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Research paper

Optimisation of decision making for construction projects of assembly buildings based on improved PSO algorithm

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Abstract: A cutting-edge construction method called fitted construction allows for several parallel lines of work to speed up construction and enhance building quality. However, achieving optimal project decisions for global construction projects demands a high level of objective decision-making. To enhance the decision-making process, this research utilizes particle swarm algorithms to optimize construction project decisions in assembled buildings. To tackle the issue of early convergence in particle swarm algorithms, three swarm enhanced particle swarm algorithms are proposed by merging the variational mechanism of the differential evolution algorithm and quantifying the decision making tasks for assembly building construction projects to be solved by the enhanced particle swarm algorithm. Regarding the research results, the upgraded particle swarm algorithm achieved a fundamental convergence in 20 iterations whilst resolving the Sphere, Rosebrock, Rastrigin, and Griewank functions. The improved particle swarm algorithm converges to an optimal solution of –19.208 within 20 iterations on the Holder function, with an optimal domain of [8.055, –9.665]. The results of the optimization study for the decision-making problem of the assembly building project demonstrate that implementing Sigmoid smoothing yields a minimum duration problem of 0.755 and a minimum duration of 45 days. The optimal cost and time required to solve the problem of economic maximisation strategy using the enhanced particle swarm method are 500,000 and 52 days, respectively. The results indicate that the improved particle swarm approach outperforms conventional algorithms in the decision-making process for assembly building projects, maintaining computational accuracy throughout.

Keywords: assembly building, DE algorithm, global optimisation search, project decision making, PSO algorithm

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1. Introduction

The options for constructing a home are widening due to advances in modern industrial technologies. Conventional on-site house construction is relatively tedious and involves the transportation of raw materials including concrete, steel, mud, and sand to the worksite before component production, resulting in a significant worksite area, extended duration, and potential air pollution from dust [1, 2]. Later, to address the issue of prolonged construction duration, the technique of prefabricated buildings emerged. The primary approach involves producing the required housing components for building a house in a factory setup. The components are then transported to the construction site for assembly [3]. The assembly building (AB) construction method greatly saves time on site. Although the quality of AB components produced in the factory is superior, technical specifications for on-site construction are also elevated. Consequently, regulations for component dimensions and placement necessitate verification before the construction process commences. This approach requires a higher level of decision-making around the overall construction project, and how to make AB construction project decisions perform better is also a priority issue to be addressed. Based on this, the research theme lies in the study of the effectiveness of the assembly construction method of frame structure buildings in practice and its potential advantages in improving construction efficiency, reducing costs and improving building quality through an in-depth analysis of a guaranteed housing project in a certain place as an example.

The research comprises four major sections. The introductory section acquaints the reader with AB technology and meticulously discusses the problems of optimising strategies to be executed for the construction aspects of the undertaken projects. The second section enhances the Particle Swarm Optimization (PSO) algorithm by incorporating the Differential Evolution Algorithm (DE) algorithm to optimize the decision-making process for the AB construction project. It presents a PSO-DE algorithm customized for this project and models the problem to be solved for the AB construction project decision. Section three evaluates the efficacy of the PSO-DE algorithm using a range of functions. If the results meet expectations, a solution test for the problem of the shortest duration and optimal economic efficiency for the AB construction project decision. Part IV provides a concluding discussion of the previous sections.

2. Related works

AB has been thoroughly investigated in the domain of building project construction. Michas and Piotr propose implementing the PSO algorithm to enhance the resource scheduling plan to tackle the problem of ineffective resource scheduling for repetitive construction processes involving several construction units. They demonstrate the outstanding computational performance of the method through a duplex residential building project [4]. In order to solve the coordination limitation problem of robots in assembly building construction, Hartmann et al. proposed a cooperative construction optimal model after combining the operation constraint optimization method and two-way temporal path planner. Experimental results show that the model can significantly improve the multi-objective coordination problem of multiple robots in assembly building construction [5]. In PC building projects where the level of natural ventilation does not meet the thermal comfort and thermal sensory requirements of the occupants. Ismail places particular emphasis on the feasibility and benefits of using ICT for new solutions. According to the findings, modern thermal comfort system solutions are crucial for improving thermal comfort and reducing energy consumption in computer building projects [6]. In order to investigate the duration-cost optimal problem in the process of assembly building construction, Peng et al. proposed a combination of a multi-objective optimization algorithm followed by a most solution strategy. Experimental results show that the strategy can effectively solve the schedule-cost optimal problem [7]. In order to solve the construction site layout planning problem of assembly buildings, Yang et al. proposed an automated assembly building construction layout optimization framework after combining building information model and genetic algorithm. Experimental results show that the framework effectively reduces the transportation cost of construction materials and unnecessary time loss [8].

The PSO algorithm is an intelligent optimisation algorithm that uses a global optimisation strategy. To construct a simulated recommender system for dynamic learners based on the highest ranking for the CLM and ECLM conceptual models, Hadi et al. used the NPSO algorithm to learn the importance of different types of links between concepts. The simulation results showed that ECLM outperformed other existing methods with a mean reciprocal rating (MRR) value of 0.780 [9]. Cao et al. proposed an intelligent model for surface EMG gesture recognition by combining feature extraction, Genetic Algorithm (GA) and Support Vector Machine (SVM) for intelligent recognition of surface EMG gesture signals in the field of human-computer interaction, and proposed an Adaptive Mutation Particle Swarm Optimization algorithm to optimize the SVM parameters [10]. Blaza et al. used the PSO and GA population intelligent optimisation algorithm to model an effective large-signal electrothermal GaN HEMT, and comparative experiments with simulation results were used to show the stability of the method in the dynamic stability control of the system [11]. The model was additionally demonstrated to be a very fast and accurate simulation of a non-linear power amplifier [12]. By combining the finite element method with sensitivity analysis and parameter optimisation for genetic algorithms, Song et al. were able to couple the temperature and structure of the braking system. The approach can optimum the thermal stress and deformation of the ventilator opening in a hot environment, according to experiments [13].

In summary, although researchers have developed a large number of solutions to many problems in the field of construction, research on decision optimisation in the field of AB project construction is very scarce. According to a report by Markets and Markets, the global prefabricated buildings market is expected to grow from \$109.5 billion in 2019 to \$132.1 billion by the end of 2024, at a CAGR of about 3.9%, far exceeding concrete and steel mix [14]. The above data indicate that assembly building occupies a mainstream position in the modern construction field, therefore, the research conducted on its construction decision optimization has a high potential application value.

3. PSO-based optimisation algorithm design and ab construction project decision model design

3.1. Design of PSO algorithm incorporating DE algorithm

The main idea of Kennedy's particle swarm algorithm is to randomly scatter M particles in an N-dimensional target space. The objective problem is then solved by the set of particle coordinates in the N-dimensional space. Its position update process is shown in Eq. (3.1).

$$\begin{cases} v_i(t+1) = \omega v_i(t) + c_1 r_1 (P_i - z_i(t)) + c_2 r_2 (P_g - z_i(t)) \\ z_i(t+1) = z_i(t) + v_i(t+1) \end{cases} \tag{3.1}$$

As shown in Eq. (3.1), z_i denotes the position of the ith particle; v_i denotes the velocity of the ith particle; P_i denotes the optimal position solution of the ith particle; P_g denotes the current optimal position solution; t denotes the tth iteration; ω is the inertia factor used to adjust the search for a better result; c_1,c_2 are the individual learning factor and the social learning factor, respectively; and r_1 and r_1 are the random numbers in the interval from 0 to 1.DE is also a global optimisation algorithm proposed by Storn and Price for real number optimisation problems [15]. The mutation algorithm is shown in Eq. (3.2).

$$H_i(g) = X_{p1}(g) + F \cdot (X_{p2}(g) - X_{p3}(g)) \tag{3.2}$$

As shown in Eq. (3.2), three different random numbers X_{p1}, X_{p2} and X_{p3} are selected randomly from the initialized population. g denotes the gth generation;F is the variation factor, which determines the degree of variation, and too large to easily converge. After completing the variance superposition operation by Eq. (3.2) to generate new individuals to complete the variation, the population diversity is increased by crossover, whose equation is given by Eq. (3.3).

$$u_i, j(g) = \begin{cases} h_i, j(g) \ \text{rand}(0,1) \le P_{cr} \\ x_i, j(g) \ \text{rand}(0,1) > P_{cr} \end{cases} \tag{3.3}$$

As shown in Eq. (3.3),$u_i, j(g)$ is the crossover vector, $h_i, j(g)$ denotes the component of rand(0, 1), rand(0, 1) denotes a random number within [0,1], and P_{cr} is the crossover operator is also a random number which also takes values in the range [0,1], from which it is decided whether the crossover occurs. Finally, a selection is made and its equation is given in Eq. (3.4).

$$x_i(g+1) = \begin{cases} u_i(g) \ f(u_i(g)) > f(x_i(g)) \\ x_i(g) \ f(u_i(g)) \le f(x_i(g)) \end{cases} \tag{3.4}$$

As shown in Eq. (3.4), $u_i(g)$ and $x_i(g)$ denote the fitness of the two types of individuals in generation $g$respectively. the crossover vector is optimally selected by comparing its suitability with the original vector, leaving the one with the higher suitability behind to complete the selection of the best and the worst. To overcome this problem, the PSO algorithm is improved by incorporating the DE algorithm to produce a more intelligent optimisation algorithm. The algorithmic flow is shown in Fig. 1.

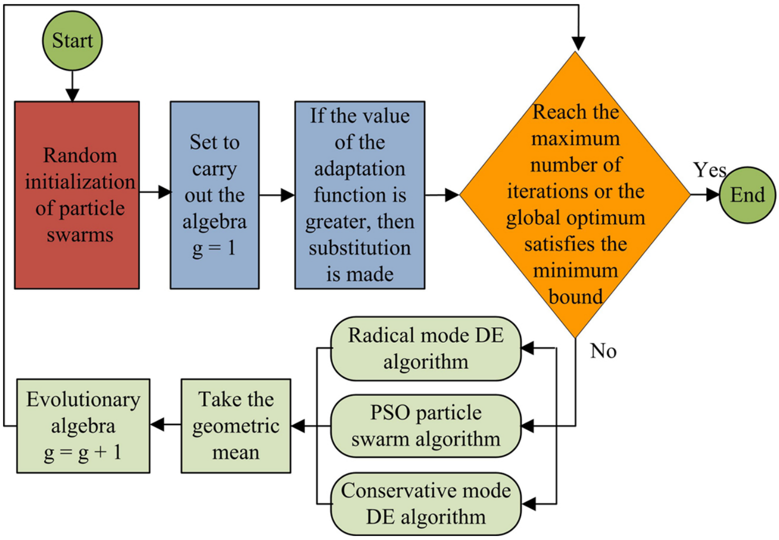

Fig. 1. PSO-DE algorithm flow

The PSO-DE three population algorithm is shown in Fig. 1, where three populations are used for the calculation, namely the radical DE algorithm, the conservative DE algorithm and the PSO algorithm. The variability of the DE algorithm can be adjusted by adjusting the value of the crossover operator P_{cr}. A lower value of P_{cr} reduces the degree of variability i. e. the conservative DE algorithm and a high value of P_{cr} increases the degree of variability. While the stable DE algorithm is suitable for finding OSs in a small range with multiple local extremes, the radical DE increases the ability to search for OSs in a large range. The use of the PSO algorithm for parallel computation on top of the Radical DE and Conservative DE algorithms allows good search performance even in the face of dynamic multi-objective problems. It is crucial to observe that the inertia factor of the single PSO algorithm is no longer appropriate for the adapted algorithm, so the study proposes a non-linear inertia factor adjustment method to optimise the algorithm inertia weights, whose equation is given in Eq. (3.5).

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min})e^{-m\left(\frac{t}{t_{\max}}\right)^2} \tag{3.5}$$

As shown in Eq. (3.5), m is the control factor for the smoothness of the $\omega - t$ curve for this equation. ω denotes the inertia weights, and $\omega_{\max}$ and $\omega_{\min}$ denote the maximum and minimum values of the weights, respectively. In order to imitate the premature convergence of the PSO-DE algorithm, it is also necessary to mutate when stagnation occurs, the study proposes a temporary mutation method, whose algorithm is shown in Eq. (3.6).

$$\begin{cases} x_i(t) = x_i(t-1) = x_i(t-2) = \ldots = x_i(t-m) \\ x_i(t-m+1) = x_{\min} + \mathrm{rand}(0,1) \times (x_{\max} - x_{\min}) \end{cases} \tag{3.6}$$

As shown in Eq. (3.6), when the above equation holds and $x_i(t) \neq x_i(\eta)$, carry out the variation shown below $x_i(\eta)$ is the value of the ith component of the OS for the whole population m is the upper limit of the number of stalls.

3.2. AB construction project strategy problem model construction

A public housing project located in a specific area was selected as a case study for the study, consisting of five buildings, each with four 2-story units, with a total floor area of 19,206 m^2 and a land use area of 3,199 m^2. The length of each building is 62.97 meters and the width is 10.97 meters. Each floor is 3 meters high with a net interior height of 2.9 meters. Table 1 presents the flow chart and constraints for parameter conversion.

Table 1. Parameter conversion

i	Item No.
k	Resource Number
R_k	Supply of a resource
r_{ik}	Project i's demand for k resources
s_i	Start time of item i
f_i	Completion time for item i
A_t	Collection of projects being completed at time t
ω	Compensation factor
D	Deadline
T	Actual duration
H	Delayed work
λ_k	Resource costs
G_i	Collection of immediately preceding tasks for project i

Assuming that the resource usage at each moment is less than the maximum resource, the solution for the shortest duration is converted to Eq. (3.7).

$$\min\ d \begin{cases} \sum\limits_{i \in A_i} r_{ik} \leq R_k \\ \max\limits_{j \in G_i} f_j \leq s_i \\ d = \max\limits_{i}(f_i) - \min_i(f_i) \end{cases} \tag{3.7}$$

To ensure greater stability when using scattered data, the Sigmoid function is employed for smoothing the number of days in Eq. (3.7), which serves as the objective function. This helps to mitigate the large fluctuations that might arise during the convergence process, see Eq. (3.8).

$$S(x) = \frac{1}{1 + e^{-x}} \tag{3.8}$$

After compressing the duration days d, smoothing is carried out using the Sigmoid function, and it should be noted that the economic benefits are not considered in this equation. Because of the actual construction project, the tasks are sequential, and the task i will only be processed when all the construction of task G_i is completed. The solution equation for seeking the maximum economic benefit is shown in Eq. (3.9).

$$\min\left\{H\omega + \left(\sum_k \left(\max_{i\in N_k} f_i - \min_{i\in N_k} s_i\right)\lambda_k\right)\right\}$$
$$\begin{cases} \sum_{i\in A_t} r_{ik} \le R_k \\ \max_{j\in G_i} f_i \le s_i \\ d = \max_i f_i - \min_i s_i \\ H = \max\{T - D, 0\} \end{cases} \tag{3.9}$$

As shown in Eq. (3.9), $\sum_{i\in A_t} r_{ik} \le R_k$ indicates that the sum of the resources used for each task is less than the maximum amounts of resources R_k. If the duration is fixed, it is imperative to minimise expenditure to achieve maximum economic efficiency. The challenge is to reduce both overrun and construction costs. The total duration represents the duration from the start of the project until completion of the final task. Any excess duration over the actual time incurred is reimbursed to us. Given this constraint, the algorithm converges to determine the most economically effective sequence of task decisions and solve for the optimal solution (OS).

4. Performance test of PSO-DE algorithm to solve ab construction project decision making problem

After transforming the parameters of the AB construction project decision problem and building a PSO-DE algorithm that can solve the problem, its usefulness in solving the real problem needs to be confirmed. The performance of the PSO-DE algorithm is first tested and then used to optimise the AB construction project decision problem once the expectations have been met and the results analysed.

4.1. PSO-DE algorithm performance testing

Take a guaranteed housing project in a certain place as an example research object, the project is a frame structure, there are 5 blocks, each block includes 4 units of six floors, the building area is 19,206 m^2, covers an area of 3,199 m^2. single floor east-west length of 62.97 m, north-south width of 10.97 m. the height of the storey is 3 m, the net height of the interior is 2.90 m. The main part of the house adopts the assembly construction method with pre-ordered components, air-conditioning panels are poured on-site, prefabricated wall panels are used for both the inner and outer wall panels of the main structural part, and laminated panels are used for the structural floor slabs and staircases, while the staircases and balconies are in prefabricated assembled form. The data therein are all derived from field visits.

First, the performance of the PSO-DE algorithm was evaluated using the test functions, with the maximum number of iterations set to 1500 and the number of algorithm runs set to 20. These test functions included Sphere, Rosebrock, Rastrigin and Griewank. Figure 2 shows the mean, maximum, minimum and standard deviation of the PSO-DE algorithm test functions.

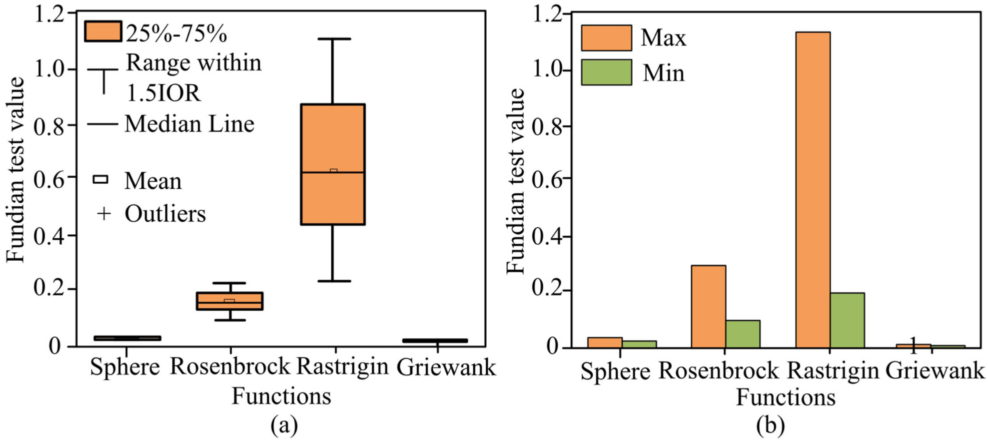

Fig. 2. Sphere, Rosebrock, Rastrigin, Griewank function test results: (a) Functional analysis box plot, (b) Functional analysis histogram

In Fig. 2, the PSO-DE performs very well after 20 iterations, and the Sphere and Griewank functions have converged significantly after 20 iterations, with mean and standard deviation performance approaching baseline levels. However, the performance of the Rosebrock and Rastrigin test functions was poor, especially for Rastrigin, probably due to the fact that this function is a cosine modulated transfer function, which frequently produces local minima during the test iterations, and the over-distributed minima lead to inefficient convergence. In order to verify the excellent performance of the PSO-DE algorithm, the Holder test function is used to test the optimization of the three algorithms, GA, PSO and PSO-DE algorithms, and the results are shown in Fig. 3.

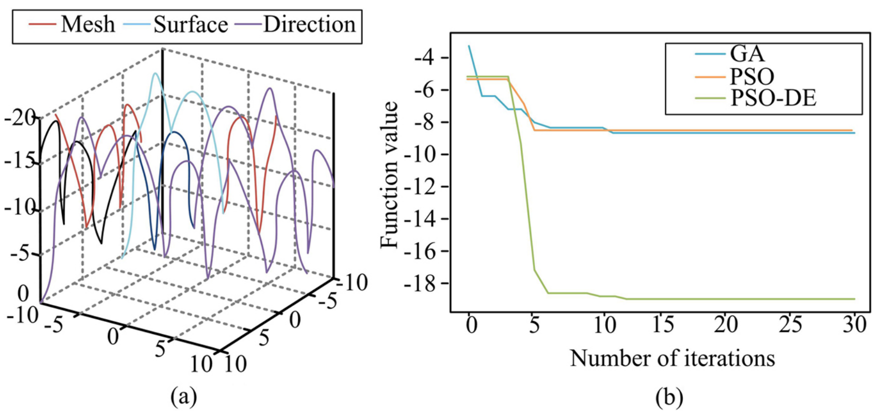

Fig. 3. Holder function test results: (a) Holder, (b) Holder function test results

Figure 3 presents a simplified 3D diagram of the holder function, indicating the occurrence of numerous local minima and the substantial obstacles involved in optimization. The regional minimum is –19.4. Additionally, Fig. 6(b) displays the results of optimizing the holder function using four algorithms. The PSO algorithm has the best findings, considering that the optimal domain is [–8.101, 6.478] and the OS is –9.504; nevertheless, it does not converge to the actual function's solution. The results of the PSO-DE algorithm curve indicate that the optimal range is [8.055, –9.665], with an OS of –19.208, which converges to the true solution range of the function. In contrast, the ABC function completes convergence within five iterations, though its outcomes are comparable to those of the GA and PSO algorithms, which cause the local OS to converge prematurely. The comparison indicates that the introduction of the PSO-DE variation mechanism for the DE algorithm has proven remarkably efficient in allowing stuck algorithms to continue iterating, significantly increasing the accuracy of solutions. To obtain a more accurate assessment of PSO-DE's performance, testing was conducted on the Sphere, Ackley, and Beale functions using PSO, GA, and PSO-DE, with the findings presented in Fig. 4.

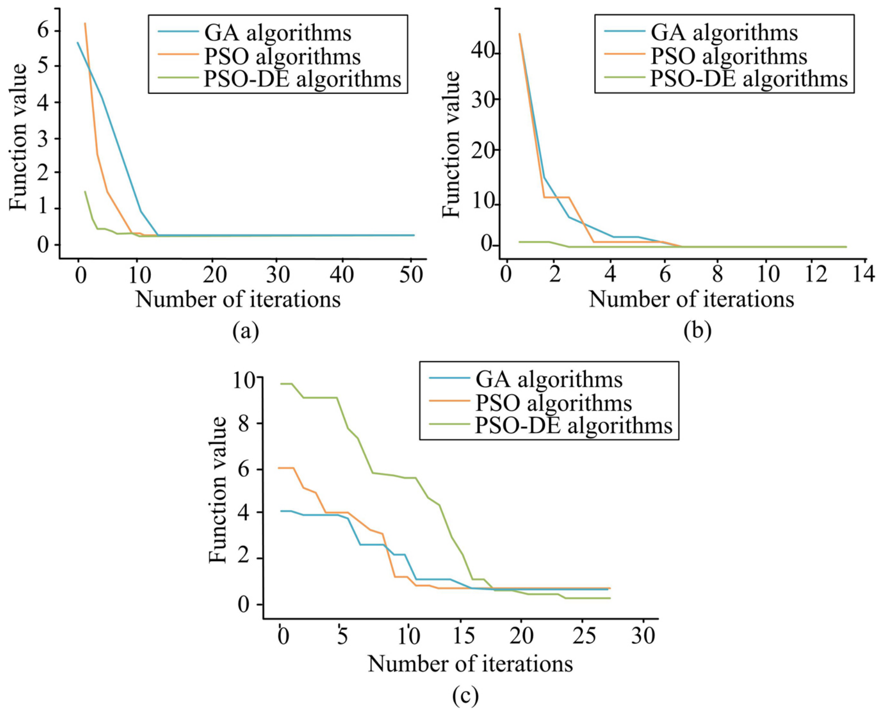

Fig. 4. Function test chart: (a) Sphere, (b) Beale, (c) Ackley

As demonstrated in the above Figures, the results of function tests for the Sphere, Beale and Ackley functions are presented. Since the Sphere function has clear convexity and is simple to optimise, the solution for all three algorithms perform well and the optimal solutions can be found easily. Figure 4(b) displays the resolved Beale function, which is a multi-peaked function, and although all three algorithms yield optimal solutions, the rate of achieving optimal solutions via PSO-DE is more prominent. As the three populations communicate with each other and descend simultaneously from the spikes, they converge at a better rate and direction. Consequently, the results signify the superior computational performance of the PSO-DE algorithm in solving multi-peaked optimization problems. All methods depicted in Fig. 4(c) converge within 20 iterations, with the PSO algorithm and GA technique reaching convergence more rapidly, after approximately 12 cycles. However, due to its population exchange and variation mechanism, which can be constantly updated and adjusted, it eventually converges to the global OS. This also shows the trade-off between computational speed and computational accuracy of the PSO-DE algorithm, sacrificing some of the computational speed for higher computational accuracy.

4.2. Optimizing quality analysis of decision making issues in AB construction projects

Firstly, the PSO-DE algorithm is used to solve the shortest duration decision-making problem, and the more advanced Deep Reinforcement Learning (DRL) and Hybrid Intelligent Algorithms (HIA) are used to compare the experiments, and the duration is smoothed using the Sigmoid function, and the results of its solution are shown in Fig. 5.

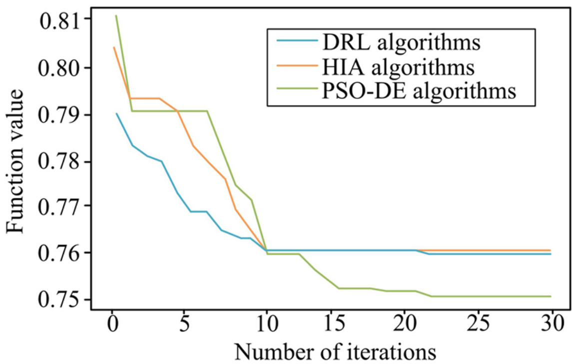

Fig. 5. Results of the PSO-DE algorithm for the shortest duration decision problem

As shown in Fig. 5, all three reach convergence when the number of iterations reaches 10, and the results of the HIA algorithm and the DRL algorithm are consistent. However, in the subsequent solution, the PSO-DE algorithm continues to converge to the optimal solution through mutation, which has a higher algorithmic complexity compared to the HIA algorithm and the DRL algorithm, and the speed of operation will be slower will be established in the shortest duration function, using the PSO-DE algorithm iteration, and then use the Sigmoid function for smoothing to obtain the objective function value of 0.755, the shortest duration of its The shortest construction period can be reduced to 45 days. Figure 6 displays the outcome of the comparative experiments conducted using the traditional DRL algorithm and the HIA algorithm.

As shown in Fig. 6, convergence is essentially complete when the number of iterations reaches 5–10 rounds, but it essentially stagnates after ten rounds. In contrast, the PSO-DE algorithm starts slower, but after quickly locking in the optimal solution domain, the convergence is repeated and the speed is reduced. The PSO-DE algorithm results in an economically optimal scheduling decision with a cost of 500,000 and a duration of 52 days. In this decision problem,

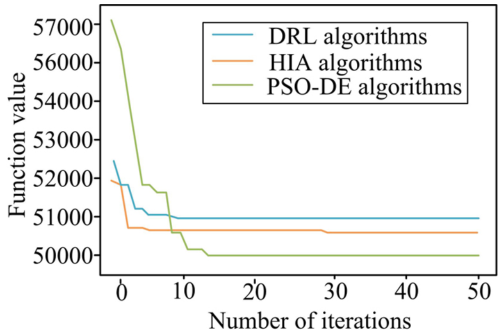

Fig. 6. Results of the PSO-DE algorithm for the economically efficient optimal scheduling decision problem

there is a need to balance the penalties for project overruns and the cost of resources, and the PSO-DE algorithm balances these two factors to achieve the optimal result.

The simulation test object is set to be an assembled structural design of a 3-story villa, which is made of a combination of prefabricated component walls, prefabricated component columns, prefabricated component beams, and prefabricated component panels. In order to visually and quickly compare the optimization effect of the building structural design of a random floor before and after the application of the model proposed in this study, the study draws the structural design template before and after the application, as shown in Fig. 7.

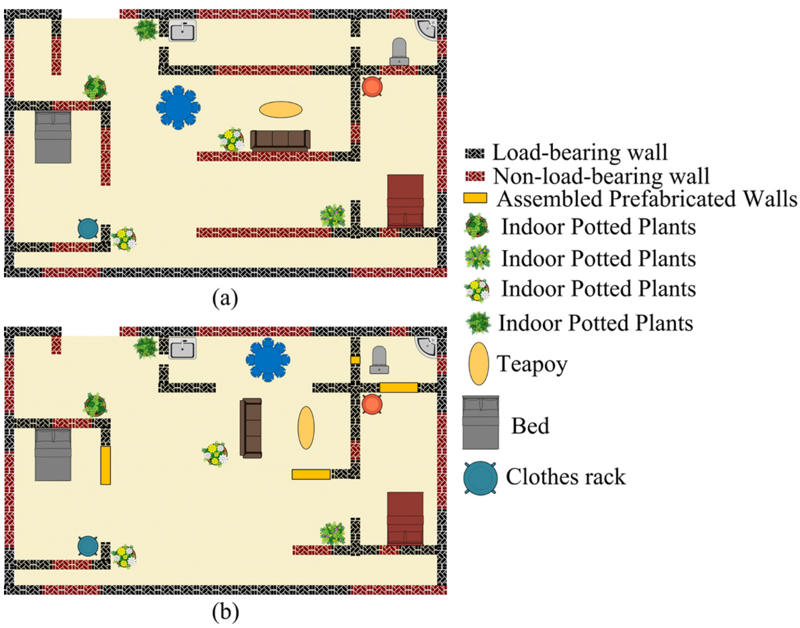

Fig. 7. Wall configuration diagram before (a) and after (b) optimization

Figure 7(a) shows the wall configuration before optimization and Fig. 7(b) shows the wall configuration after optimization. In Fig. 7, the black walls are load-bearing walls, the red walls are non-load-bearing walls, and the yellow rectangles are assembled prefabricated walls. As can be seen in Fig. 7, after optimization by the Decision Optimization Model for Assembly Building Construction Project, most of the non-load-bearing walls were removed and the layout format was slightly changed. Some of the necessary wall connection structures were added with assembled prefabricated walls, which carried out to reduce the material and expense of concrete walls, save time and improve the space utilization.

5. Conclusions

The fused DE method's variational properties are examined, and a PSO-DE approach that combines three swarm algorithms is proposed to resolve the decision problem of the AB project. As per the performance test outcomes, the PSO-DE algorithm does not sufficiently respond to inquiries regarding the minimum value of the dense distribution for the Sphere, Rosebrock, Rastrigin, and Griewank function as its convergence reached completion after 20 iterations. In comparison to GA, PSO, and ABC algorithms on the Holder function, the results show that PSO-DE algorithm completes convergence within 10 times, the optimal domain is [8.055, –9.665], and the OS is –19.208. The PSO-DE algorithm converges significantly more quickly than the other functions for addressing multi-peak optimisation issues, and the results are stable and have good robustness performance, according to the results of evaluating the Sphere function, Beale function, and Ackley's function using GA, PSO, and PSO-DE. The PSO-DE algorithm determined that for the AB project choice problem, sigmoid smoothing yields a minimal duration problem of 0.755 and a minimum length of 45 days. While it can consistently converge after stagnation to produce the best solution, it requires more computing time compared to DRL and HIA functions, which are typically used to tackle the AB project choice problem. The optimum cost and duration for the PSO-DE algorithm to address the maximisation of economic efficiency are 500,000 and 52 days, correspondingly. The study indicates that the PSO-DE algorithm surpasses conventional algorithms for the AB project choice problem with respect to computational precision. Nevertheless, there is room for improvement in terms of computational speed – an area that future research could address.

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