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Multi-objective optimization analysis of construction management site layout based on improved genetic algorithm

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ABSTRACT

In construction management, the rationality of on-site layout is crucial for project progress, cost, and safety. In order to improve the rationality of on-site layout, a multi-objective optimization model combining ant colony algorithm and Pareto optimal solution was constructed based on genetic algorithm, and this model was applied to practical engineering cases. The results show that in terms of computational time, the genetic algorithm takes an average of 1702.0 s, while the improved algorithm takes an average of 421.0 s, which is 1281s less and 85.9% more than before the improvement. The performance of the improved algorithm is the best, and the optimal solution can be obtained through multiple iterations. The improved algorithm has improved the efficiency of on-site layout optimization, and possesses practical application value for the layout of construction management sites. It offers a certain reference for the reasonable setting of construction management sites.

1. Introduction

Recently, as the boost of China's economy, the construction industry is an essential pillar industry of China's economic advancement, and industry advancement has prompted construction enterprises to self transform. The on-site layout (OSL) is an essential part of the construction, and project management may take consideration into the OSL. However, in the entire project construction management, there is not enough emphasis, and on-site management personnel often plan the OSL on the ground of their own experience, without a scientific management system [1]. The Genetic Algorithm (GA) is a computational model that simulates the natural selection and genetic mechanisms of Darwin's biological evolution theory, as well as a method of searching for optimal solutions (OSO) through simulating the natural evolution [2]. Ant colony algorithm (ACA) is a probabilistic algorithm utilized for finding optimal paths, inspired by the behavior of ants discovering paths while searching for food [3]. Therefore, the multi-objective optimization (MOO) model combining the global search capability of GA and the local search algorithm of ACA, as well as the Pareto optimal solution, is applied to the field of construction project management. The aim of the study is to be able to explore the solution space more comprehensively and maintain a balance between multiple objectives. The core achievements of this study are reflected in the efficiency of using GA to search for global optimal solutions and the accuracy of ACA in searching for local optimal solutions. The proposed model can explore the solution space more deeply and comprehensively for dealing with multi variable and multi constraint problems in construction project management, improving the possibility of finding the optimal solution. The proposed model applies Pareto optimal solutions, effectively achieving a balance between multiple project management objectives such as cost, time, and quality, and optimizing the overall performance of project management. The main contribution of this study is to improve the overall management efficiency and success rate of projects. The proposed model is integrated into a wider range of project management systems, providing managers with real-time, data-driven decision support. This study provides a new approach to using hybrid optimization techniques to solve complex engineering problems, and future research can explore more algorithm fusion and application scenarios based on this foundation. The research mainly includes four parts. The first part is a summary of research on the layout of construction management sites. The second part introduces the MOO of construction management site layout (SL) using improved GA. The first section is about the construction of a layout model for the construction management site. The second section focuses on MOO of construction management SL using Pareto ant colony GA. The third part is the analysis of MOO results for the layout of construction management sites using improved GA. The first section introduces the parameter settings of ACA and GA. The second section is the optimization analysis of the improved algorithm. The fourth part is the conclusion of MOO analysis of construction management SL using improved GA.

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2. Related works

The scientific and reasonable layout of the construction management SL is helpful for improving construction efficiency and systematic management. Many experts have conducted relevant research in this regard. Ning et al. utilized a hybrid GA ant colony MOO model for planning the construction SL to reduce noise pollution to workers, addressing the transportation costs and potential safety risks caused by the interaction between on-site facilities. The results indicate that the model is effective and feasible [4]. Xue and other professionals use improved biogeographical optimization algorithms to schedule the production of prefabricated components, which facilitates the formulation of more scientific and reasonable production plans, reduces costs, and improves the efficiency of the entire prefabricated building project. The results indicate that the model has a certain effect [5]. To collect and process all data used for SL modeling using systematic methods, Le's team has built a multi-objective dynamic temporary construction SL design framework to save costs and ensure preferences for temporary facility relationships. The results indicate that the model has practicality [6]. Lee analyzes the construction plan of modular projects through building information models to address the issue of on-site construction planning, and completes the application analysis of efficiency and necessity. The results indicate that this method has good effectiveness [7]. Scholars such as Schwabe, to complete the layout planning task of construction sites, combined the business rule management system of industry foundation classes and open source rule engine Drools to assist managers in decision-making tasks. The results indicate that this method can safely achieve planning tasks [8]. Li and other researchers proposed a dynamic visualization platform that combines GA and low rank matrix for dynamic planning of building component storage areas, which can automatically identify vacant locations on site in real-time. The results show that the construction efficiency of this method has been improved by 19.4%, and the processing cost has been reduced by 21.9% [9].

Improved machine algorithms have wide applications in various aspects. A large number of scholars have conducted relevant research and achieved good results. For addressing the high economic costs in the closed-loop logistics network of fresh food, scholars such as Huo Q have built a relevant logistics network model on the ground of GA. The results show that the MOO satisfaction of the model reaches 92%, which has a certain effect [10]. Chen designed an improved GA based green cold chain logistics location and path optimization method to address the distribution efficiency and cost issues of cold chain logistics, effectively reducing carbon emissions and costs during the cold chain distribution process, and accelerating convergence speed. The results indicate that this method is feasible [11]. To enhance the efficiency of urban green economy, professionals such as Liu T have proposed a model for urban green economy planning that combines machine learning and GA for simulation analysis, and measures inputs and expected outputs. The results indicate that the model is effective [12]. Ala 's team designed long-term and short-term memory and particle swarm optimization to improve efficiency and security for the classification accuracy of patient medical data. Various indicators and benchmarks were determined, and the results showed that the accuracy of this method was 92% [13]. In order to reduce the cost of warehouse systems, Attari et al. built an automatic reverse storage mathematical model to improve profits, optimize latency, and total costs. The results showed that the algorithm has good performance [14]. Ala et al. designed an intelligent trading system with Markov logic network to improve operational efficiency for efficient retail supply management, and the results showed the feasibility of the system [15].

In summary, there have been many good results in the layout of construction management sites and the improvement of GA, but there is still relatively little research combining the two. In order to improve construction efficiency and implement system management, the global search capability of GA and the local search algorithm of ACA were combined with the multi-objective processing strategy of Pareto optimal solution to construct an optimization model for the construction site layout plan. Taking the renovation project of the teaching building as an example, verify the model.

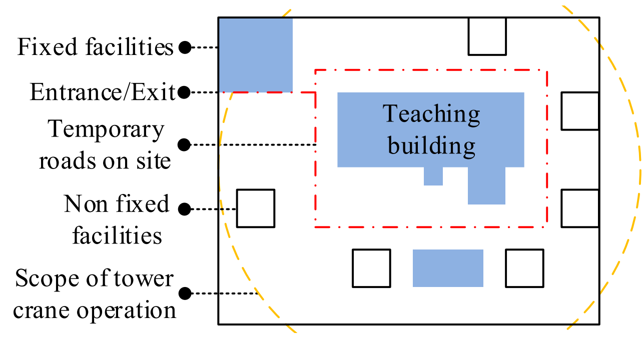


Fig. 1. Layout plan of construction site.

3. Multi-objective optimization of construction management site layout on the ground of improved genetic algorithm

To improve the rationality of OSL and optimize project management safety, cost, and environmental objectives, a GA is used to establish a construction SL model, thereby establishing an optimization objective function for cost. At the same time, Pareto ant colony GA is used to establish a MOO model for construction management SL, which optimizes the cost objective mathematical function of the SL.

3.1. Building a layout model for construction management sites

To achieve the integration, coordination, and integration of the entire project construction, the purpose of the construction SL of the building project is to assist the entire project construction and integrate various parts such as management personnel, materials, facilities, etc. The MOO of construction management SL is aimed at the aspect of layout. Firstly, the cost optimization algorithm is used to obtain the plan for SL. Secondly, it further strengthens the collaborative work of various processes through management methods, which can achieve multiple goals of optimal cost, good safety, and minimal construction impact on the environment. Before solving this problem, it is assumed that the total area required for all facilities is the same, that is, any facility can be placed in any vacant space, and any vacant site can accommodate the facilities to be arranged. Secondly, it is assumed that the mechanical and facility projects have already been clarified. The location of the final fixed facilities has been determined in advance [16]. The layout plan of the construction site is shown in Fig. 1.

In Fig. 1, the construction task lasts for 10 months, and the flat area of the construction site is rectangular, with dimensions of 100 m long and 80 m wide. The teaching building covers an area of 682.8m^2, with a total construction area of 3099.0m^2. The building has five floors above ground and a height of 20.950 m from the outdoor ground to the roof surface. Reinforced concrete frame structure with seismic fortification intensity of 8°. The QTZ80 (TC5610) tower crane was selected for the project to facilitate lifting, with a working radius of 55 m. The construction site roads are set up in the inner area of the building's peripheral facilities to facilitate on-site transportation and save transportation distance. Due to the numerous materials, machinery, and complex facilities involved in the construction site, especially the large size of some project sites, the management area will be divided to distinguish which are needed at the current stage of the site and which are not needed at the site. Secondly, it searches for various locations on the site plane and organizes, registers, and cleans up any unnecessary items on site. And the construction site plane design management zoning is shown in Fig. 2.

In Fig. 2, there are eight parts: material stacking area, machinery

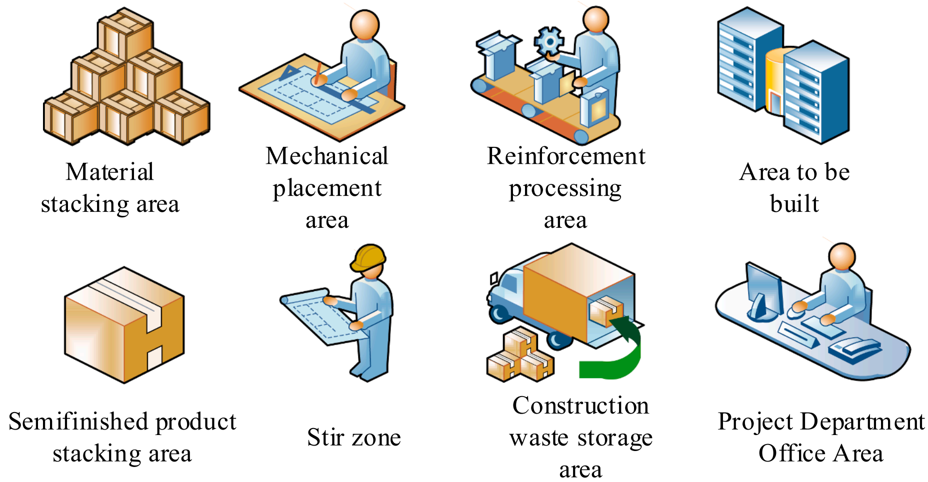


Fig. 2. Construction site graphic design management zoning.

placement area, including tower cranes, material elevators, steel processing area, building area to be constructed, semi-finished product stacking area, construction waste stacking area, mixing area, and project department office area. There are many elements that influence the layout of the construction site, and the three major elements of a construction project are time, quality, and cost. So the construction management SL can be optimized from these three aspects. When studying the layout of construction management sites, it is difficult to quantify the construction quality, which limits the direct indicators that can be used for mathematical modeling. The study chose transportation time and cost, which are relatively easy to measure and calculate, as the main quantitative indicators. The objective function is defined as considering both transportation time and cost simultaneously. That is, the established construction SL model only considers its transportation time and cost. Transportation time refers to the time for personnel movement and the transportation of building materials, depending on the means of transportation and distance. Its transportation time is set to, as expressed in Eq. (1).

$$T = \sum\nolimits_{j=1}^{n} \sum\nolimits_{i=1}^{n} \frac{t_{ij} d_{ij}}{v_{ij}} + \sum\nolimits_{j=1}^{n} \sum\nolimits_{i=1}^{n} \frac{f_{ij} d_{ij}}{u_{ij}} \tag{1}$$

In Eq. (1), n serves as the quantity of facilities. t_{ij} serves as the transportation frequency. d_{ij} serves as the transportation distance between two facilities. v_{ij} serves as the speed of the selected transportation method between two facilities. f_{ij} is the frequency of personnel turnover. u_{ij} is the walking speed of a person. The design cost is C, the cost includes two aspects: material transportation cost and construction cost of temporary facilities. The cost calculation expression for the flow of engineering materials between facilities and facility layout on the construction site is shown in Eq. (2).

$$C = \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} \left[d_{ij} \sum\nolimits_{k=1}^{n} \left(p_{ijk} q_{ijk} \right) \right] + \sum\nolimits_{i=1}^{n} t_{ij}(x_i, y_i) \tag{2}$$

In Eq. (2), p_{ijk} is the transportation price per unit quantity of materials. q_{ijk} is the transportation quantity of materials between two facilities. $t_{ij}(x_i, y_i)$ is the cost required to establish a temporary facility at a certain location. The objective function for optimizing the construction SL is the synthesis of these two indicators. Due to the different dimensions of these two indicators, it is necessary to dimensionalize them and assign them appropriate weights to obtain the comprehensive objective function. It uses the min max standardization method to dimensionalize, and the function expression is shown in Eq. (3).

$$y_i = \frac{x_i - \min x_i}{\max x_i - \min x_i} \tag{3}$$

In Eq. (3), $\max x_i$ and $\min x_i$are the maximum and minimum values that can be obtained from the numerical value x_i. From this, the dimensionless values of cost and transportation time can be obtained separately. In terms of weight allocation between the two objectives, this study determines the specific values of the weights of the transportation distance and cost sub objectives using expert scoring method, as shown in Eq. (4).

$$S = \min(\omega_1 T^* + \omega_2 C^*) \tag{4}$$

In Eq. (4), ω_1 and ω_2 are the weights of transportation distance and cost, respectively. Where T^* is the minimum total time cost after optimization, as shown in Eq. (5).

$$T^* = \min \sum\nolimits_{j=1}^{n} \sum\nolimits_{i=1}^{\min} \frac{t_{ij} d_{ij}}{v_{ij}} + \sum\nolimits_{j=1}^{n} \sum\nolimits_{i=1}^{\min} \frac{f_{ij} d_{ij}}{u_{ij}} \tag{5}$$

C^* is the minimum total cost after optimization, as shown in Eq. (6).

$$C^* = \min \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{\min} \left[d_{ij} \sum\nolimits_{k=1}^{\min} \left(p_{ijk} q_{ijk} \right) \right] + \sum\nolimits_{i=1}^{\min} t_{ij}(x_i, y_i) \tag{6}$$

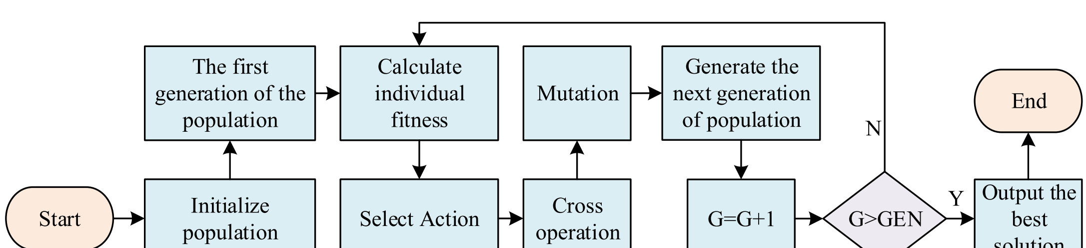


Fig. 3. Flow of genetic algorithm.

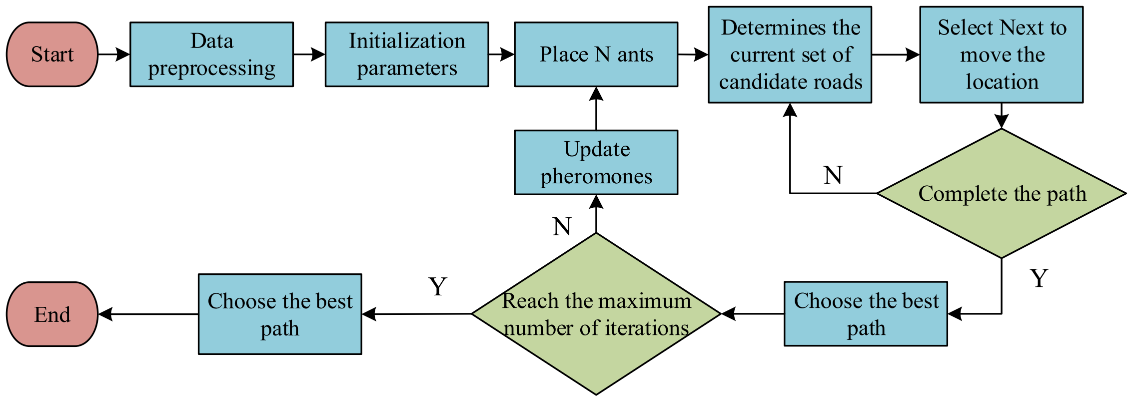


Fig. 4. ACO algorithm flow.

3.2. Multi-objective optimization of construction management SL based on improved genetic algorithm

After constructing a construction management SL model, the construction management SL can be seen as a secondary allocation problem. GA is a self-learning heuristic optimization algorithm. It randomly generates a set of initial solutions, calculates the fitness function values of each initial solution, and uses them as a criterion to judge the quality of the solution. Then, through genetic operations, the OSO is selected and passed on to the next generation [17]. The quality of the next generation solution is affected by the quality of the previous generation solution. The process is showcased in Fig. 3.

In Fig. 3, the GA algorithm through special methods and operations transforms the problem-solving process into a process resembling the crossover and mutation of chromosome genes in biological evolution. The design of the construction SL adopts a proportion selection operator. The content of its selection operator is that the probability of genetic operation on a single selection in the population is proportional to its fitness function value [18]. This study sets population size N, population $P = \{a_1, a_2, ..., a_n\}$.One individual $a_j \in P$ is randomly selected with an adaptation value of $f(a_j)$, and the probability value of each individual in the next generation population, as shown in Eq. (7).

$$P(a_j) = \frac{f(a_j)}{\sum_{i=1}^{n} f(a_j)}, a_j = a_1, a_2, ..., a_n \tag{7}$$

Each iteration generates a random number between [0,1] as a pointer to lock the selected individual. The above formula indicates that the larger the fitness function value of an individual, the higher the probability of being selected and retained. On the contrary, the probability of being selected and retained is smaller. The retained individuals can pair up and then cross again. F_{a_i} serves as the fitness of individual a_i, and the probability of individual a_i being chosen and passed through genetic manipulation to the next generation population is shown in Eq. (8).

$$P_{a_i} = F_{a_i} \Big/ \sum_{a_i=1}^{n} F_{a_i} \tag{8}$$

ACO performs the best in solving secondary allocation problems. Its outstanding features include positive feedback, parallelism, and self catalysis, as well as strong robustness, excellent distributed design, and easy integration with other algorithms. However, its most prominent shortcomings are long search time and easy to fall into local optima [8]. The ACO algorithm process is shown in Fig. 4.

In Fig. 4, the ACO algorithm first preprocesses the data, then initializes parameters to prevent N ants. Then, the algorithm determines the current candidate road set for each ant and selects the next moving position on the ground of probability. If the path is not completed, redefine the road set. If the path is completed, the best path is selected, and the best path is selected when the maximum quantity of iterations is achieved. If the maximum quantity of iterations is not achieved, update the pheromone and reposition the ants. It determines the heuristic information of the problem on the ground of its characteristics, and the heuristic information of different problems varies. Therefore, ACA can more effectively solve various problems. For the quadratic allocation problem, the heuristic information$n_{ij}(t)$ can be expressed as Eq. (9).

$$n_{ij}(t) = \frac{1}{e_{ij}(t)} \tag{9}$$

In Eq. (7), f_i is the sum of flows between facility i and other facilities. d_j is the sum of the distances between position j and other positions. $p_{ij}^k(t)$ represents the probability of state transition of ant k from point t to point j at time i, as shown in Eq. (10).

$$p_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{l \in N_i^k} [\tau_{il}(t)]^\alpha \cdot [\eta_{il}(t)]^\beta} \tag{10}$$

In Eq. (10), $\tau_{ij}(t)$ serves as the pheromone information at iteration t. $\eta_{ij}(t)$ serves as the heuristic information between facility i and location j. α and β represent the relative influence parameters of pheromones and heuristic information, respectively. N_k^i is a selectable location near the i point. After all ants complete a task, the pheromones generated by each ant on the path should be updated. In addition to being influenced by passing ants, the pheromones on the path will also evaporate over time. Update the expression of pheromone calculation, as shown in Eq. (11).

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}^{best} \tag{11}$$

In Eq. (11), $\rho(0 < \rho < 1)$ is the residual factor of pheromone information. $\Delta\tau_{ij}^{best}$ is the increment of pheromones. τ_{ij}^{best} is solved as shown in Eq. (12).

$$\tau_{ij}^{best} = \begin{cases} \dfrac{1}{F_{\phi^{best}}} \\ 0 \end{cases} \tag{12}$$

In Eq. (12), ϕ^{best} is the OSO retrieved in this iteration. $F_{\phi^{best}}$ is the objective function solved as ϕ^{best}. The MOO problem is written as the following mathematical model, as shown in Eq. (13).

$$\min f(X) = (f_1(X), f_2(X), ..., f_n(X)) \tag{13}$$

In Eq. (13), $f(X)$ represents all objective functions that need to be considered, with the goal of achieving the minimum value. The relevant conditions are showcased in Eq. (14).

$$s.t. g_i(X) \leq 0 \tag{14}$$

The range of decision variables is shown in Eq. (15).

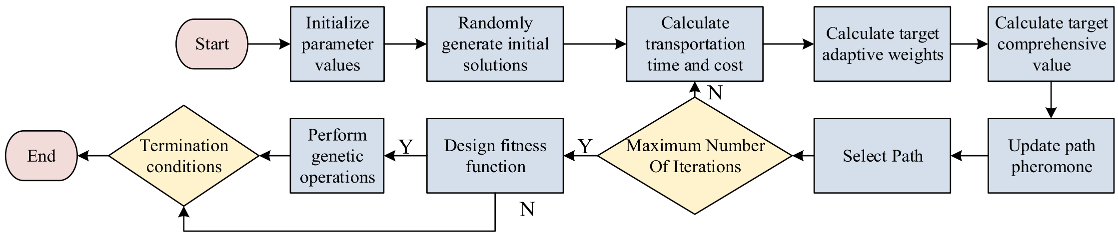
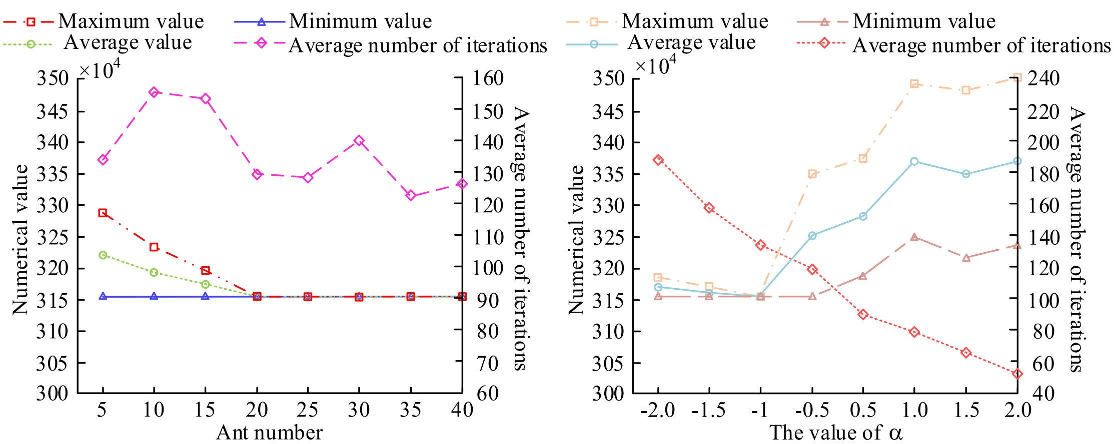


Fig. 5. Process for improving algorithms.



(a) The Influence of Different Ant Numbers on Algorithm Results

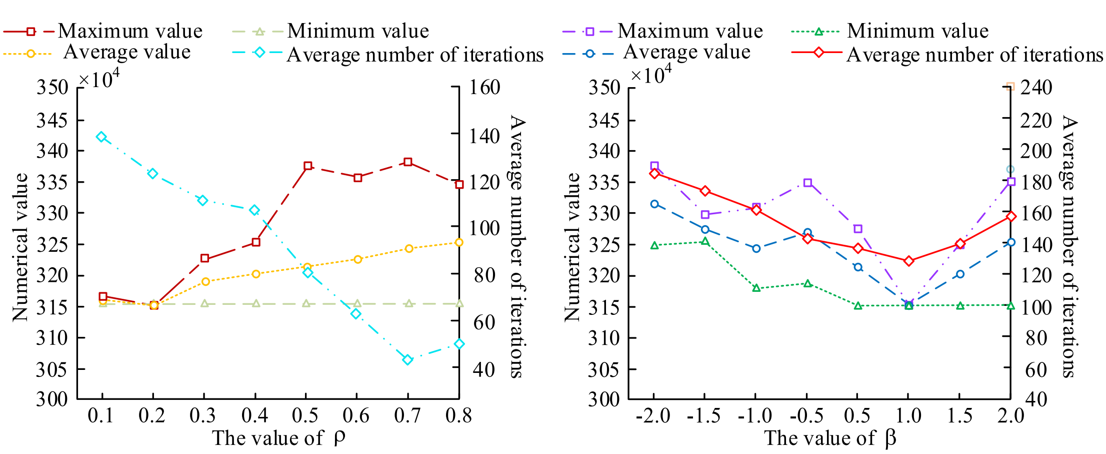
(b) The influence of different pheromone influencing parameters on algorithm results

Fig. 6. Solution of the algorithm with different parameter values.

$$X = (x_1, x_2, \dots, x_m)^T \tag{15}$$

For enhancing the initial solutions, thereby enhancing the quality of offspring solutions, and improving the operational efficiency and performance of GA, the optimal initial solution is found through ACO. Then, through the powerful search function of GA, it can be further optimized to design an algorithm that combines the two algorithms, improving the efficiency and performance of solving quadratic allocation problems [19]. This study transforms MOO problems into single objective problems, and then searches for the OSO through single objective optimization methods. Then it solves the MOO problem of building construction management SL, setting two goals first, cost and safety. Afterwards, the study synthesized these two objectives into a single objective and optimized it using Pareto ant colony GA. The process of improving the algorithm is shown in Fig. 5.

In Fig. 5, the initialization parameter values are randomly generated to generate initial solutions, calculate cost and transportation time, calculate target adaptive weights, calculate target comprehensive values, and update path pheromones. Then it selects the path for each ant and determines whether it is the maximum number of iterations. If it matches, design a fitness function, perform genetic operations, and finally output the Pareto solution set.



(a) The influence of different pheromone residual factors on algorithm solving

(b) The Influence of Different Heuristic Information on Parameters on Algorithm Solving

Fig. 7. Solution of the algorithm when two parameters have different values.

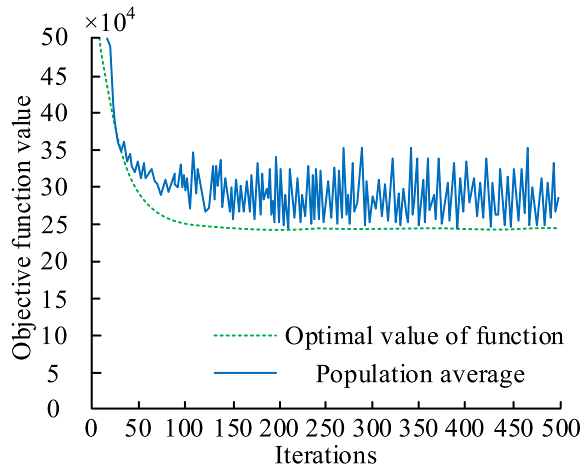


Fig. 8. MATLAB operation function values.

4. MEthods/experimental: analysis of multi-objective optimization results for OSL of construction management using improved genetic algorithm

This study introduces the parameter setting of ACA and GA, as well as the optimization analysis of improved algorithms.

4.1. Parameter setting of ant colony algorithm as well as GA

The parameters of ACA include the number of ants, pheromone influence parameter α, heuristic information influence parameter β, and pheromone residual factor ρ. To achieve optimal search results and keep other parameters unchanged, the influence of different ant numbers and pheromone influence parameters α on the algorithm solution was studied. The relevant results is showcased in Fig. 6.

In Fig. 6(a), when the quantity of ants is 20 or more, the OSO for each running problem is 3,153,023, and the average number of iterations at this time is 130. When the number of ants is 20–40, the maximum, minimum, and average values remain consistent. This indicates that increasing the number of ants to a certain extent can improve the algorithm's global optimization ability and stability. In Fig. 6(b), the average number of iterations decreases as α increases. This indicates that the convergence speed accelerates with the increase of α. The numerical changes in the mean and minimum values indicate that the speed of convergence is not necessarily related to whether the OSO can be found. The acceleration of convergence speed greatly increases the likelihood of the algorithm falling into local optima. At $\alpha = -1$, the algorithm performs best and can find the OSO multiple times. It maintains other parameters unchanged and studies the impact of different pheromone residual factors ρ and different heuristic information influence parameters β on algorithm solving. The relevant results is showcased in Fig. 7.

In Fig. 7(a), the convergence rate accelerates with the increase of ρ. But the average value of the comprehensive objective function increases with the growth of ρ, and the OSO cannot be found. This indicates that an increase in ρ can cause the algorithm to fall into local optima. The algorithm performs best when $\rho = 0.2$, and can obtain the OSO through multiple iterations. In Fig. 7(b), the heuristic information affects the stability of the algorithm when the parameter β is 1. At this time, the average, maximum, and minimum values are all the same results, and iteration can also obtain the best solution. After determining the assignment of parameters, the study inputs each parameter value into the algorithm. Due to the randomness of a single run, it cannot guarantee that all Pareto solutions can be obtained. Therefore, the program is run multiple times to ensure that all Pareto solutions can be output.

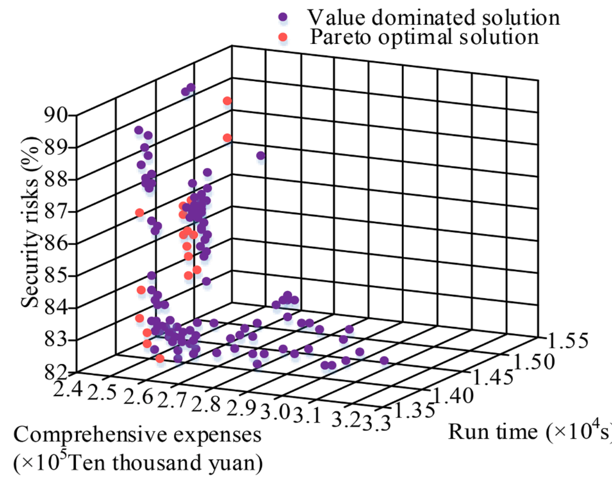


Fig. 9. Improved model iteration results.

4.2. Optimization analysis of improved algorithms

The study used software MATLAB for calculations and verified that the computer hardware configuration for the simulation experiment was Intel (R) Core (TM) i7–7700 CPU @ 3.60 GHz, 16.0GB of memory, and a 64 bit operating system. Firstly, it determines the parameter values of the GA. The initial population size is set to 100, with a crossover probability of 0.4, a mutation probability of 0.05, and an iteration count of 500. The results are shown in Fig. 8.

In Fig. 8, the optimal value of the model function is 25.35×10^4. On the ground of this optimization, the corresponding solution can be obtained by placing the facilities in the corresponding positions in sequence. The objective function value of the population average rapidly decreases before 50 iterations, and at this point, the model quickly concentrates towards the optimal solution in the initial stage. The curve fluctuates significantly during 150–500 iterations, indicating an unstable balance between exploration and utilization in the model. This indicates that the improved algorithm can effectively avoid falling into local optima too early, maintain a balance between multiple project management objectives such as cost, time, and quality, and optimize the overall performance of the project. The project department shall establish a decision-making level to implement decision management for the project and incorporate it into the scope of the construction SL management mechanism. The iteration results are shown in Fig. 9.

In Fig. 9, the iteration results of the improved model have 23 optimal feasible solutions, with construction costs mostly ranging from 240,000

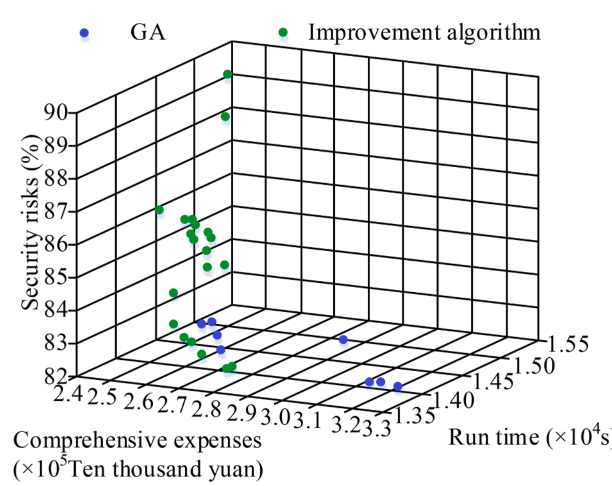
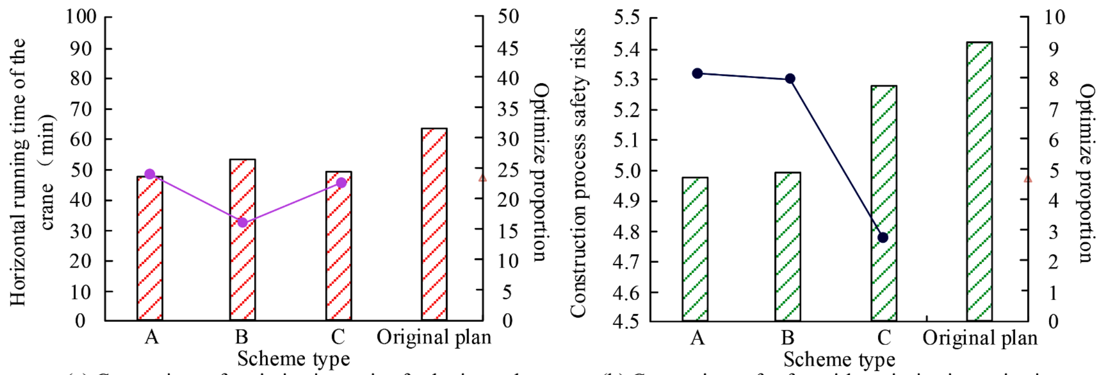


Fig. 10. Comparison of optimal solution sets for different algorithms.



(a) Comparison of optimization ratios for horizontal running time of cranes in different schemes

(b) Comparison of safety risk optimization ratios in different construction schemes

Fig. 11. Comparison of the optimized proportion of crane horizontal operation time and construction process safety risks between the three schemes and the original scheme.

Table 1
Statistical test results of objective function before and after optimization.

Multi objective optimization statistics	Average value	Standard deviation	Mean standard error	Correlation	*P*	T-test	*F*	Sig (Double tailed)
Before optimization	82.10	13.908	4.398	/	/	/	/	/
After optimization	87.00	9.832	3.109	/	/	/	/	/
Comparison before and after optimization	4.90	5.971	1.888	0.930	0.000	−2.595	21.519	0.029

to 260,000 yuan and an average safety risk coefficient of 85.65%. For removing the impact of accidental elements as much as possible, simulation tests were run 10 times and the best optimization outcomes were chosen for comparing. After all the programs have finished running, the Pareto solution set is output, and three optimization solutions are finally obtained, named Scheme 1, Scheme 2, and Scheme 3. Scheme 1 prioritizes the layout of the building materials warehouse, Scheme 2 prioritizes the layout of the mechanical and electrical equipment warehouse, and Scheme 3 prioritizes the setting up of the construction machinery warehouse. The cost of Scheme 1 is 38.34 million yuan, and the transportation time is 85,402 s. The cost of Scheme 2 is 38.49 million yuan, and the transportation time is 81,918 s. Scheme 3 has a cost of 3875 and a transportation time of 80,250. The original scheme had a cost of 40.26 million yuan and a transportation time of 85,952 s. The comparison of the OSO of different algorithms is shown in Fig. 10.

In Fig. 10, the improved algorithm has higher computational efficiency, resulting in more Pareto OSO and higher quality. In terms of computational time (CTI), the GA algorithm takes an average of 1702.0 s, while the improved algorithm takes an average of 421.0 s. In calculation outcomes, the GA algorithm obtained 9 OSO, while the improved algorithm obtained 23 OSO, which increased the quantity of OSO by 1.6 times. And the OSO obtained by the improved algorithm dominates the OSO from the GA algorithm. Consequently, the improved algorithm not only improves the efficiency of problem solving, but also optimizes the scope and quality of understanding, which is of great significance for solving complex optimization problems. The comparison between the three schemes and the original scheme in terms of the optimization ratio of crane horizontal operation time and construction process safety risks is shown in Fig. 11.

In Fig. 11, the horizontal transportation time of the crane in the original plan was 63 min, while the A, B, and C plans were 48 min, 53 min, and 49 min, respectively, saving an average of 21.83%. Overall, both in terms of the numerical value of the objective function and from the perspective of plane layout, the three optimized schemes have a certain degree of improvement compared to the original scheme. This indicates that the algorithm is indeed feasible and effective in optimizing the layout of construction sites, and has certain reference value. Regarding the evaluation and decision-making of the optimization plan, construction management personnel need to further consider various factors and make a comprehensive comparison before making a selection. Statistical analysis was conducted on the objective function before and after optimization, and the results are shown in Table 1.

In Table 1, $P = 0.000$, indicating that the improvement in transportation time and cost optimization by the improved algorithm is unlikely to be caused by random mutation. The effect of improving the algorithm is credible and statistically effective.

5. Results and discussion

To improve the rationality of OSL, a GA is used to build a construction SL model, thereby establishing an optimal objective function for cost. At the same time, Pareto ant colony GA is used to establish a MOO model for construction management SL, which optimizes the cost objective mathematical function of the SL. The results show that the OSO can be obtained through multiple iterations. The optimal value of the improved model function is 25.35×10^4. On the ground of this optimization, the corresponding solution can be obtained by placing the facilities in the corresponding positions in sequence. The iteration results of the improved model have 23 optimal feasible solutions, with construction costs mostly ranging from 240,000 to 260,000 yuan and an average safety risk coefficient of 85.65%. In calculation outcomes, the GA algorithm obtained 9 OSO, while the improved algorithm obtained 23 OSO. The number of OSO increased by 1.6 times, and the OSO from the improved algorithm all dominated the OSO obtained by the GA algorithm. Consequently, the improved algorithm obtains more and higher quality solutions with higher computational efficiency. The improved algorithm has significant advantages in both efficiency and effectiveness, and it has important practical application value for construction project management that needs to handle large-scale multi-objective optimization problems. This method can provide more high-quality decision support, which helps project managers make better choices in multi-objective decision-making environments. Although this study provides valuable insights, it does not delve into the key influencing factors in construction management. Future research should analyze the risk factors of the project in detail to more comprehensively ensure the overall feasibility and sustainability of the project.

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CRediT authorship contribution statement

Hui Yin: Writing – original draft, Software, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

No conflict of interest was declared by the author.

Data availability

No data was used for the research described in the article.

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