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Research paper

The optimization model of building construction based on BIM and improved NSGA-III algorithm

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Abstract: Currently, there are difficulties in dealing with higher construction requirements and standards in subway construction management. Therefore, a multi-objective optimization model was constructed based on building information management technology, and an improved non-dominated sorting genetic algorithm III was introduced to optimize the model solution. And experimental verification was conducted. These experiments confirmed that the average HV of the improved algorithm was 0.67, which was higher than the original algorithm's 0.65, indicating that it had higher convergence and reliability. The solution results of the non-dominated sorting genetic algorithm II showed that the optimized cost was 185.1899 million yuan. The cost of optimizing the original non-dominated sorting genetic algorithm III was 184.6469 million yuan. The total cost of optimizing the research algorithm was 184.1165 million yuan. In addition, the research algorithm had the shortest construction period, ideal cost, and significantly higher quality and safety levels than the comparison algorithms. And its time consumption was only 20 seconds, significantly lower than the comparison algorithms. And its cost was between 183 million to 187.5 million yuan, with higher stability and relatively concentrated distribution of solutions. Overall, the subway construction optimization model based on building information management and non-dominated sorting genetic algorithm III has high effectiveness and can be effectively applied in practical construction management.

Keywords: BIM, NSGA, subway buildings, multi-objective optimization, pareto solution, construction period, cost

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1. Introduction

Construction Project Management (CPM) is a core competitiveness of construction enterprises, which directly affects project quality, construction period, and investment costs. For modern construction projects, quality and safety are the top priority. Strengthening construction management is a key measure to ensure project quality and safety. Therefore, in the construction of construction projects, it was necessary to effectively solve various problems in the construction management process to achieve BCOM [1]. Based on this, many scholars had verified it. Parsamehr et al. constructed a construction optimization management decision plan using BIM, which effectively obtained and processed relevant data while achieving BC monitoring [2]. Jalaei et al. addressed the environmental impact in CPM and implemented a full life cycle assessment of BCOM buildings using BIM and quantitative frameworks, effectively optimizing BC costs while reducing waste emissions [3]. Meharie et al. used fusion methods such as linear regression and support vector machine to effectively manage highway construction projects, and constructed cost models to achieve cost control and improve project construction efficiency. The results indicate that the technology has excellent effects [4]. Xue et al. proposed an optimal design method for energy consumption in BCOM by utilizing artificial neural networks and NSGA-II, which not only improved building performance but also reduced BC time [5].With the gradual changes in the market environment, fully utilizing relevant digital technologies has become an important way for Building Construction Optimal Management (BCOM) to optimize management [6]. Pham Q D et al. constructed an optimization framework for cost estimation and optimization in BC by utilizing machine learning, effectively reducing resource waste while reducing the actual costs of BC [7].

Based on the above research, it can be found that, taking the subway Building Construction (BC) as an example, it has greater risk and more influencing factors compared to general BC, involving multiple objectives such as cost, quality, construction period, progress, etc. Therefore, the multi-objective balanced optimization and scientific management of such construction projects also need to be paid attention to [8–10]. In the solution of BC Multi-objective Optimization (MOP), the application of Non-dominated Sorting Genetic Algorithm III (NSGA-III) has more practical significance. Based on this, the study constructs a multi-objective management system for subway construction projects using BIM, its purpose is to address the current difficulties of subway CPM in meeting higher construction requirements and standards.

2. Method

Digitalization is the main method for optimizing current BC, wherein BIM is widely used in BC optimization. Therefore, this section mainly utilizes the organic combination of BIM and traditional management models to construct a multi-objective management system for subway construction projects, and improves NSGA-III to achieve the optimization of model solving.

2.1. BIM based multi-objective management system and functions

In response to the current difficulty of subway CPM in meeting higher construction requirements and standards, a multi-objective management system for subway construction projects has been constructed by combining BIM with traditional management models. To build a subway BC optimization model, it is necessary to establish a corresponding construction project management system as a prerequisite [11]. Therefore, based on previous research, by summarizing and summarizing the actual cases of the project, five main influencing factors of subway CPM have been identified [12–14] in Figure 1.

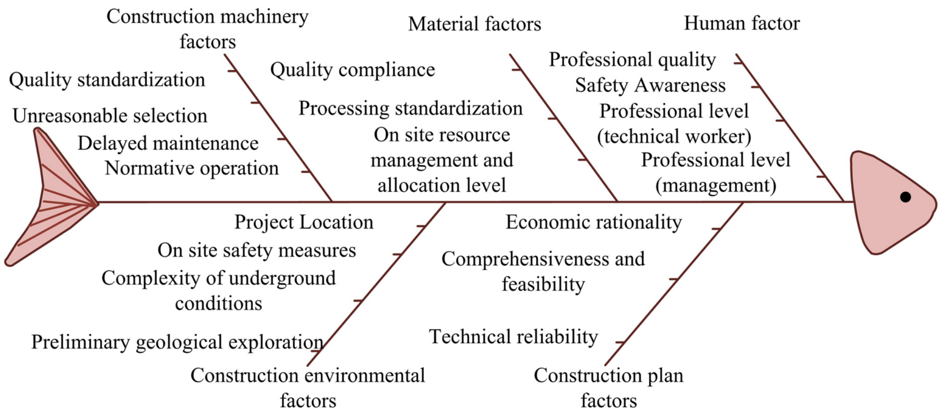


Fig. 1. Schematic diagram of the main influencing factors of subway construction projects

From Figure 1, the five main influencing factors of subway CPM include construction machinery, materials, personnel, construction environment, and construction plans. Under the influence of five major factors, subway CPM has four major goals, namely quality, cost, construction period, and safety goals. For the overall goal of subway BC, Equation (2.1) is the corresponding formula for the four major goals [15].

$$Z = \sum_{i=1}^{n} \varpi_i y_i, \quad B = \sum_{i=1}^{n} (B_{si} + B_{hi}), \quad A = \sum_{i=1}^{n} \tau_i, \quad U = \sum_{i=1}^{n} U_i \varpi_i \tag{2.1}$$

In Equation (2.1), Z represents the overall quality of the project. ϖ_i represents the proportion of each sub project. y_i represents the quality of each sub project. n represents the total number of each sub project. B represents the total cost of the project. B_{si} and B_{hi} represent the direct and indirect costs of each sub project, respectively. A represents the total construction period. τ_i represents the construction time of each key work. U represents the overall safety of the project. U_i represents the safety of each sub project. Under the guidance of four major objectives in equation (1), the current subway construction project management relies too much on the constraints of management personnel and rules and regulations, resulting in information asymmetry. Therefore, the study combines BIM with current project management to optimize the multi-objective management system in Figure 2.

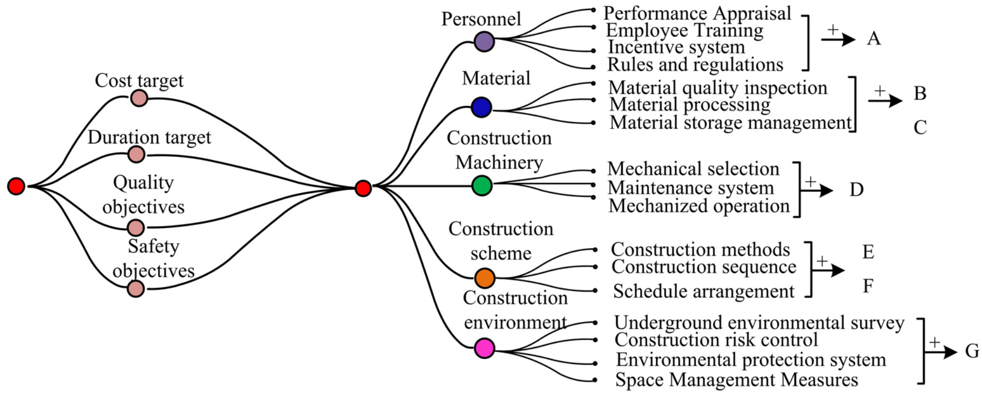


Fig. 2. A multi-objective management system for subway construction projects based on BIM technology

From Figure 2, compared to traditional multi-objective project management, the addition of BIM information technology has increased the level of information technology under five major influencing factors. Based on this optimized management system, research has begun to construct a subway construction project MOP. There is a nonlinear relationship between multiple objectives in subway BC, so different optimization models are constructed based on this relationship function. Equation (2.2) is the duration-cost optimization model.

$$B_i = B_{si} + B_{hi} = B_{shi} + \gamma_i (\tau_{ki} - \tau_i)^2 + B_{hsi} + \psi_i (\tau_{li} - \tau_i)^2 \tag{2.2}$$

In Equation (2.2), B_i represents the actual cost of each construction process. B_{shi} and B_{hsi} represent the direct cost of the longest duration and the indirect cost of the shortest duration, respectively. τ_{ki} and τ_{li} represent the longest and shortest construction time, respectively. γ_i and ψ_i represent the marginal coefficients of cost impact for each construction process. Equation (2.3) represents the minimum total construction cost.

$$\mathrm{Min}B = \sum_{i=1}^{n} B_i = \sum_{i=1}^{n} (B_{si} + B_{hi}) = \sum_{i=1}^{n} \left[B_{shi} + \gamma_i (\tau_{ki} - \tau_i)^2 + B_{hsi} + \psi_i (\tau_{li} - \tau_i)^2\right] \tag{2.3}$$

Equation (2.4) is the duration-quality optimization model.

$$\mathrm{Max}Z = \sum_{i=1}^{n} Z_i = \sum_{i=1}^{n} \mathrm{In}\left(\mathrm{c_i}\tau_\mathrm{i} + \mathrm{e_i}\right) \tag{2.4}$$

In Equation (2.4), Z_i represents the actual quality of each construction process. c_i and e_i represent the marginal coefficients of quality impact for each construction process. Equation (2.5) represents the duration-safety optimization model.

$$\mathrm{Max}U = \sum_{i=1}^{n} U_i = \sum_{i=1}^{n} (\vartheta_i (\tau_i - \tau_{ki}) + U_{li}) \tag{2.5}$$

In Equation (2.5), ϑ_i represents the marginal coefficient of safety impact for each construction process. U_{li} represents the minimum safety level for each construction process. The MOP proposed in the study is composed of Equations (2.3), (2.4), and (2.5), along with the minimum construction period optimization model $\mathrm{Max}A = \max\left(\sum_{i=1}^{n} \tau_i\right)$.

2.2. Construction and solution analysis of MOP

In the constructed MOP, the improved NSGA III is introduced to form a complete subway BC optimization model. Compared to traditional NSGA, NSGA-III reduces the complexity of actual algorithms and reduces the time required for actual calculations. Compared to NSGA-II, it has improved the non-dominated sorting method. It converts crowding into reference points, uniformly generating reference points in the unit hyperplane, thereby reducing computational complexity and time, making it more suitable for solving high-dimensional optimizations [16–18]. NSGA-III first performs a non-dominant sorting on the initial population, with the number of individuals in the parent population set to N. Through sorting, selection, and other methods, offspring populations are generated. The set of selected individuals is set as $S(t)$, and the selected non-dominated levels from $S(t-1)$ to $S(t)$ are called critical layers [19]. Subsequently, $N - |S(t-1)|$ individuals are selected using relevant reference points from the critical layer. Equation (2.6) represents the number of reference points.

$$K = \binom{W + J - 1}{J} \tag{2.6}$$

In Equation (2.6), K represents the number of reference points. W represents the number of objectives to be optimized. J represents the number of evenly divided objectives to be optimized. Before selecting an individual, it is necessary to quantify the relevant objective function in Equation (2.7).

$$f'(p) = f(p) - O_a^{\min} \tag{2.7}$$

In Equation (2.7), $f'(p)$ represents the quantified objective function. $f(p)$ represents the objective function. $O_a^{\min}$ represents the minimum value of multiple targets on different dimensions a. After quantifying the function, the extreme points are obtained using the Alternative Splicing Factor (ASF), as expressed in Equation (2.8).

$$ASF(X, L) = \mathrm{MAX}_{a=1:W}\left(f'(p)/L_a\right) \tag{2.8}$$

In Equation (2.8), $ASF(X, L)$ represents the extreme points of W targets on different dimensions a. L represents the weight vector, L_a represents the weight vector under the minimum objective dimension. By using Equation (2.8), the minimum points of each objective function can be obtained, thereby obtaining the corresponding function values [20]. According to Equation (2.9), all individuals can be normalized to the same plane as the reference point.

$$f_a^{n'}(p) = \frac{f_a'(p)}{ba} = \frac{f(p) - O_a^{\min}}{ba} \tag{2.9}$$

In equation (2.9), *ba* represents the intercept of each point on the coordinate axis. Then NSGA-III combines the ideal point with the reference point to form a reference line and finds the shortest reference line, while connecting the target individuals in each target group with the reference point. Finally, the offspring generated by the latest iteration are screened. However, the population diversity and Pareto frontier solutions of NSGA-III in practical solutions can have a significant impact on the results. Therefore, to obtain better Pareto solutions, research has improved NSGA-III. Figure 3 shows the improved NSGA-III.

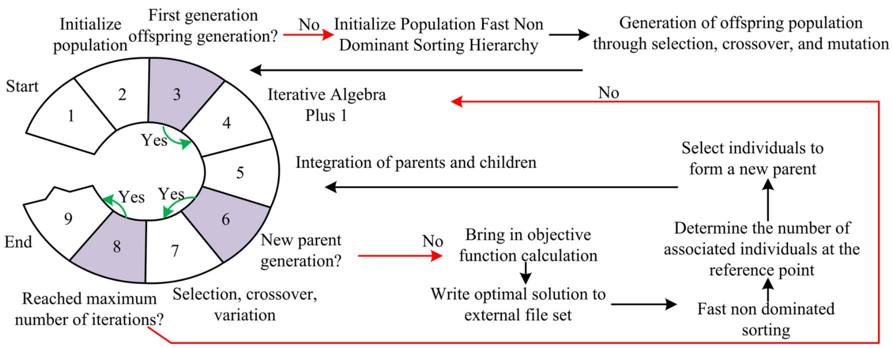


Fig. 3. Schematic diagram of the improved NSGA-III

From Figure 3, the probability of cross mutation is first increased, and the dynamically changing mutation probability is used to improve the diversity of the population, thereby ensuring the stability of the solution and the convergence of the algorithm. In improving the probability of cross mutation, Simulated Binary Xrossover (SBX) is used to enable offspring to obtain some useful genetic material from their parents in Equation (2.10).

$$\left\{ \begin{array}{l} \widetilde{p}_{1j'}(\tau) = 0.5 \cdot \left[\left(1 + \xi_{j'}\right) p_{1j'}(\tau) + \left(1 - \xi_{j'}\right) p_{2j'}(\tau) \right] \\ \widetilde{p}_{2j'}(\tau) = 0.5 \cdot \left[\left(1 - \xi_{j'}\right) p_{1j'}(\tau) + \left(1 + \xi_{j'}\right) p_{2j'}(\tau) \right] \end{array} \right. \tag{2.10}$$

In Equation (2.10), $p_{1j'}$ and $p_{2j'}$ represent the relevant individuals of two parent populations. $\xi_{j'}$ represents the propagation factor in Equation (2.11).

$$\xi_{j'} = \left(2\nu_{j'}\right)^{\frac{1}{\sigma+1}}, \quad \left[1/2\left(1 - \nu_{j'}\right)\right]^{\frac{1}{\sigma+1}} \tag{2.11}$$

In Equation (2.11), $\nu_{j'}$ represents a constant between 0 and 1. σ represents the distribution index. Based on this, the improved probabilities of crossover and mutation are represented by Equations (2.12) and (2.13).

$$\Im'_d = \Im_d \times \left(1 - \frac{\varsigma}{\max \varsigma}\right) \tag{2.12}$$

In Equation (2.12), $\Im'_d$ and $\Im_d$ represent the crossover probabilities after and before improvement, respectively. ς represents the current iteration. ς represents the maximum iteration.

$$\Im'_f = \Im_d \times \left(1 - \frac{\varsigma}{\max \varsigma}\right) \tag{2.13}$$

In Equation (2.13), $\Im'_f$ represents the improved mutation probability. Finally, in the reliability experiment of verifying the improved NSGA-III, the original and improved algorithms are studied to solve the Diode Transistor Logic with Zener Diode (DTLZ2) test function. Equation (2.14) represents its objective function and constraint conditions.

$$\begin{cases} ((\pi/2)\, p_2)\,(1+\Re\,(p)), & \min f_3\,(p) = \sin\left((\pi/2)\, p_1\right)(1+\Re\,(p)) \\ \Re\,(p) = \sum_{h'=3}^{m'} (p_{h'} - 0.5)^2, & s.t. 0 \le p_{h'} \le 1, \quad h' = 1, 2, \cdots, 12 \end{cases} \tag{2.14}$$

In Equation (2.14), $f\,(p)$ represents the objective function. $\Re\,(p)$ represents a common scaling factor. h' represents a constant between 1 and 12. In addition, Hyper Volume (HV) is introduced in the convergence and diversity verification in Equation (2.15).

$$HV = \zeta\left(\cup_{\ell=1}^{|S|} \aleph_\ell\right) \tag{2.15}$$

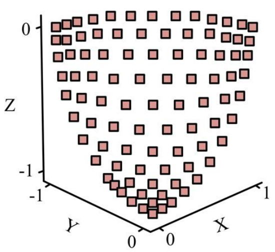
In Equation (2.15), ζ represents the Lebesgue measure. $|S|$ represents the number of individuals in the solution set. $\aleph_\ell$ represents the supervolume formed by the reference point and the first individual in the solution set.

3. Results and discussion

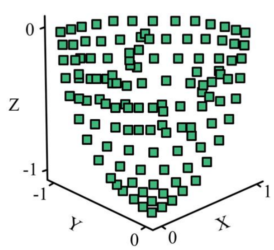
To verify the effectiveness of the BC optimization model, simulation experiments and actual cases were used to analyze it. Therefore, this section mainly analyzed the performance and solution of the algorithm, and analyzed its MOP results in practical cases.

3.1. Analysis of algorithm performance and solution results

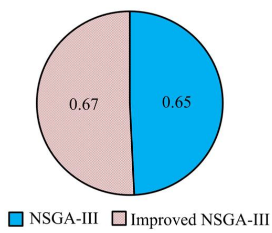
Firstly, the reliability and convergence of the algorithm were verified. Among them, 20 calculations were performed in the comparison of HV values in Figure 4.



(a) NSGA-III solution results for DTLZ2



(b) Improved NSGA-III solution results for DTLZ2



(c) Comparison of HV means between improved NSGA-III and NSGA-III

Fig. 4. Reliability and convergence verification of the improved NSGA-III

Based on Figure 4, the improved NSGA-III Pareto frontier surface covered the Pareto frontier surface in DTLZ2, resulting in more results than the original algorithm and more diversity of solutions. In addition, the improved NSGA-III had a mean HV of 0.67, which was higher than the original algorithm's 0.65, indicating higher convergence. Based on this, the actual case was analyzed using a subway construction project in a certain city in southern China as an example. The total length of the subway construction project involved in this case was 2.8 kilometers, and the construction environment was relatively complex with high groundwater levels. There were many uncertain factors in the construction process, which had high requirements for construction cost, quality, duration, and safety and regarding the rationality of the project progress and to ensure the timely completion of the project, Table 1 showed the construction process.

Table 1. Process content of case construction engineering

No.	**Project name**	**Immediate work**	**No.**	**Project name**	**Immediate work**
1	Construction preparation	2	8	Assembly and debugging of shield tunneling machine down the well	9
2	Preliminary engineering	3	9	Shield tunneling machine excavation	10
3	Station construction enclosure engineering	4, 5, 6	10	Track engineering	11
4	Earth excavation and support construction	5,6	11	Station equipment installation	12
5	Subway Station Construction	6, 11, 12	12	Mechanical and electrical equipment installation	13
6	Shaft sinking	7, 8, 9	13	System commissioning	14
7	Tunnel secondary lining	8	14	Test run	–

According to Table 1, except for processes 3, 4, 5, and 6, all other processes are carried out according to normal procedures. Invite experts to rate the actual construction process of the case, with a maximum score of 1 and a minimum score of 0. Figure 5 shows the various parameters of MOP in actual situations.

In Figure 5, A-C represented the shortest and longest construction time of each construction process, as well as the highest actual construction quality of each construction process. D-F represented the lowest quality of actual construction in each construction process, and the highest and lowest safety of actual construction in each construction process. G-J represented the direct and indirect costs of the longest construction period for each construction process, as well as the direct and indirect costs of the shortest construction period for each construction process. According to Figure 6, the longest construction period for each construction process was 20 months, and the maximum direct cost for each construction process was 78.298 million

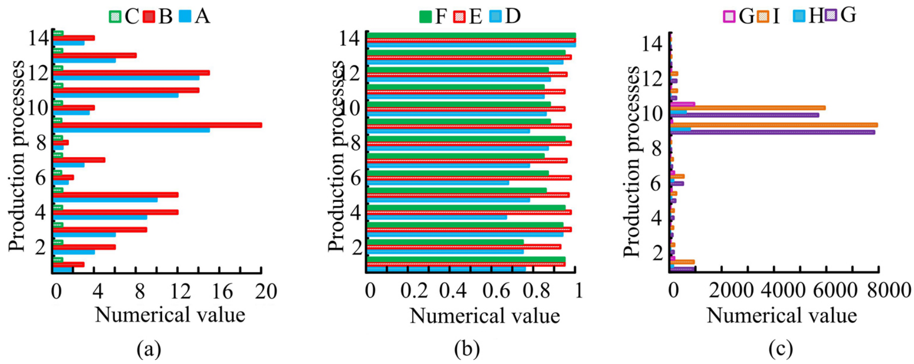


Fig. 5. The parameter values of MOP in practical cases; (a) Content of different process parameters A~C, (b) Content of different process parameters D~F, (c) Content of different process parameters G~J

yuan. Therefore, by substituting the specific parameters into Equations (2.3), (2.4), and (2.5) and adding them to the minimum construction period optimization model formula, the subway BCMOP could be obtained. Based on the parameter settings and MOP construction in Figure 6, the MOP in the actual case was solved to verify the superiority of the improved NSGA-III and further validate the superiority of the constructed model. When solving NSGA-II, the population size was set to 90 and the iteration was set to 25000. When solving NSGA-III, the population size was set to 92 and the iteration was also set to 25000 in Figure 6.

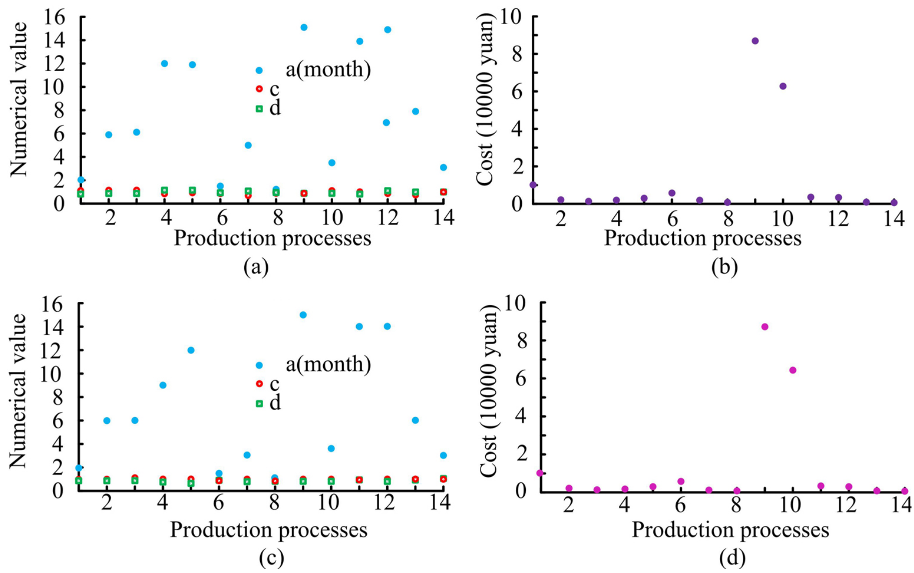


Fig. 6. Solution results of NSGA-II and NSGA-III; (a) The solution results of a, c and d NSGA-II algorithm, (b) The solution results of b NSGA-II algorithm, (c) The solution results of a, c and d NSGA-III algorithm, (b) The solution results of b NSGA-III algorithm

In Figure 6, the solution results of NSGA-II confirmed that the optimized cost was 185.1899 million yuan, and most of the time it was within the shortest working period, stable at around 0.9. Although costs had decreased, most of the results had been concentrated in high-cost areas, and this construction method would not become the primary choice for actual construction decisions. In addition, the optimized cost of NSGA-III was 184.6469 million yuan, and the quality of most construction processes was above 0.9. The Pareto frontier solution of NSGA-III was more uniform, with quality and safety becoming more stable. Figure 7 showed the improved NSGA-III solutions.

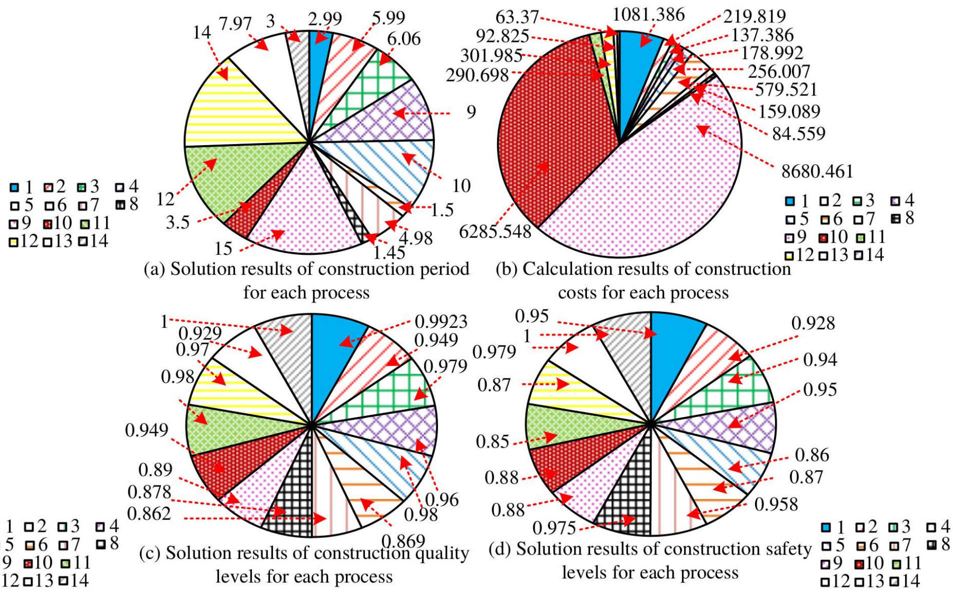


Fig. 7. Results of the improved NSGA-III solution; (a) Solution results of construction period for each process, (b) Calculation results of construction costs for each process, c) Solution results of construction quality levels for each process, (d) Solution results of construction safety levels for each process

According to Figure 7, the total cost of the improved NSGA-III was 184.1165 million yuan, which was lower in cost and shorter in construction. Quality and safety had been improved, but they were basically the same as before. Compared with before improvement, the actual results were evenly distributed and the diversity of solutions was significantly increased. After optimization, the overall cost of the project was better, and the quality and safety of the project had been significantly improved. Overall, the improved NSGA-III had high performance and effectiveness.

3.2. Analysis of actual case results

It was worth noting that the above solutions were selected based on the preference of maintaining the same quality and safety after optimization, with lower costs. Figure 8 showed the comparison between MOP results and running time in a practical case.

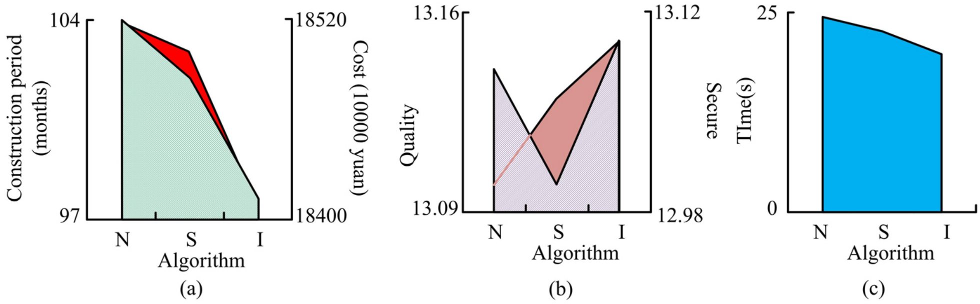


Fig. 8. Comparison of MOP results and running time in actual cases; (a) Comparison of duration and cost of different algorithms, (b) Comparison of quality and safety levels of different algorithms, (c) Comparison of runtime of different algorithms

In Figure 9, N, S, and I represented NSGA-II, NSGA-III, and the improved NSGA-III, respectively. Based on Figure 9, in the comparison of construction periods, the improved NSGA-III had the shortest construction period and the ideal cost, which was lower than 184.2 million yuan. Its quality and safety level were also significantly higher than NSGA-III and NSGA-II. In addition, in the comparison of runtime, the improved NSGA-III only took 20 seconds, significantly lower than the comparison algorithms. Overall, the improved NSGA-III had higher optimization performance. Based on this, the study compared the Pareto solution set solved by some algorithms for the cost objective function in Figure 9.

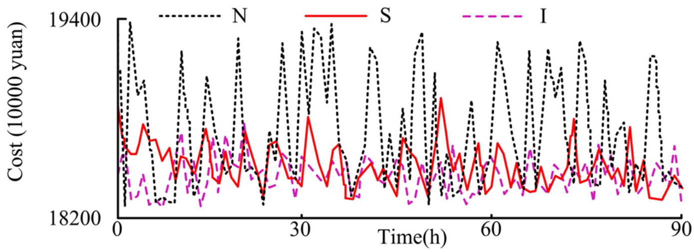
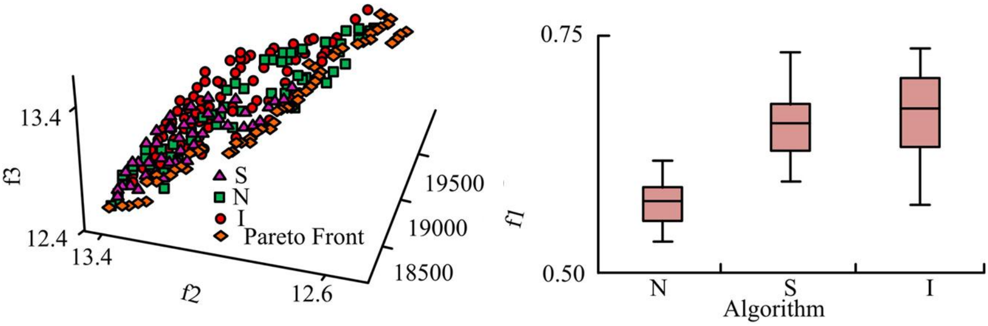


Fig. 9. Comparison results of algorithm cost optimization

According to Figure 9, NSGA-II had significant cost fluctuations and poor stability. The original NSGA-III and the improved NSGA-III had better stability and ideal cost optimization. However, the original NSGA-III cost fluctuation range was between 183 million and 189 million yuan, while the improved NSGA-III cost fluctuation range was between 183 million and 187.5 million yuan, indicating higher stability and a relatively concentrated distribution of solutions. Finally, Figure 10 compared the smoothness and HV of Pareto front surface solved by three algorithms.

Based on Figure 10, the Pareto front surface obtained by the improved NSGA-III was smoother, with a more uniform distribution of solutions and a larger proportion in the Pareto front surface. NSGA-III generated more solutions than NSGA-II and the original NSSGA-III. In addition, the box of the improved algorithm was the longest, indicating that the distribution



(a) Pareto frontier comparison (b) Comparison of algorithm HV indications

Fig. 10. Comparison of the smoothness and HV of Pareto frontal surface

of evaluation indicators was more uniform, and the stability of algorithm performance was also better than comparative algorithms'. Overall, the BCMOP constructed by utilizing BIM had effectiveness, and the introduction of improved NSGA-III to solve it also significantly improved the model performance.

4. Discussion

Subway CPM is one of the important contents of engineering construction, which requires prioritizing project quality and fully meeting construction cost and schedule requirements in construction management. In specific experimental analysis, through multiple scheme comparisons, it was found that the total cost of the improved NSGA-III was 184.165 million yuan, lower than NSGA-II's 185.1899 million yuan and the original NSGA-III's 184.6469 million yuan. In addition, in the comparison of construction periods, the improved NSGA-III has the shortest construction period and a relatively ideal cost, less than 184.2 million yuan. The improved NSGA-III in quality analysis is also significantly superior to other technologies, demonstrating excellent performance. In addition, the study also compared the techniques proposed in reference [5] and reference [21]. Compared to the original engineering management effect, the methods proposed in reference [5] and reference [21] can reduce enterprise costs, improve construction period, and ensure quality. However, compared with the research technology, the total cost of reference [5] and reference [21] is 185.0585 million yuan and 18.4965 million yuan, respectively. At the same time, in the comparison of construction cycles, the overall research technology cycle is shorter, with a reduction of 4.5% and 7.2% in construction cycles compared to references [5] and [21]. However, in terms of quality comparison, references [5] and [21] are basically consistent with the research technology, and both meet the quality requirements of project construction.

Overall, the technology proposed by the research institute has better performance and comprehensive effects in practical applications compared to similar technologies, and can significantly improve the construction efficiency of subway projects. This further demonstrates that the BCMOP constructed using BIM is effective, and the introduction of improved NSGA-III to address it also significantly improves model performance. However, research only considers mutation probability and optimal solution for algorithm improvement, and more improvement ideas need to be introduced in practical problems.

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