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Research paper

Digital collaborative space layout design for building performance based on multi-objective optimization and performance oriented

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Abstract: With the progress of technology and the improvement of quality of life, the digital collaborative spatial layout design of building performance is increasingly valued in the construction industry. Traditional spatial layout design methods are often limited to a single performance indicator, ignoring the multidimensional and complex nature of building performance. To effectively achieve collaborative optimization between architectural spatial layout and performance, a multi-objective optimization and performance oriented architectural performance collaborative spatial layout design method ground on improved Grey Wolf algorithm is developed. It has fast convergence speed and strong global search ability, combined with multi-dimensional indicators of building performance, multi-objective optimization is achieved. Comparative experiments are conducted on the improved Grey Wolf algorithm. The results showed that its loss value and fitting coefficient were 0.003 and 0.9655, respectively, which were better than the comparison algorithms. Subsequently, experimental verification was conducted on the proposed spatial layout design method. The building energy consumption and environmental quality scores of the proposed method were 1187 kWh and 8.6 points, respectively, which were superior to the comparison methods. The significance of the research lies in promoting the digital transformation of the construction industry and enhancing the scientificity and accuracy of architectural design. The coordinated optimization of architectural spatial layout and performance provides strong support for sustainable urban development and new ideas and methods for the future development of the construction industry.

Keywords: collaborative design, differential evolution, grey wolf algorithm, multi-objective, performance oriented, spatial layout

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1. Introduction

In modern urban planning and construction, the spatial layout of buildings is not only related to their aesthetics and practicality, but also directly affects their energy efficiency, environmental friendliness, and the comfort of residents [1, 2]. In the construction of smart cities, digital collaborative spatial layout design has shown broad application prospects. Through deep integration with technologies such as the Internet of Things, big data, and artificial intelligence, digital collaborative spatial layout design can achieve real-time monitoring and dynamic control of urban building clusters. For example, intelligent transportation, smart parks, etc. Traditional spatial layout design methods often only focus on a single performance indicator, ignoring the multi-dimension and complexity of building performance [3]. Meanwhile, existing optimization algorithms often struggle to achieve a good balance between multiple objectives when dealing with Multi-Objective Optimization (MOO) problems [4]. The Grey Wolf Optimization (GWO) has fast convergence speed and strong global search ability, making it suitable for handling complex MOO problems [5]. Therefore, a MOO and performance oriented collaborative spatial layout design method for building performance based on improved GWO is designed with the hope of improving the effectiveness of spatial layout design. The innovation of the method lies in the combination of the GWO and the digital collaborative spatial layout design of building performance. Through MOO techniques, various performance indicators of the building can be comprehensively considered to achieve the optimal overall performance.

2. Related works

MOO problems have become a key issue in the field of optimization. Y. Tian et al. proposed an operator selection algorithm based on reinforcement learning. Experiments showed that this method was more effective than evolutionary algorithms in problems with MOO [6]. Y. Hua et al. reviewed the performance degradation of evolutionary algorithms in solving MOO with irregular Pareto frontiers. Based on the review content, benchmark testing with irregular issues was merged and summarized, and the causes of irregular issues were analyzed [7]. T. Wei and J. Zhong. designed a generalized resource allocation framework. This framework could improve the overall performance of MOO algorithms [8].

Optimizing the space layout design is also a key area for scholars. L. Chen et al. proposed an interactive visualization analysis system to address the optimization challenges in the spatial layout planning of fire stations. The case analysis results indicated that this method could better identify and improve layout hazards in fire stations [9]. B. Yang et al. proposed a new strategy for automatically representing spatial semantics and topology in planar raster images. It had excellent performance on three different datasets [10]. J. Zhi et al. developed a new layout framework for optimizing the environment of human-computer interaction. It could generate reasonable designs even in narrow spaces and among users with different preferences [11]. S. Wang et al. developed a new two-stage method for automated planar design of residential buildings with given exterior wall boundaries.Based on the results, the spatial layout and floor plan were produced. The planar generation results were superior to those of existing methods [12].

In summary, the current architectural spatial layout design is still limited by the complexity of the "form-function" problem and related technical conditions. In addition, current spatial layout design methods do not consider building performance, resulting in layout optimization effects that are not applicable. To this end, a new digital collaborative spatial layout design method for building performance is constructed based on MOO and performance orientation.

3. Digital collaborative space layout design for building performance based on multi-objective optimization and performance oriented

3.1. Improved GWO based on DE

Due to its high search efficiency, fast convergence speed, and simple and easy to understand logical structure, GWO algorithm has been widely applied in MOO. In the grey wolf society, the gray wolf pack has four classes, α, β, δ, and ω, based on the adaptability of each individual in its population, from high to low. The hunting mechanism is that the wolf pack always searches and surrounds under the leadership of α, β, and δ wolves. The behavior of gray wolves surrounding prey during hunting is displayed as equations (3.1) and (3.2).

$$\vec{D} = |\vec{C} \cdot \vec{X}_P(t) - \vec{X}(t)| \tag{3.1}$$

In equation (3.1), $\vec{D}$ stands for the distance between the individual gray wolf and its prey, t stands for the iteration size, $\vec{X}_P$ represents the prey position vector, and $\vec{C}$ is the coefficient vector.

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A} \cdot \vec{D} \tag{3.2}$$

In equation (3.2), $\vec{X}$ represents the position vector of the gray wolf. $\vec{A}$ stands for the coefficient vector. The $\vec{A}$ is shown in equation (3.3).

$$\vec{A} = \vec{a} \cdot \vec{r}_1 - \vec{a} \tag{3.3}$$

In equation (3.3), $\vec{a}$ represents the convergence factor. The modulus $|\vec{r}_1|$ of $\vec{r}_1$ stands for a random number in 0 and 1. The $\vec{C}$ is shown in equation (3.4).

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{3.4}$$

The modulus $|\vec{r}_2|$ of $\vec{r}_2$ is also a random number between 0 and 1. After identifying the location of the prey in the gray wolf pack, the prey is surrounded under the leadership of α wolf. The expression for tracking the position of prey by gray wolves of different classes is shown in equation (3.5).

$$\begin{cases} \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \end{cases} \tag{3.5}$$

In equation (3.5), $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$ stand for the distance between α, β and δ and other individuals. $\vec{X}_\alpha$, $\vec{X}_\beta$ and $\vec{X}_\delta$ respectively stand for the current location of α, β and δ. $\vec{C}_1$, $\vec{C}_2$ and $\vec{C}_3$ represent random vectors. The step size and direction of other individual wolves towards α, β, and δ are $\vec{X}_1$, $\vec{X}_2$, and $\vec{X}_3$, as shown in equation (3.6).

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{cases} \tag{3.6}$$

The final position $\vec{X}(t+1)$ of individual ω wolf is shown in equation (3.7).

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{3.7}$$

The solution of GWO needs to first separate α, β, and δ wolves. Through these three layers of wolf hunting targets, the positions of other gray wolves are updated, and the targets are finally surrounded together. Due to the poor population diversity, slow convergence speed, and susceptibility to local optima in a single GWO, Differential Evolution (DE) algorithms have strong convergence ability. Therefore, to enhance the accuracy and response speed of GWO, the study integrates DE into the GWO to form the DE-GWO algorithm, which improves the global search ability while ensuring optimization speed and accuracy. The optimization process of the DE-GWO algorithm is shown in Fig. 1.

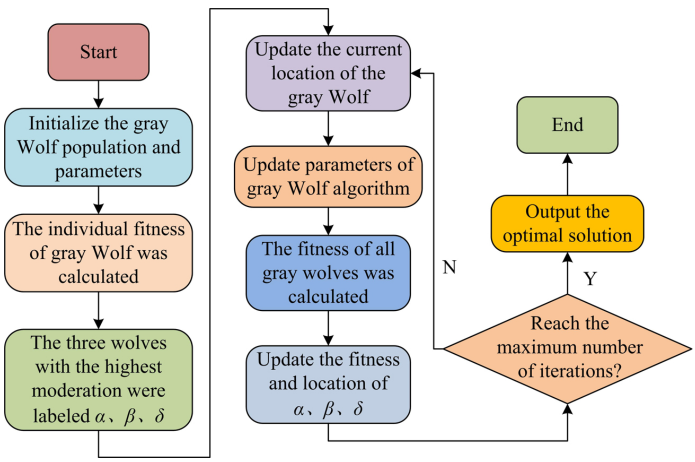


Fig. 1. Optimization process of DE-GWO algorithm

From Fig. 1, the DE-GWO algorithm first initializes the desired parameters and GWO settings. Then, mutated gray wolves are introduced to initialize the population and increase diversity. Next, individual adaptability is calculated and the termination criterion is used to determine whether to continue the iteration. If it is not met, the DE algorithm is used to optimize the GWO parameters, update the gray wolf position, and promote population evolution. If the conditions are met, the training model is used for prediction.

3.2. Multi-objective optimization model for building layout based on performance oriented and DE-GWO

A reasonable architectural layout can not only improve the spatial utilization rate of a city, but also improve the urban environment and enhance the quality of life of residents [15]. In architectural layout design, performance orientation mainly refers to the functionality and efficiency of the building as the core [16]. The performance oriented architectural layout optimization proposed in the study aims to achieve higher spatial efficiency, environmental comfort, and economic benefits while meeting the basic functional requirements of the building [17]. The calculation of spatial efficiency is shown in equation (3.8).

$$\eta = \frac{m_1}{m_2} \cdot \left(1 - \frac{m_3}{m_1}\right) \tag{3.8}$$

In equation (3.8), m_1, m_2, and m_3 represent the total construction area, total land area, and ineffective space area, respectively. The environmental comfort o is shown in equation (3.9).

$$o = w_1 \cdot t_1 + w_2 \cdot c_1 + w_3 \cdot l_1 \tag{3.9}$$

In equation (3.9), t_1, c_1, and l_1 represent ventilation index, lighting index, and green coverage rate, respectively. w_1, w_2 and w_3 represent the corresponding weights. The calculation of economic benefits is shown in equation (3.10).

$$n = \frac{p_1}{p_2} \cdot \left(1 - \frac{p_3}{p_1}\right) \tag{3.10}$$

In equation (3.10), p_1, p_2, and p_3 represent total revenue, total cost, and maintenance cost, respectively. The comprehensive performance indicator is shown in equation (3.11).

$$P = w_\eta \cdot \eta + w_o \cdot o + w_n \cdot n \tag{3.11}$$

In addition, a new MOO model for building layout is developed based on the DE-GWO algorithm and performance orientation. Fig. 2 displays the specific steps.

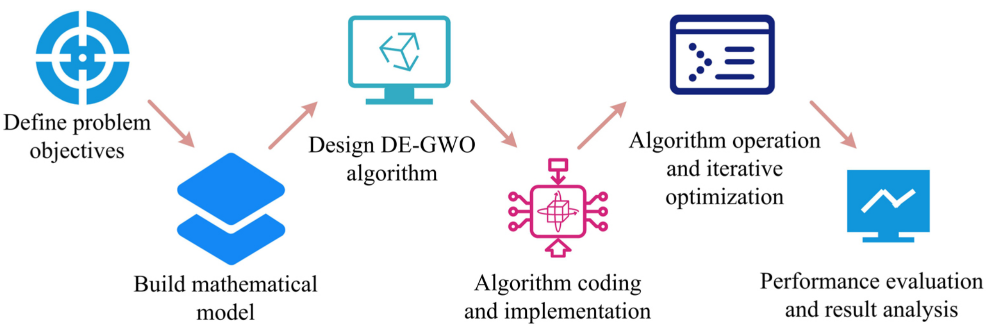


Fig. 2. Multi-objective optimization model of new building layout

In Fig. 2, the MOO model for new building layouts based on the DE-GWO algorithm and performance orientation mainly has six steps. The first is to clarify the problem objectives. The second step is to establish a mathematical model. The third step is to design the DE-GWO algorithm. The fourth step is algorithm coding and implementation. The fifth step is algorithm operation and iterative optimization. The sixth step is performance evaluation and result analysis.

3.3. Design of human-machine collaborative spatial layout based on multi-objective optimization model

To improve the overall effect of architectural spatial layout, this study proposes a human-machine collaborative spatial layout design method based on a MOO model. Human-machine collaborative spatial layout design refers to fully utilizing the creativity of designers and the optimization ability of computers in the design process [18, 19]. The MOO is the core in human-machine collaborative spatial layout design. The comprehensive objective function of MOO is displayed in equation (3.12).

$$F(x) = w_1 f_1(x) + w_2 f_2(x) + \ldots + w_n f_n(x) \tag{3.12}$$

In equation (3.12), $F(x)$ is the comprehensive objective function. $f_i(x)$ stands for each individual objective function. w_i represents the corresponding weight. The performance evaluation index is displayed in equation (3.13).

$$P' = \sqrt[n]{\prod_{i=1}^{n} p_i^{\sigma_i}} \tag{3.13}$$

In equation (3.13), the performance index P' is a quantitative evaluation for the overall performance of the design scheme. Performance indicator p_i is a separate performance indicator. σ_i represents the corresponding weight. The human-machine collaborative spatial layout design of a MOO model for building layout ground on performance oriented and improved GWO algorithm can be refined into the following eight steps, as shown in Fig. 3.

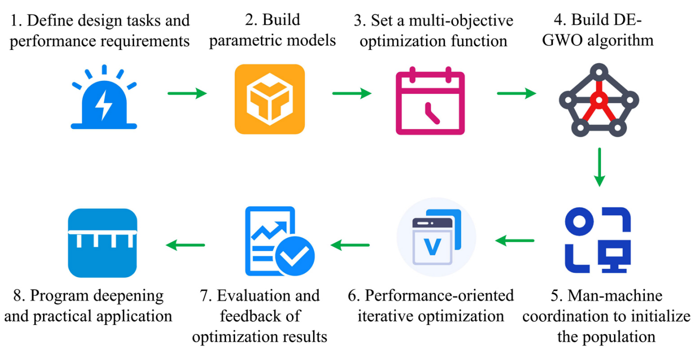


Fig. 3. Human-machine collaborative spatial layout design steps based on MOO model

In Fig. 3, the layout design of human-machine collaborative space based on MOO model mainly consists of eight steps. The weight adjustment of human-machine collaboration is shown in equation (3.14).

$$w_i^{\text{new}} = w_i^{\text{old}} \cdot (1 + \lambda \cdot \Delta E_i) \tag{3.14}$$

In equation (3.14), w_i^{new} and w_i^{old} respectively represent the weights of the objective function $f_i(x)$ before and after adjustment. λ represents the adjustment coefficient. ΔE_i represents the performance change of the objective function $f_i(x)$.

4. Performance analysis and spatial layout design effect analysis of improved GWO

4.1. Performance comparison and analysis of DE-GWO

The study first verifies the performance of the proposed DE-GWO algorithm. The experiment is carried out in MATLAB 2022a and simulated using Simulink 2022a. The operating system is Windows 11, the memory is 8 GB, the CPU clock speed is 3 Hz, the graphics card is GTX-1650, the central processing unit is i7 7820X, and the data analysis is conducted using SPSS 26.0. The convergence performance and population size simulation of GWO algorithm and DE-GWO algorithm are shown in Fig. 4.

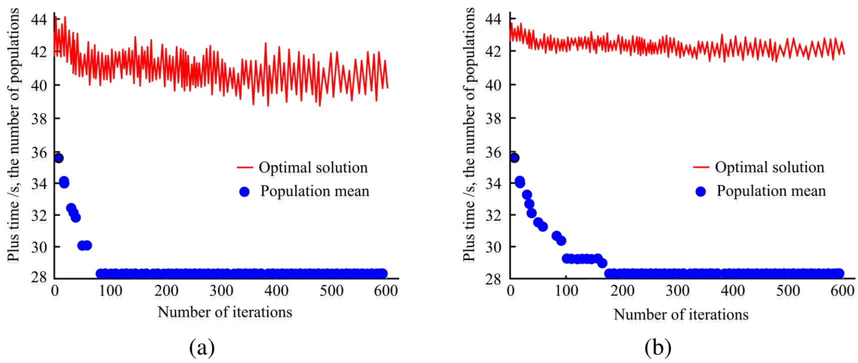


Fig. 4. Convergence performance and population number simulation situation of the two algorithms: (a) DE-GWO, (b) GWO

In Fig. 4a, the proposed DE-GWO algorithm converged at 82 iterations, which had a stable population of around 40. In Fig. 4b, the GWO algorithm converged at 191 iterations and had a stable population of around 43. The convergence performance of the proposed DE-GWO algorithm was superior to that of the GWO. To verify the convergence speed and global search capability of the proposed DE-GWO algorithm, iterative convergence experiments were conducted using unimodal Schwefe function and multimodal Rastrigin function. The DE-GWO algorithm was compared with genetic algorithm (GA), particle swarm optimization (PSO) algorithm, and whale optimization algorithm (WOA), and the results are shown in Fig. 5.

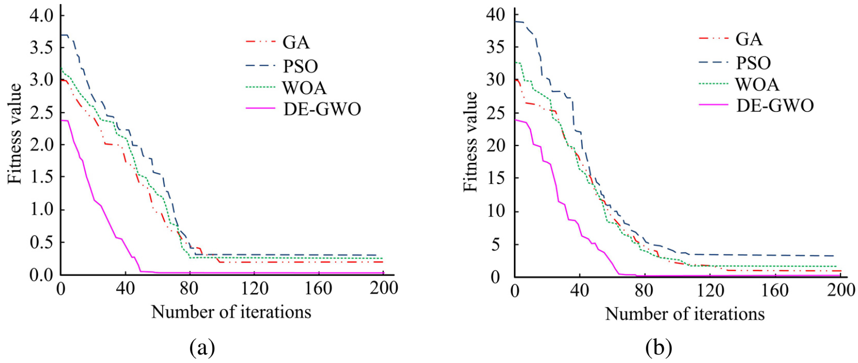


Fig. 5. Iterative convergence results in Schwefe function (a) and Rastrigin function (b)

From Fig. 5a, it can be seen that in the Schwefe function, the fitness value of the proposed DE-GWO algorithm is smaller, at 0.006, and the convergence speed is faster, approaching convergence after about 50 iterations. From Fig. 5b, it can be seen that in the Rastrigin function, the fitness value of the DE-GWO algorithm is still the smallest, and it tends to converge at around 70 iterations, which is superior to the three advanced optimization algorithms of GA, PSO, and WOA. The results indicate that the DE-GWO algorithm proposed by the research institute has a fast convergence speed and good global search performance. To further demonstrate the superiority of the DE-GWO, comparative experiments are conducted with GWO, Sparrow Search Algorithm (SSA), and GA. Loss curve, optimal solution comparison results, and fitting degree are selected as comparison indicators. The loss curves for two different datasets are displayed in Fig. 6.

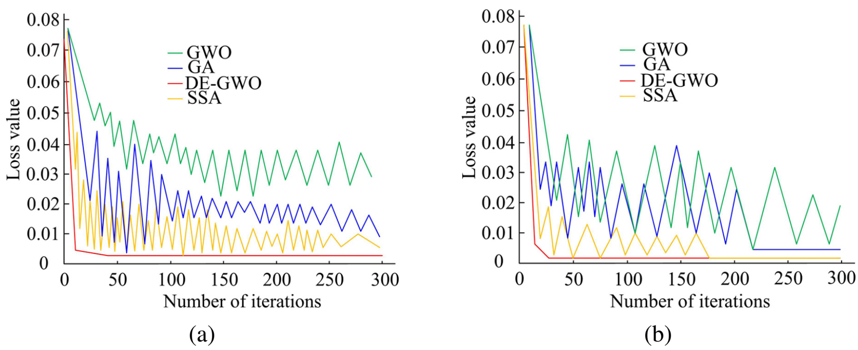


Fig. 6. Comparison results of loss curves of four algorithms in two different data sets: (a) Data set 1, (b) Data set 2

From Fig. 6a, in data set 1, the loss curve of the proposed DE-GWO algorithm was lower than that of the three comparison algorithms, with the minimum loss value of 0.003. SSA was 0.005, GA was 0.009, and GWO was 0.031. The minimum loss value of DE-GWO was 0.003, significantly lower than comparison methods. From Fig. 6b, in data set 2, the loss curve of the proposed DE-GWO algorithm was lower than that of the three comparison algorithms, with the minimum loss value of 0.002. Compared with the SSA algorithm's 0.003, GA algorithm's 0.007, and GWO algorithm's 0.018, the proposed method was significantly lower. From the perspective of the loss curve dimension, the DE-GWO algorithm proposed in the study had better performance. Finally, the fitting degree of the four algorithms in dataset 1 is compared. The comparison results are shown in Fig. 7.

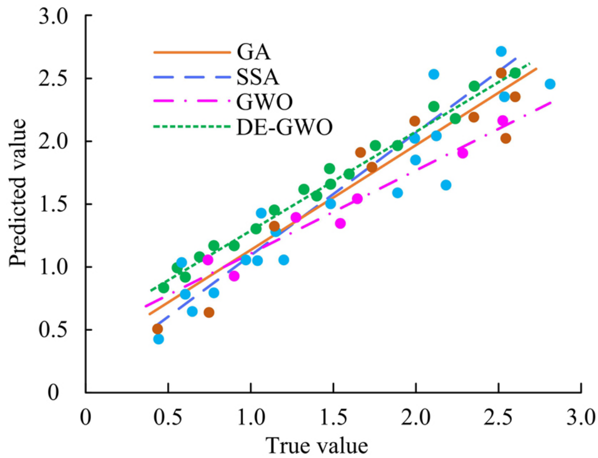


Fig. 7. Comparison of fit degree of the four algorithms

From Fig. 7, the fitting curve of the GE-GWO was better than that of the GA, SSA, and GWO. The fitting coefficient of GE-GWO was 0.9655. The GA was 0.9167, SSA was 0.9105, and GWO was 0.8583, indicating that it was significantly higher. From the perspective of fit dimension, the overall performance of the GE-GWO proposed in the study was better than that of the comparative algorithms. Based on the above dimensions, the optimization performance of the GE-GWO was better than that of other comparison algorithms. Therefore, its application in MOO of spatial layout had a better effect.

4.2. Analysis of spatial layout design effect based on MOO algorithm

After verifying the superiority of the DE-GWO, the study also validates the effectiveness of the spatial layout method based on this algorithm. A case study of a commercial complex project in a certain city is used as a specific environment. This commercial complex covers various business formats such as shopping, catering, and entertainment, which has typical needs for optimizing architectural spatial layout. To comprehensively evaluate the effectiveness of spatial layout design, the study selects indicators such as building energy consumption, space utilization rate, and user satisfaction for comparative analysis. In terms of comparison methods, the traditional spatial layout design method (Method A) and the spatial layout design method based on GWO (Method B) serve as references. The spatial utilization efficiency of commercial complexes under three methods through simulation are shown in Fig. 8.

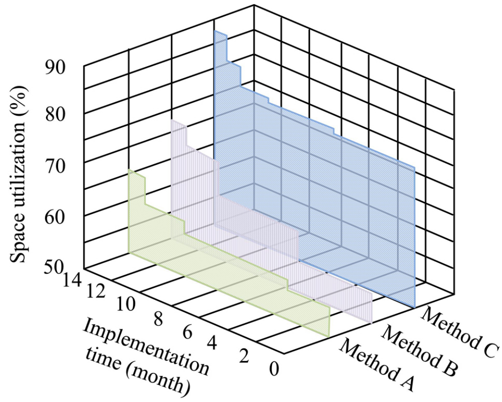
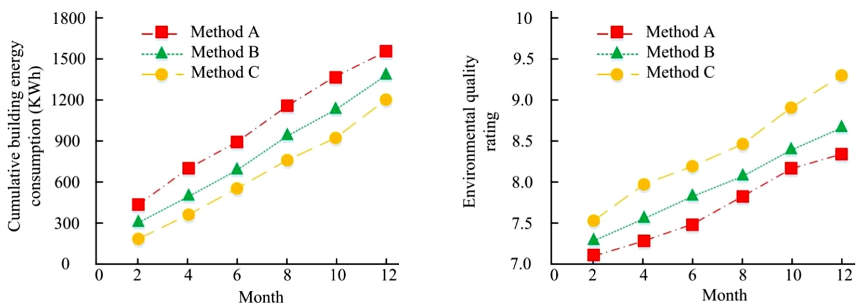


Fig. 8. Comparison results of space utilization rate of commercial complex under the three methods

From Fig. 8, after 14 months of implementation, the spatial utilization rate of Method C was as high as 88%, which was 22 percentage points higher than traditional Method A and 14 percentage points higher than Method B based on GWO algorithm. The above results demonstrated the significant advantages of method C in optimizing spatial layout and reducing ineffective space. The comparison results of annual energy consumption and environmental quality rating data of commercial complexes under three methods are shown in Fig. 9.



(a) (b)

Fig. 9. Comparison results of annual energy consumption (a) and environmental quality score data of commercial complex (b) under the three methods

According to Fig. 9a, the annual building energy consumption of Method C was 1187 kWh, Method B was 1382 kWh, and Method A was 1523 kWh. This result indicated that the annual building energy consumption of Method C was significantly lower than that of Methods A and B. From Fig. 9b, the average environmental quality score curve of Method C was better than that of the comparison methods. Among them, the annual average environmental quality score of Method C was 8.6 points, which was significantly higher than 7.5 points of Method A and 7.8 points of Method B. From the annual energy consumption and environmental quality rating, the spatial layout design method proposed in the study had better energy efficiency than the comparative methods, which helped to reduce building operating costs. In addition, the visual comfort, user satisfaction and other indicators of the three methods are displayed in Table 1.

Table 1. Comparison results of visual comfort, user satisfaction and other indicators of the three methods

Index	Method A (Traditional method)	Method B (based on GWO algorithm)	Method C (Based on DE-GWO)
Distribution uniformity of pedestrian flow	6.8	7.5	8.5
Format complementarity	7.0	7.8	8.8
Visual comfort	7.2	7.9	8.9
Customer satisfaction	7.3	8.0	9.1

According to Table 1, the spatial layout design method (Method C) based on the DE-GWO performed well on multiple key indicators. Method C demonstrated strong competitiveness in terms of uniformity of human flow distribution, complementarity of business formats, visual comfort, and user satisfaction. The uniformity score of its pedestrian flow distribution reached 8.5 points, which was 1.7 points and 1 point higher than Method A and Method B, respectively, indicating that its design could better guide pedestrian flow, avoid congestion and idle areas. At the same time, the complementarity of business formats, visual comfort, and user satisfaction ratings all ranked first, demonstrating the excellent performance of Method C in improving the overall operational effectiveness and user experience of commercial complexes. In summary, the spatial layout design method based on the DE-GWO algorithm outperformed traditional methods and GWO in multiple dimensions.

5. Conclusions

To improve the performance of traditional spatial layout design methods, the DE-GWO was introduced and combined with performance oriented design concepts, a digital collaborative spatial layout design method for building performance based on MOO was proposed. The DE-GWO provided a powerful tool for dealing with complex MOO problems due to its excellent convergence speed and global search ability. The performance oriented design concept ensured that various performance indicators of the building could be comprehensively considered during the design process. The performance of the DE-GWO was tested. The fitting coefficient of the GE-GWO was 0.9655. The GA was 0.9167, SSA was 0.9105, and GWO was 0.8583, which were all below the research method. In addition, the proposed spatial layout design method revealed that its spatial utilization rate was as high as 88%, 22 percentage points higher than traditional method A and 14 percentage points higher than method B based on GWO. The score for the uniformity of human flow distribution reached 8.5 points, which was 1.7 points and 1 point higher than Method A and Method B, respectively. The above results indicated that this method could effectively improve building performance, enhance spatial utilization efficiency and user satisfaction, providing strong technical support for modern urban planning and architectural design. However, this study mainly verified the spatial layout design effect of the proposed model in commercial complexes, and its application in some special types of buildings has not been deeply explored, such as historical buildings, hospitals, and schools. Therefore, in future research, detailed data of different building types should be further collected to train the model, and the proposed model should be applied to more special types of building spatial layout design to verify its adaptability in different building types.

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