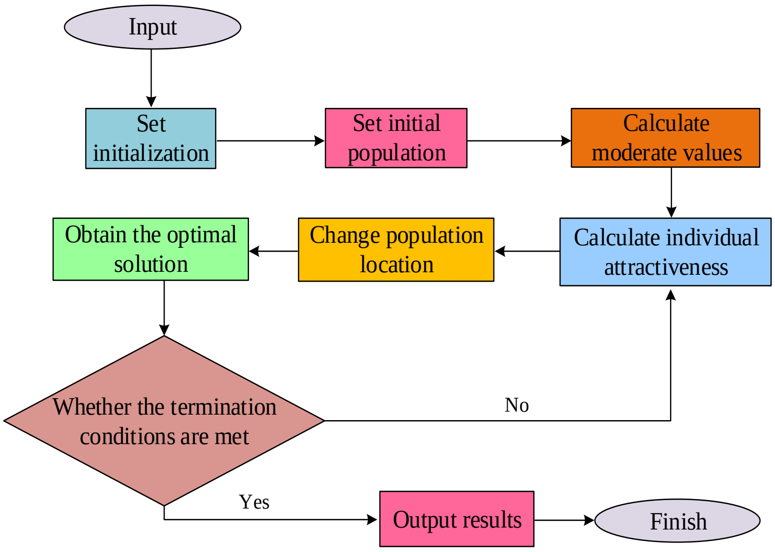


Fig.5 Algorithm flowchart of GOA

move is updated by iteration. The iteration of GOA is shown in Fig. 5.

In Fig. 5, the algorithm prioritizes the calculation of the current optimal individual to attract other individuals to approach with the current optimal individual position. The optimal individual is computed iteratively each time until the current optimal solution is output when it satisfies the decision condition. However, the population carries out individual actions with a random number method of search may lead to the problem of uneven moving range (Yan *et al.*, 2023). Therefore, the study introduces an elite reverse learning strategy to strengthen the individual's moving aggressiveness and complete the global exploration as balanced as possible. The research process uses chaos theory to calculate the change of the population. Moreover, the population generation process is transformed to the chaotic space through the mapping function. Logistic fully chaotic iterative method is chosen to calculate, and the process is shown in Equation (13).

$$S_{t+1} = 4S_t(1-S_t), t = 1, 2, \ldots, N-1 \tag{13}$$

In Equation (13), S_{t+1} is the fully chaotic iterative function. S_1, $S_2,\ldots S_N$ is denoted as a sub-variable. The chaotic variables are transformed and dispersed in the exploration range, avoiding small-scale activities of individuals. In order to ensure the locomotor activity of grasshopper individuals, an elite decision-making algorithm is introduced to optimize the GOA (Srinivasulu *et al.*, 2023). In this case, the elite weights of the elite reverse learning strategy are expressed as shown in Equation (14).

$$\begin{cases} w = \{w_i\} & i = 1, 2, \ldots n \\ w_i == \dfrac{f(X^*_{g(n-i)})}{\sum_{j=1}^{n} f(X^*_{gj})} & j = 1, 2, \ldots n \end{cases} \tag{14}$$

In Equation (14), X_g^* denotes the set of elite individuals after strategy practice. X_{gj}^*denotes the i th elite individual generated after optimization. w_i denotes the weight of the i th individual. w denotes the weight of the fitness value for the individual. f denotes the reverse learning strategy function. The research methods determine the renovation term through multi-factor analysis of building energy efficiency renovation, and calculate the renovation cost of the renovation measures as the limiting term. The energy consumption and cost factors are synchronously placed in the improved GOA for population evolution, and the optimal solution for renovating is obtained through the iteration of the algorithm.

3. Results and Discussion

This chapter examines the adaptive variations of the algorithm through test set testing, with the objective of evaluating the accuracy of the algorithm's decision-making capabilities through sample predictions. The operational stability of the algorithm is evaluated through repeatability tests. A comparison of the energy consumption of the building before and after renovating demonstrates the energy-savings achieved by the algorithm. Furthermore, the decision-making advantage of the research algorithm is determined by comparing the cost of renovating under iterative changes.

3.1 Performance test of improved GOA

To decide the optimal design solution from the multi-objective of building renovation, the improved GOA method is used, and the algorithm parameters c_{max} =1 and c_{min}=0.00001 are set. The number of elites in the decision-making is 10% of the number of populations. Two test sets are selected to test the performance of the algorithm for adaptation. The content of the dataset includes energy efficiency data of buildings and the performance and price of building materials. The ratio of the training set to the dataset is fixed at 10:1, and the number of iterations is set to 120. The specific results are shown in Fig. 6.

In Fig. 6(a), the fitness of the GOA gradually increases with the number of iterations in test set 1. The optimal fitness calculated in the test reaches more than 80% after 10 iterations, while the actual average fitness coincides with the optimal fitness after the number of iterations reaches 40, with its fitness converging to 100%. In Fig. 6(b), in test set 2, the trend of the algorithm's fitness is consistent with that in test set 1, while the best fitness curve in test set 2 converges more slowly. The best fitness reaches more than 80% when the number of iterations is carried out to 30 times. However, the actual average fitness

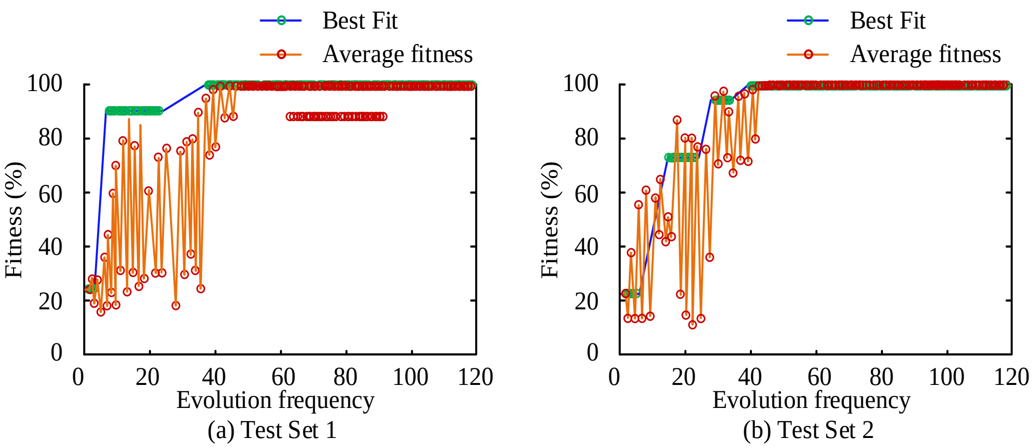


Fig.6 Fitness changes in the test set

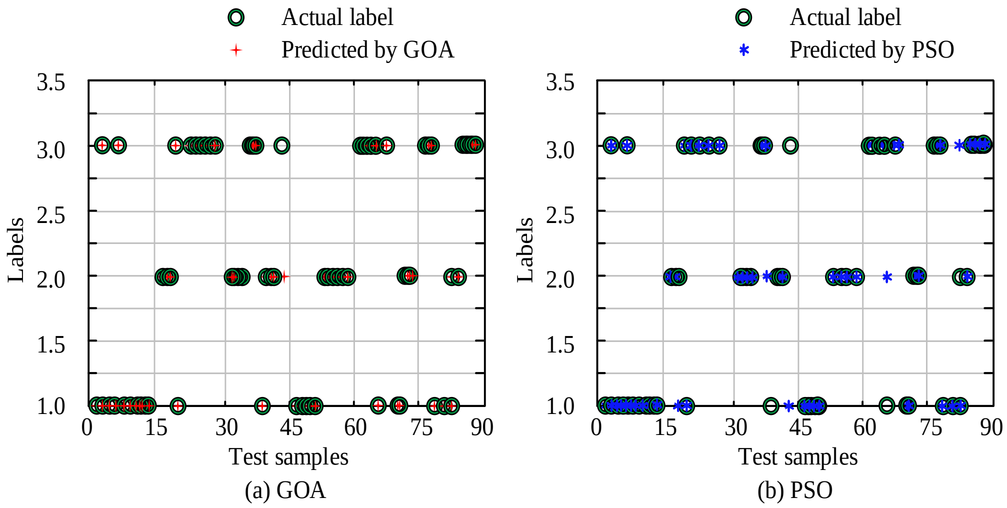
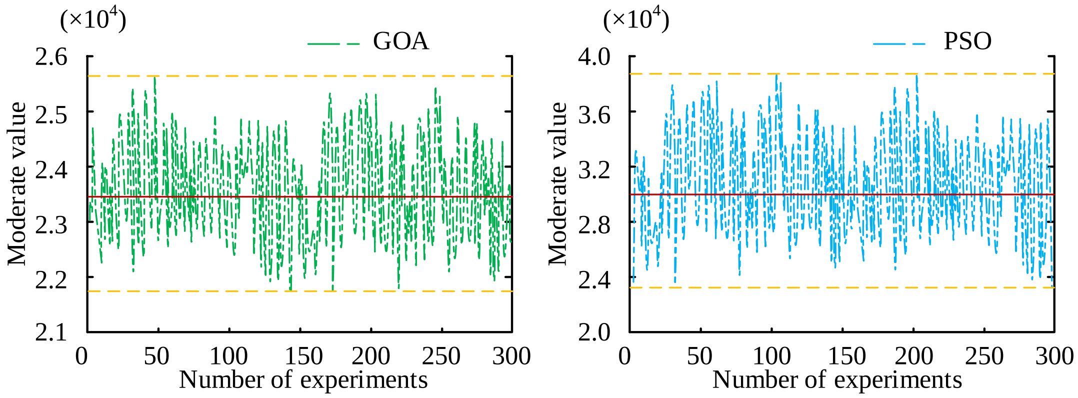


Fig.7 Comparison of decision accuracy of algorithms

change is more stable. When the number of iterations reaches 40 times after the best fitness curve coincides with the best fitness curve, the fitness tends to be close to 100%. It indicates that the actual decision-making results of the algorithm are more stable. The algorithm can basically search for the optimal solution when the number of iterations is carried out after 40 times. Concurrently, the test setting incorporates energy efficiency data and material energy-saving effects associated with the research focus, which can effectively reflect the enhancement of building energy efficiency by the research algorithm. To evaluate the decision-making ability of the algorithm, the prediction accuracy of the algorithm is compared with other methods. The specific results are shown in Fig. 7.

In Fig. 7(a), the samples used for testing are randomly distributed in the coordinate axis interface, and the predicted positions of the MODM samples calculated by the GOA accurately coincide with the actual sample positions, and the prediction accuracy of the GOA can reach 98.8%. In Fig. 7(b), under particle swarm optimization (PSO), the predicted positions of MODM samples and the actual sample positions can also reach the basic coincidence, and the prediction accuracy of PSO algorithm can reach 93.3%. The research algorithm has improved prediction accuracy by 5.5% compared to this algorithm. It indicates that the optimization effect of GOA is better than PSO algorithm in the test set. The error rate of the GOA during the test is only 1.2%, while the error rate of the PSO algorithm is at 6.7%, showing a significant difference. Therefore, the GOA performs better for the MODM effect of the building. In order to determine the decision stability of the algorithm, the GOA and PSO algorithm are selected to be taken simultaneously for 300 tests. The fitness values of the two groups of models in the experiment are shown in Fig. 8.

In Fig. 8(a), the change in the fitness value of the improved GOA over 300 repetitions of the experiment shows a regional fluctuation. The upper and lower limits of the predicted fitness values are 2.56×10^4 and 2.18×10^4, respectively. The mean value of the improved GOA during the calculation of the fitness values is 2.34×10^4, and the extreme deviation of the data is 0.38×10^4. In Fig. 8 (b), the fluctuation of the fitness values of the PSO algorithm in 300 repeated experiments is much larger. The upper and lower limits of the fitness values predicted by the PSO algorithm are 3.87×10^4 and 2.36×10^4, respectively. The mean value of the improved GOA in the process of moderation value calculation is 3.01×10^4, and the extreme value of the data is 1.51×10^4. It indicates that the improved GOA model has less variability of decision-making results under multiple repetitions, and the actual decision-making behavior is closer to the optimal solution. In comparison to the PSO algorithm, the improved GOA is more advantageous for multi-project decision-making regarding building renovation measures. It is also more



(a) GOA (b) PSO

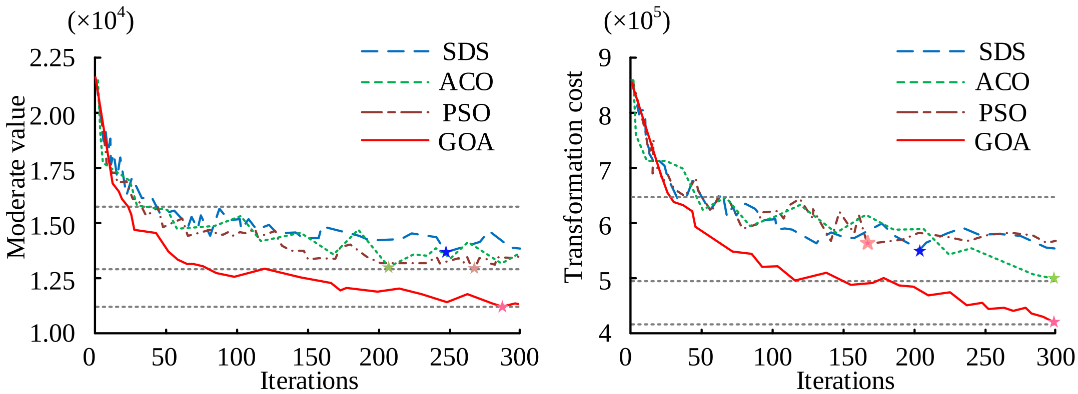
Fig.8 Comparison of repeatability tests for moderate values

applicable to the integrated decision-making process, whereby the actual energy-saving effect and renovation spending are taken into account.

3.2 Optimization effect of improved GOA for multi-objective decision making for building energy efficiency renovation

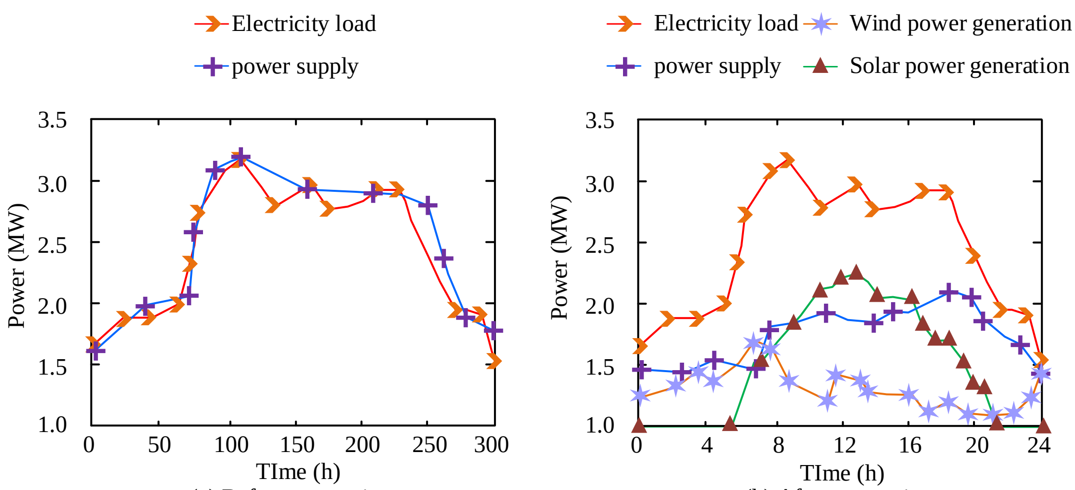
The adaptability of the improved GOA in building remodeling decision-making is confirmed after the performance test of the model to compare the multi-project decision-making with multiple algorithms for real application scenarios. The running operating system in the setup algorithm is Windows 10 and the \running memory is 8GB. The results of the comparison of the fitness value and the remodeling cost are shown in Fig. 9.

In Fig. 9(a), the fitness values of all four groups of algorithms in the early stage show a decreasing trend with the number of iterations. The stochastic diffusion search (SDS) algorithm, ant colony optimization (ACO) and PSO algorithms basically finish convergence after the number of iterations reaches 50, and its fitness value no longer decreases with the



(a) Fitness comparison (b) Transformation cost

Fig.9 Comparison between moderate value and renovation cost



(a) Before renovation (b) After renovation

Fig.10 Changes in energy consumption within buildings

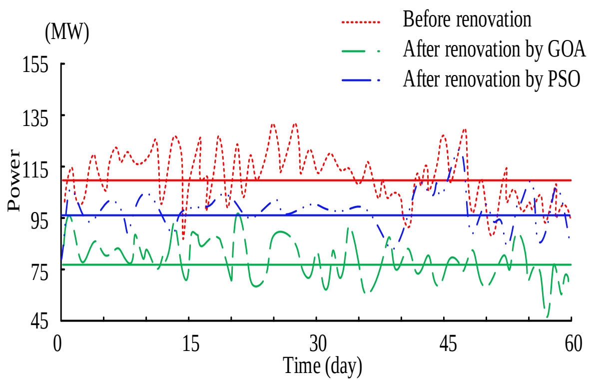


Fig.11 Comparison of energy consumption optimization in building renovation

number of iterations. The improved GOA also consistently optimizes the fitness at a later stage and the final fitness value is reduced to 1.13×10^4. In Fig. 9(b), the four groups of algorithms before 50 iterations have similar reduction in renovation cost. After 50 iterations, the SDS algorithm, the ACO algorithm, and the PSO algorithm basically stop decreasing, while the GOA maintains continued optimization. At this point, the global optimal renovation cost decreases to 4.07×10^5 yuan. It indicates that in the improvement of GOA has the strongest global search ability, and stably maintains the reduction of the renovation cost with the optimization of the moderate value during the iteration process. To compare the energy-saving effect before and after the GOA decision optimization, the power consumption graph is plotted as shown in Fig. (10).

In Fig. 10(a), the trend of the electrical load in the building is rising and then falling. The power load of the building is significantly higher during the daytime than the night time. The supply curve of the power also exhibits a first rise and then a fall. In Fig. 10(b), the average power load of the building in a day after renovating with the improved GOA exhibits 2.45 MW. The magnitude of the power supply curve of the actual power supply system decreases significantly after the inclusion of the wind-powered and solar-powered pathways. The average power supply of the power supply system is 1.76 MW, which is 23.7%-49.6% lower than the power consumption before the modification. The average power supply of the wind power supply in the whole day is 1.19 MW. The power supply of the solar power supply method in the daytime is significantly higher, with an average of 1.51 MW under the daytime hours. It shows that the energy consumption of the building after the renovation of the improved GOA has been significantly reduced. However, considering the constraints of the new energy supply, a long-term observation of the energy change of the building is carried out. The data results are shown in Fig. 11.

In Fig. 11, the energy consumption of the building renovated by the improved GOA decision-making under long time period shows a significant decrease. The average daily power consumption of electricity power of the building before renovation is 109.61 MW, while the average daily power consumption of electricity power of the optimized building is 76.47 MW. The lowest daily power consumption of electricity power of the building after renovation is 47.62 MW, and the actual energy-saving is shown as 15.34%-38.29%. The optimization estimation with PSO algorithm shows that the average value of electricity consumption of the renovated building is 92.53 MW, with energy-savings ranging from 8.94% to 18.16%. It shows that the energy-saving effect of the building optimized by the improved GOA is more obvious and more stable. The improved GOA exhibits obvious advantages over the optimization effect of PSO algorithm, and makes better decisions on energy-saving measures for buildings. The environmental quality of the building after renovation is also evaluated to confirm the user experience in the building. The data results are shown in Fig. 12.

In Fig. 12(a), the air quality index (AQI) of the building before renovating is in the range of 155-250, and the AQI after renovating is maintained in the range of 104-215. The AQI of the building after renovation is optimized compared to the pre-renovation. In Fig. 12(b), the ambient temperature of the building before remodeling is between 25-26°C, while the ambient temperature after remodeling is between 24-26°C. The ambient temperature has decreased compared to the pre-renovation of the building. This indicates that the actual air quality of the building has been optimized accordingly after the renovation. At the same time, the ambient temperature of the building after the energy-saving renovation is also reduced,

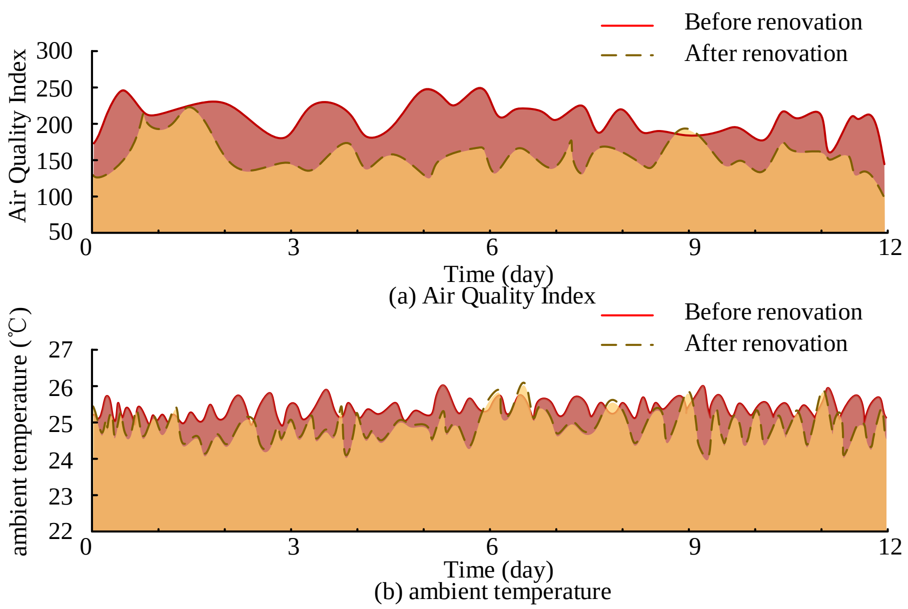


Fig.12 Changes in environmental indicators for building renovation

indicating that the energy reduction of electrical equipment in the building can affect the reduction of ambient temperature. In summary, the improved GOA decision-making building energy efficiency renovation is more effective in saving energy while providing a more comfortable environment for users in the building.

3.3 Discussion

Based on the above research results, it can be concluded that the renovated buildings have improved in terms of energy conservation and environmental optimization. After optimizing with the improved GOA algorithm, the energy consumption structure inside the building shifted from non renewable energy consumption to hybrid energy consumption. The changes in the energy structure of buildings also had corresponding impacts on the surrounding environment and climate. Jowkar *et al.* proposed energy-saving optimization methods for sustainable building renovations (SBR). However, this study did not consider the energy demand after building renovation, which may lead to a decrease in resident satisfaction (Jowkar *et al.*, 2022). The research algorithm for energy-saving renovation of buildings was based on the building's own energy demand, which was more suitable for the optimization purpose of existing buildings. From the perspective of energy-saving optimization, Xu *et al.* proposed an optimization decision model that evaluated both cost and renovation effectiveness. This study analyzed the energy-saving effect and climate improvement factors of renovated buildings through benefit evaluation (Xu & Juan, 2022). However, the environmental improvement effect of this method after cost coordination was not significant. However, after the research method was transformed, the temperature and air quality of the building environment are significantly optimized. It can be concluded that research methods had significant advantages in optimizing the energy-saving renovation of buildings. Moreover, from the perspective of the decrease in environmental temperature after the renovation, the renovation measures may have reduced greenhouse gas emissions. The improvement of air quality also verified this optimization result, so the research method has also improved the air pollution problem through building renovation.

4. Conclusion

To ensure that both the energy-saving effect and the renovation cost of the building met the expectations, the study improved the GOA with the elite reverse learning method. The process employed a partitioning approach to categorize the scope of the building, monitoring the real-time electricity consumption of the building and identifying the equipment with the highest energy consumption based on the partition. Logistic complete chaos iterative method was used to calculate the population change in the process, and elite inverse strategy method was used to avoid the algorithm tends to local optimal solution. The performance test results showed that the improved GOA algorithm had stable decision results in the test set and could quickly search for the global optimal solution after short-term iterations. In practical application results, the addition of new energy transformation greatly reduced the energy consumption of buildings. The performance test results showed that the improved GOA algorithm had stable decision results in the test set, and could quickly search for the global optimal solution after short-term iterations. After the building renovation, the wind power supply system in a stable wind environment could provide an average power supply of 1.19MW, while the solar power supply system with sufficient solar energy could provide an average power supply of 1.51MW. For the energy consumption of the building under the long time period, it showed that the daily consumed electric power power of the renovated building was 62.47 MW on average. The actual energy-saving range performance was 15.34%-38.29%, which indicated that the renovated building had a stable energy-saving effect was stable. However, there are still certain limitations in the research methods for energy-efficient building retrofits. Due to the fact that the decision-making objectives in renovation are more focused on objective quantitative factors, there is insufficient data collection on residents' renovation intentions, which may lead to a decrease in residents' satisfaction. Therefore, future research directions can increase the collection of user intention data and coordinate the renovation of buildings based on the renovation intentions of residents, in order to provide a better algorithm model for multi-objective decision making in energy-saving renovation of buildings.

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