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Application of Improved Frog Leaping Algorithm in Multi objective Optimization of Engineering Project Management

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ABSTRACT

The development of information has promoted the development of various industries, and the development of industries will inevitably lead to intensified competition, including the construction industry. To enhance the competitiveness of construction enterprises in the industry, a multi-objective optimization model for construction project management has been proposed. At the same time, carbon emission was included as one of the optimization objectives in the experiment. This can also align the construction industry with the concept of modern green development. A non-dominated sorting genetic algorithm with elite strategy was proposed to improve the hybrid frog leaping algorithm, and the improved hybrid frog leaping algorithm was used to solve multi-objective optimization problems. The improved hybrid frog leaping algorithm performed better in solving multi-objective optimization problems. The improved hybrid frog leaping algorithm found a total of 132 Pareto solution sets, while the non-dominated sorting genetic algorithm with elite strategy only found 23 Pareto solution sets. And the solution set of the improved hybrid frog leaping algorithm is closer to the optimal position. The optimized duration and cost of the improved hybrid frog leaping algorithm are lower, with an optimal duration of 135 days and a minimum cost of $20,000. A multi-objective optimization model for engineering project management incorporating carbon emissions was successfully constructed in the study, and the multi-objective optimization problem was solved.

1. Introduction

The arrival of the information age has promoted the development of the construction industry, and the competition among various enterprises has become increasingly fierce. The management requirements for project engineering have also become increasingly strict [1]. Traditional project management always excessively pursues a certain goal while neglecting the importance of other goals. For example, in the construction project of a certain shopping mall in 2021, the excessive pursuit of cost control resulted in a serious decline in wall quality. If the project fails to detect problems during completion inspection, it is highly likely to cause major safety accidents in

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subsequent use [2]. The various goals in engineering project management are in a contradictory and unified relationship. The problems in one aspect can have an impact on the entire engineering project [3]. Therefore, modern engineering project management should seek a balance point between the goals of each engineering project and achieve the unified realization of each goal. Only in this way can enterprises achieve maximum benefits. Therefore, the multi-objective optimization of this construction project engineering is currently the main problem in the construction field [4]. With the continuous development of technology, swarm intelligence optimization algorithms are constantly updated and iterated, and more and more intelligent optimization algorithms are being applied in the field of architecture. In order to enhance the competitiveness of construction enterprises in the industry and align the construction industry with the concept of modern green development, the study proposes the use of the Hybrid Frog Leaping Algorithm (SFLA) to optimize engineering project management objectives and seek the optimal solution for achieving multiple objectives. However, SFLA cannot solve the conflict problem between project engineering management objectives, such as project cost control objectives. There is a certain contradiction between SFLA and project quality objectives. Therefore, in order to enable SFLA to be applied in multi-objective optimization of engineering project management, a Non-dominated Sorting Genetic Algorithm - II (NSGA - II) with elite strategy was proposed to improve SFLA and solve multi-objective optimization problems in engineering project management. The innovations of the research lie in applying natural heuristic algorithms to multi-objective optimization of engineering projects, and combining the advantages of NSGS II with SFLA. The research will be carried out in four parts. Section 2 provides an overview of the current research status of multi-objective optimization and skip level algorithms in construction project management. Section 3 is the application research of improving SFLA in multi-objective optimization of engineering project management. Section 4 is the analysis of simulation experiments, and the fourth part is a summary of the research content.

2. Related Works

MOP is a problem that exists in various fields. Luo and Guo have established a multi-objective complex constraint optimization model to improve the energy efficiency in micro-grids and increase the utilization of renewable energy. This model adopts a Meta heuristic strategy and decomposes the objective optimization problem using fuzzy membership and Chebyshev function. This model is more effective than other algorithms and can obtain a higher quality Pareto optimal solution set [5]. Kumar et al. used Gaussian process regression to simulate the conversion rate of carbon monoxide and the selectivity of methanol products to achieve MOP of converting synthesis gas to methanol. Bayesian optimization based on weighted multi-objective card framework can achieve the MOP of selectivity and conversion rate [6]. Machairas and Saravanos developed a deformation optimization method to improve the performance of structural components. This method transforms deformation structure optimization into a MOP problem, while optimizing passive structural components and brakes. Compared with traditional optimization schemes, this scheme has significant computational gain [7]. Deng and Qin proposed a hybrid multi-objective expected improvement method to improve the aerodynamic shape optimization problem of low-level multimodal design workpieces. This method improved the statistical multi-objective and expected super-volume, and proposed a locally developed filling criterion. The method proposed by the author has stronger robustness and higher efficiency when dealing with sub optimization problems [8]. Libotte et al. developed a MOP model to reduce the impact of environmental changes, equipment errors, and other factors on chemical systems during production. This can simultaneously improve the product performance, reduce costs, and shorten production time. This model can only be used to evaluate the uncertainty of the system [9].

The frog leaping algorithm is a common search algorithm that is widely used in the fields of construction and industry, and its application scope is mostly optimization of various objectives. In order to make fractional derivatives practical in various fields, Mohan and Yarravarapu proposed SFLA to find the optimal solution for finite impulse response, continuous-time fractional order differentiators. SFLA can solve continuous-time fractional order differentiators with finite pulse response [10]. There are problems with speed fluctuations caused by parameter changes and load disturbances in permanent magnet synchronous motors. In this regard, Xie et al. proposed an active disturbance rejection control and feedback compensation control method, and used SFLA to adjust the control parameters. This control system can suppress speed fluctuations caused by load disturbances [11]. In order to obtain experimental data in computer numerical control machining operations, Goli et al. proposed an artificial neural network and SFLA to obtain measurement data and fuse the data. The artificial neural network fused with SFLA has the highest computational efficiency [12]. Terapasirdsin and Kiattisin proposed a VLSI design wiring for SFLA to address circuit interference issues in high-frequency systems, which reduces crosstalk energy interference through signal conversion. The wiring method proposed by the author has the lowest interference noise, only 13.06% [13]. The traveling salesman problems are finding the shortest path and returning to the origin while reaching all cities. Karakoyun proposed SFLA based on K-means clustering to solve the traveling salesman problem. This algorithm divides each city into K clusters, searches for the shortest path for each cluster, and then merges all clusters. The more clusters are divided, the better the algorithm performance [14].

In the above content, the relevant references are summarized. The first paragraph is the multi-objective optimization research of various fields, including power grid efficiency optimization, chemical material synthesis optimization, material structure performance optimization, equipment workpiece optimization. The second paragraph is a summary of the relevant literature of SFLA, including SFLA's optimization of continuous-time fractional differentiator, permanent magnet synchronous motor control, CNC machining parameters, circuit interference in high frequency system, and travel dealer problems.

In summary, MOP is a problem that exists in various fields, and MOP strategies in each field are different. There is no relatively unified solution, and MOP solutions need to be designed based on the actual situation of the field. SFLA has a high utilization rate in many optimization problems and optimal search problems, but cannot solve the path optimization problem of target conflicts. Therefore, the study proposes NSGA-Ⅱ to improve SFLA and use the improved SFLA to optimize the multi-objective of building project management (PM).

3. Project Management MOP based on Improved SFLA

The main content of Section 3 is to improve the application research of SFLA in project management MOP (PMMOP), which includes two parts. 3.1 is a study of PMMOP. 3.2 is an improved research on SFLA based on NSGA - II.

3.1 Project Management MOP

In practical life, goal optimization often involves multiple objectives that constrain each other. While optimizing one goal, it may require sacrificing another goal. The complexity of MOP problem is directly linked to targets number involved. The targets number increasing leads to optimization problems complexity increasing [15]. The solution methods for optimization problems include traditional methods and direct methods. Traditional methods generally refer to the use of various theories to aggregate multiple Objective Function (OF) into a composite single OF, or to determine a main OF. It takes the remaining OFs as constraints for the main OF. The direct rule is to directly determine Pareto solution set [16]. PMMOP belongs to the discrete MOP problem, and its solution to Pareto optimal solution set is more concise. Therefore, in PMMOP, direct methods are used to solve optimization problems. The MOP model is composed of decision variables, OFs, and constraint conditions. PM refers to the use of various technologies or tools to allocate project resources to ensure that the quality requirements of the project are met within a limited time and at the lowest cost. In practical situations, engineering projects have the characteristics of complexity, uniqueness, and one-time use. Therefore, according to scholars' research, PM goals include meeting owner requirements, not exceeding planned costs, not exceeding specified deadlines, efficient utilization of resources, and meeting technical standards. At present, multi management OF is usually based on the duration and cost, and there are few related constraints, leading to the project failing to meet the owner's requirements. To avoid repeating the mistakes, the total duration, quality level, total cost and resource balance index of the project are selected as the optimization objectives. The duration cost equilibrium model and the resource constrained project scheduling duration cost model are two classic optimization problem models, both of which use the engineering execution mode as a decision variable. Therefore, the study refers to two classic models and selects the execution mode of each task in the engineering project as the decision variable of the PMMOP model. Assuming that the project has j tasks and each task has m_j execution modes, the decision variable can be represented by Equation (1).

$$x_{jm} = \begin{cases} 1, & j \text{ Select to execute in m mode} \\ 0, & other \end{cases} \tag{1}$$

In Equation (1), x_{jm} refers to the decision variable. After determining the decision variables of the model, it needs to construct the model OF. In the research, the objectives are duration, cost, quality, and resource balance index, so four corresponding OFs need to be constructed. The first is the duration OF, which assigns time attributes to each task, namely the start time, end time, and duration. The duration depends on the execution model of the task, while the project duration depends on the end time of the last task. Therefore, the duration can be represented by Equation (2).

$$TD = \max\ f_j \tag{2}$$

In Equation (2), TD refers to the project duration OF. f_j refers to the end time of the j-th task. Project cost refers to all inputs required to meet predetermined requirements, consisting of direct and indirect costs, corporate profits, and taxes. Direct costs include labor, materials, equipment, and other direct expenses. Indirect costs include management personnel expenses, finance, office, travel, and other indirect expenses in Figure 1.

Usually, when calculating project costs, the corporate profits and taxes are not considered. Therefore, the cost OF developed in the study only considers direct and indirect costs. Equation (3) refers to direct costs.

$$DC = \sum_j \sum_{m \in M_j} \left(x_{jm} \times c_{jm} \right) \tag{3}$$

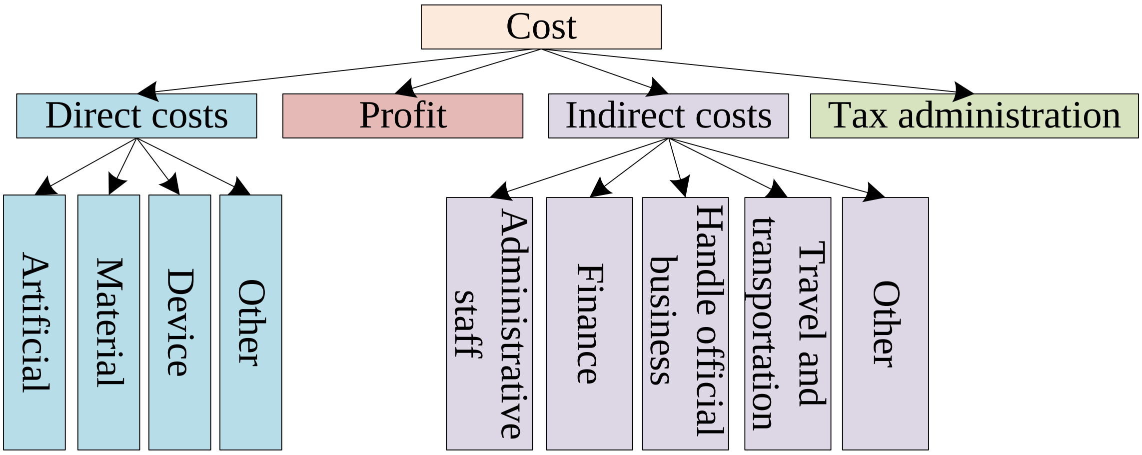


Fig. 1. Cost composition of engineering projects

In Equation (3), DC refers to the total direct cost of the project. c_{jm} refers to the j-th task's direct cost using execution mode m. Equation (4) refers to the indirect costs.

$$IC = \max f_j \times c_{ind} \tag{4}$$

In Equation (4), IC refers to the total indirect cost of project. c_{ind} refers to the indirect cost per unit time. Therefore, the objective function TC of the total engineering cost can be represented by Equation (5).

$$TC = DC + IC \tag{5}$$

But in reality, the project schedule is constrained by the contract. If the project is not completed within the specified time limit, it will increase costs. Therefore, it needs to add a penalty function to the cost objective function, which can be represented by Equation (6).

$$P = y \times c_P \times \left(\max f_j - T_{con}\right) \tag{6}$$

In Equation (6), P refers to the penalty function. y refers to a variable, which is taken as 0 if completed within the specified time limit and 1 if completed outside the specified time limit. c_P refers to the penalty coefficient. T_{con} refers to the specified construction period. After adding a penalty function, the cost objective function can be represented by Equation (7).

$$TC = \sum_j \sum_{m \in M_j} \left(x_{jm} \times c_{jm}\right) + \max f_j \times c_{ind} + y \times c_P \times \left(\max f_j - T_{con}\right) \tag{7}$$

The project quality is determined by the requirements set by the owner. The model studied and constructed is a multimodal discrete variable optimization model, and the quality level varies in each execution mode. Corresponding weights need to be set according to different execution models. Therefore, the project quality objective function can be expressed using Equation (8).

$$Q = \sum w_{tj} \sum w_{tj,r} \times Q_{j,r}^{m} \tag{8}$$

In Equation (8), w_{tj} refers to the j-th work activity's impact weight on overall quality. Q refers to the objective function of the quality requirements. $w_{tj,r}$ refers to the weight of quality indicator r in activity. $Q_{j,r}^{m}$ refers to the quality standard achieved by the j-th task in m execution mode for indicator r. Resource balance indicators include variance, imbalance coefficient, resource volatility, and idle days. Equation (9) is the variance.

$$\sigma^2 = \sum_{k=1}^{K} \sum_{t=1}^{T} \left(o_k(t) - \bar{o}_k \right)^2 \tag{9}$$

In Equation (9), σ refers to the variance of the k -th resource equilibrium demand. $o_k(t)$ refers to the usage of the k -th resource at time t. $\bar{o}_k$ refers to the average resources usage. Equation (10) is the imbalance coefficient.

$$b = \frac{o_k^{\max}}{\bar{o}_k} \tag{10}$$

In Equation (10), b refers to the imbalance coefficient of the k -th resource. $o_k^{\max}$ refers to the maximum demand of the k -th resource. Equation (11) refers to the resource fluctuations.

$$RRH = \frac{1}{2} HR - MRD \tag{11}$$

In Equation (11), RRH refers to the overall resource fluctuation level of the project. HR refers to the sum of resource fluctuations per day during the construction period. MRD refers to the resource demand for every day with the highest resource demand. Based on the particularity of the model constructed through research, it is decided to use variance as an indicator of the resource balance index. Therefore, the objective function of resource balance can be represented by Equation (12).

$$RLI = \sum_{k=1}^{K} \sum_{t=1}^{T} \left(o_k(t) - \bar{o}_k \right)^2 \tag{12}$$

In Equation (12), RLI refers to the objective function of resource balance. After completing the construction of the decision variables and the objective function, it is also necessary to set the constraints of the objective function. The first is the logical relationship constraint in Equation (13).

$$f_i - \sum_{m \in M_j} \left(x_{jm} \times d_{jm} \right) \geq f_j \tag{13}$$

In Equation (13), f_i refers to the previous task's completion time i of the j -th task. d_{jm} refers to the duration of the j -th task in execution mode m . Next is the resource demand constraint in Equation (14).

$$\sum_{j \in A_t} \sum_{m \in M_J} \left(x_{jm} \times r_{jkm} \right) \leq R_k \tag{14}$$

In Equation (14), r_{jkm} refers to the demand for resource k by work j in execution mode m . R_k refers to the maximum resource supply. Finally, there are carbon emission constraints in Equation (15).

$$\sum_{j \in A_t} \sum_{m \in M_J} \left(x_{jm} \times r_{jkm} \right) \leq E_{jm} \tag{15}$$

In Equation (15), E_{jm} refers to the carbon emissions of work activity j in execution mode m . E refers to the maximum carbon emissions.

3.2 Improved SFLA based on NSGA-II

SFLA is a population intelligent optimization algorithm developed by simulating frog foraging. Its mathematical model is to randomly generate an initial population in the initial solution space, which includes u frogs. After determining the initial population, the fitness value of each frog individual is calculated and arranged in descending order. The optimal fitness value of the frog is marked as A_g . Then the initial population is divided into n meme groups, each containing l frogs. The first frog is assigned to the first meme group, the n -th frog is assigned to the n -th meme group, and the ($n+1$)-th frog is assigned to the first group until all frogs are assigned. After completing the allocation, the fitness values of frogs in each meme group were calculated. The best individual was marked as A_b and the worst individual as A_w. Through continuous iteration, the position of frog A_w was changed. Equation (16) is the step size summarized in iteration process [17-18].

$$\begin{cases} D = a \times \left(A_b - A_w \right) \\ A_w^{'} = A_w + D, \left| D \right| \le D_{\max} \end{cases} \tag{16}$$

In Equation (16), a refers to a random number from 0 to 1. $D_{\max}$ refers to the maximum value of frog position change. $A_w^{'}$ refers to the fitness value after position update. If $A_w^{'}$ is better than A_w, it is replaced. If A_w is better than $A_w^{'}$, the frog is re-selected and iteratively updated until the convergence condition is met. The steps of SFLA are as follows. First, random initialization is performed and the initial population is generated. Then the frog level was divided. The third step is grouping. Next is to start a local search and iteratively update the frog position. The fifth step is global information sharing, updating the individuals with the best fitness values in the population. The final sixth step is to determine whether the convergence condition is met. If it meets the requirements, the algorithm ends. If it does not meet the requirements, it returns to the third step to restart in Figure 2.

In Figure 2 SFLA parameters include the initial population size, meme group number, maximum number of iterations per meme group, and maximum step size allowed for frog position updates. Each parameter will have an impact on the final result of the algorithm. Therefore, the study adopted NSGA-II to optimize the parameters of SFLA. The basic concept of NSGA-II comes from genetic algorithms, but some improvements have been made. The first is the concept of individuals and populations. The concept of individuals in NSGA-II is consistent with genetic algorithms, while populations are composed of multiple individuals combined. Next is fitness. NSGA-II sets a virtual fitness for all individuals based on fast non-dominant sorting and crowding calculation results. The third is chromosomes and genes, and the concept of chromosomes and genes in NSGA-II is consistent with genetic algorithms. Finally, there is the genetic operator, which refers to the chromosome operation method selected for optimization. The steps for NSGA-II are as follows. The first step is parameter initialization and generating a random initial population. Secondly, non-dominant sorting is used to sort the initial population and generate the first generation of subpopulations through mutation and other operations. The third step is to mix the initial population individuals with the subpopulation individuals and regroup them. Next is to calculate the crowding degree of individuals at the same level after regrouping and generate a new parent population. The fifth step is to generate new subpopulations through mutation and other operations. Finally, it needs to determine whether the convergence condition is met. If it is, the algorithm will be stopped. If it is not, the iteration will be restarted by returning to the third step in Figure 3.

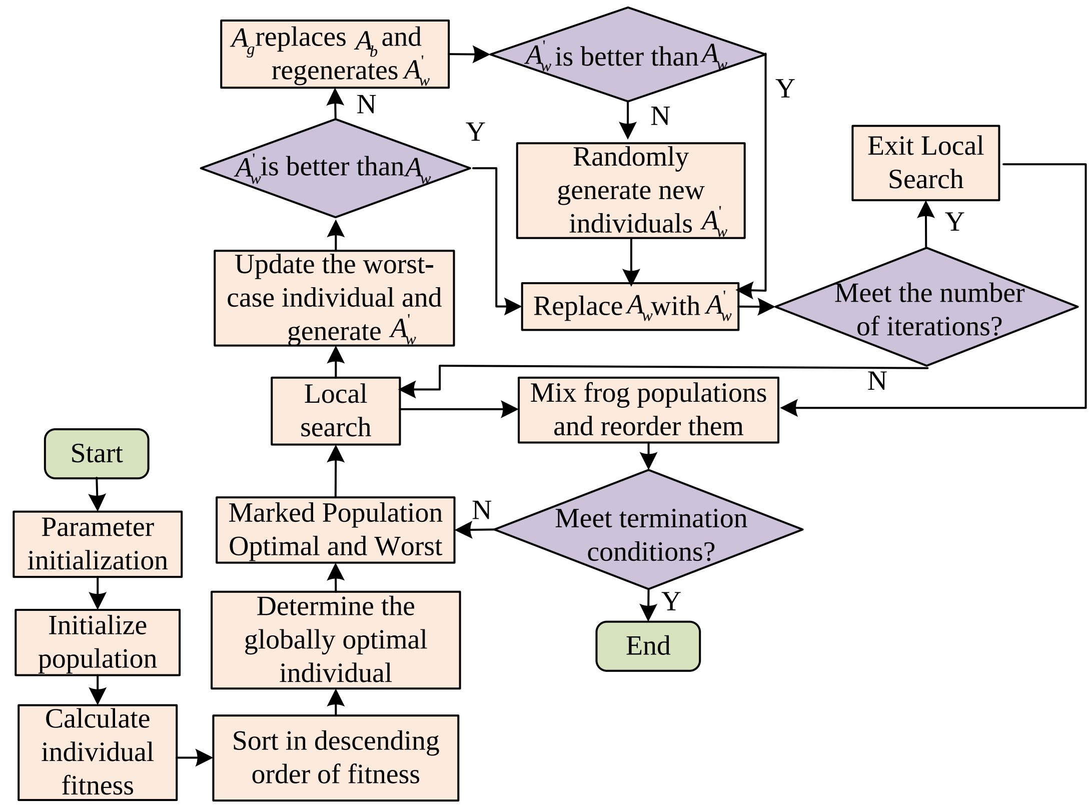


Fig. 2. SFLA basic process

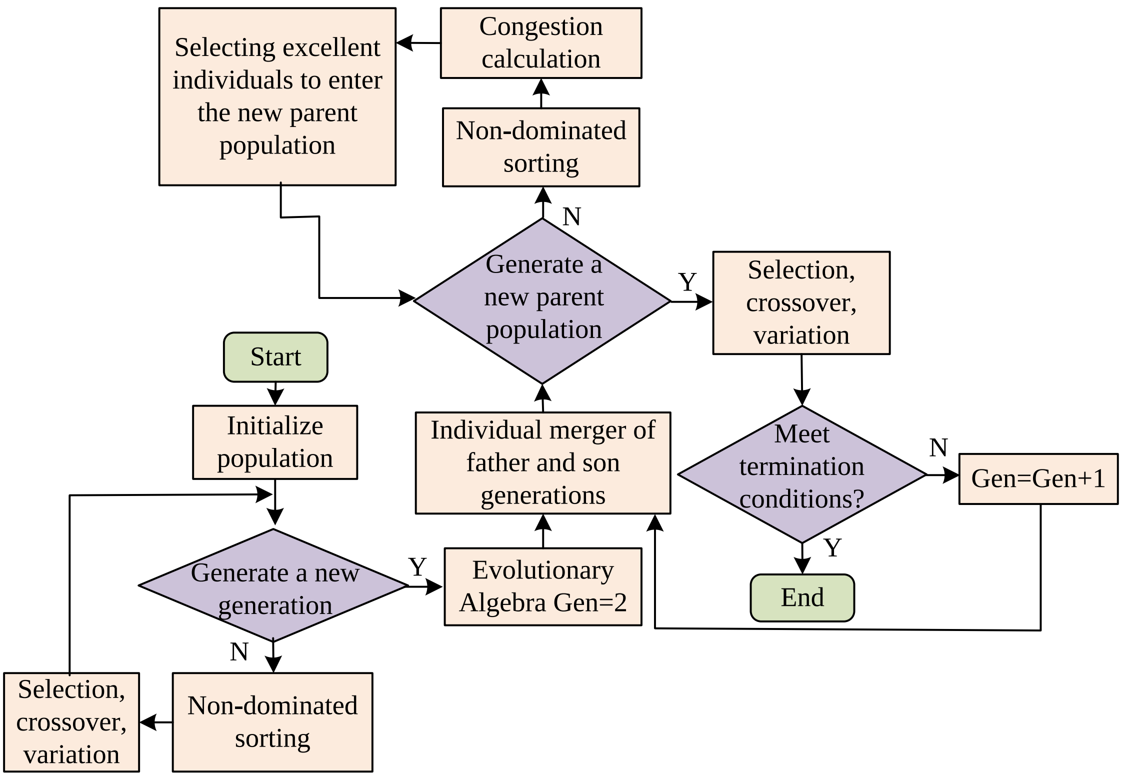


Fig. 3. Basic process of NSGA-II algorithm

In Figure 3 the improvement of SFLA by NSGA-II includes three aspects. Firstly, the specific steps for sorting candidate solutions include parameter calculation, non-dominated sorting, determining meme group number and individuals in meme group, grouping, reordering, and restoring the population size. The second is the evolution of memes. The third aspect is the traversal mechanism of constraint conditions, which introduces carbon emissions and resource supply as constraint conditions in MOP. Therefore, after the algorithm iteration is completed, it needs to determine the feasibility of the current solution. Therefore, it needs to improve the traversal mechanism of SFLA. The improvement method is as follows. Firstly, during parameter setting, the start, duration, and completion time of the work j in execution mode m are defined. Secondly, after each iterating, the experiment calculates whether the current solution meets the constraint conditions. Finally, if the current solution does not meet the constraint conditions, the start time of work will be postponed until the conditions are met in Figure 4.

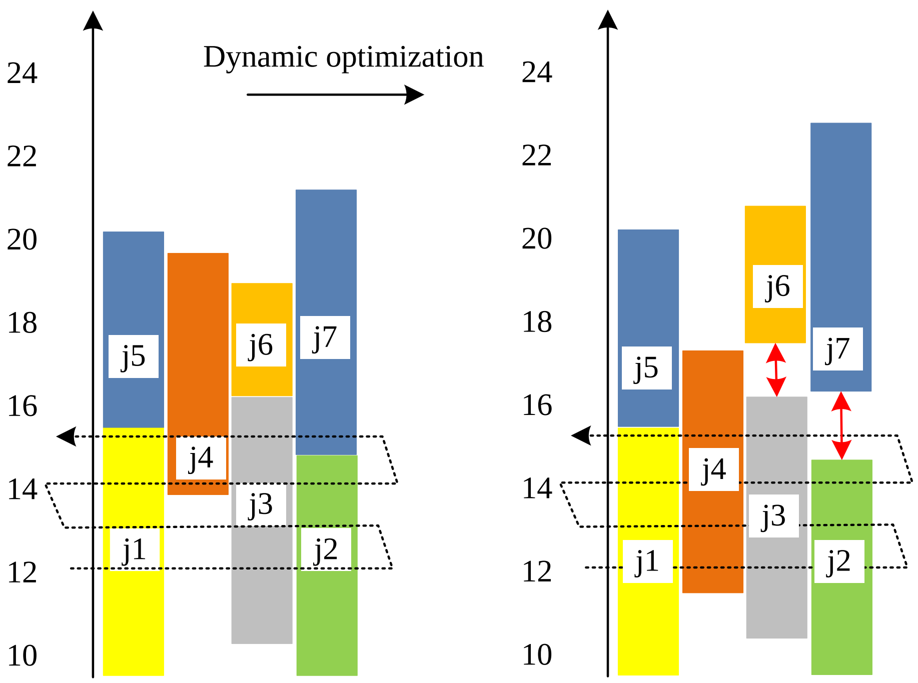


Fig. 4. Improving the constraint traversal mechanism of SFLA

In Figure 4 the steps for improving SFLA based on NSGA-II are as follows. The first step is to initialize project parameters. Next is the initialization of SFLA parameters. The third step is to determine the encoding method of the model. Next is to generate the initial population. The fifth step is to use quick domination for sorting. Then, the meme groups are divided. The seventh step is intra group meme evolution, which is divided into steps such as parameter initialization, cross operation, and determining whether an individual needs to be updated. The eighth step is global information sharing. Finally, there is an iterative update of the algorithm until the termination condition is met in Figure 5.

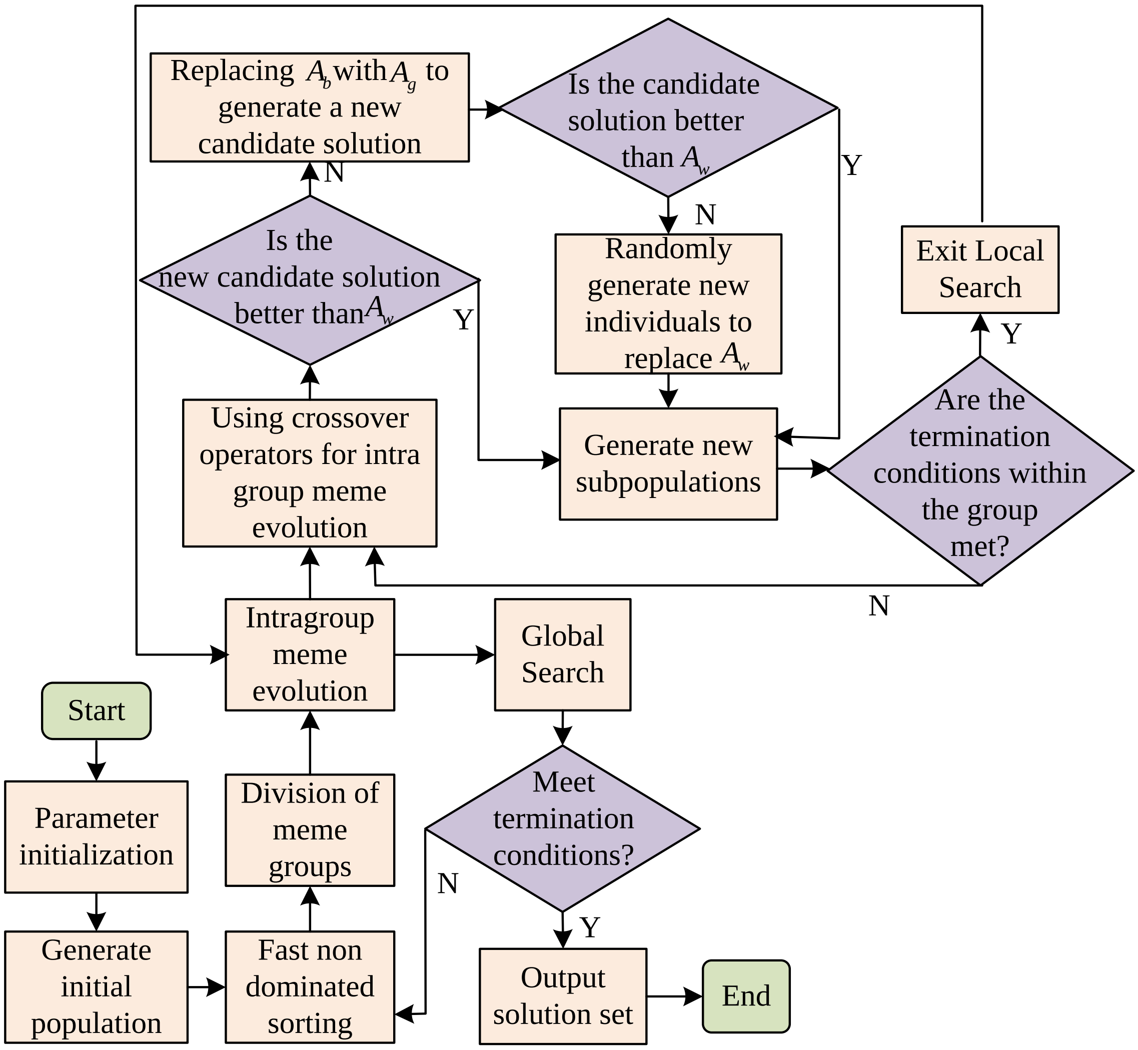


Fig. 5. Improve the basic process of SFLA

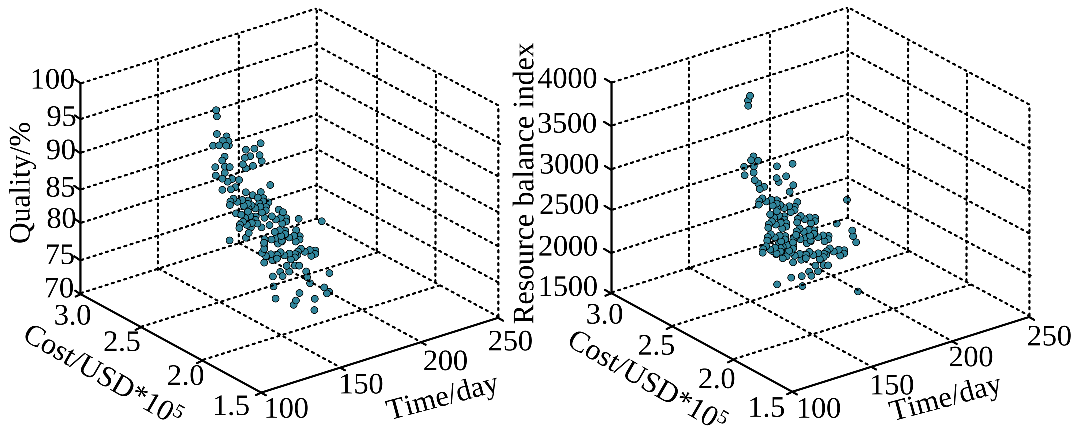
4. Simulation Experiment Results Analysis

The study takes a certain engineering project as the research object and analyzes the basic project parameters in the project. The project includes a total of 18 work activities, each corresponds to several different execution modes, and the various parameters corresponding to each different execution mode are also different. Table 1 shows some project parameters.

Table 1
Partial project parameters

Job Number	Immediate work	Execution Mode	Time(day)	Cost (USD)	Natural resources	Device		
/	/	/	/	/	/	Type	Number	Power
1	/	1	15	2600	172	W1	1	5.2
						W2	1	4.1
		2	16	2250	146	W1	1	5.2
						W2	1	4.1
		3	21	1800	118	W1	1	5.2
						W3	1	3.2
		4	24	1300	71	W1	1	5.2
						W3	1	3.2
3	/	1	15	4800	320	W5	2	7.2
						W6	1	3.1
		2	21	4200	159	W5	2	7.2
						W7	1	4.1
		3	33	3000	98	W5	2	7.2
						W7	1	30.2
5	1	1	21	22000	903	W6	2	3.1
						W8	1	30.2
		2	25	16500	754	W7	2	4.1
						W8	1	30.2
		3	29	14000	531	W7	2	4.1
						W8	1	30.2
		4	31	10000	384	W6	2	3.1
						W8	1	30.2
7	5	1	8	32000	3351	W11	1	6.1
		2	16	25000	1652	W11	1	6.1
		3	17	21000	1268	W11	1	6.1

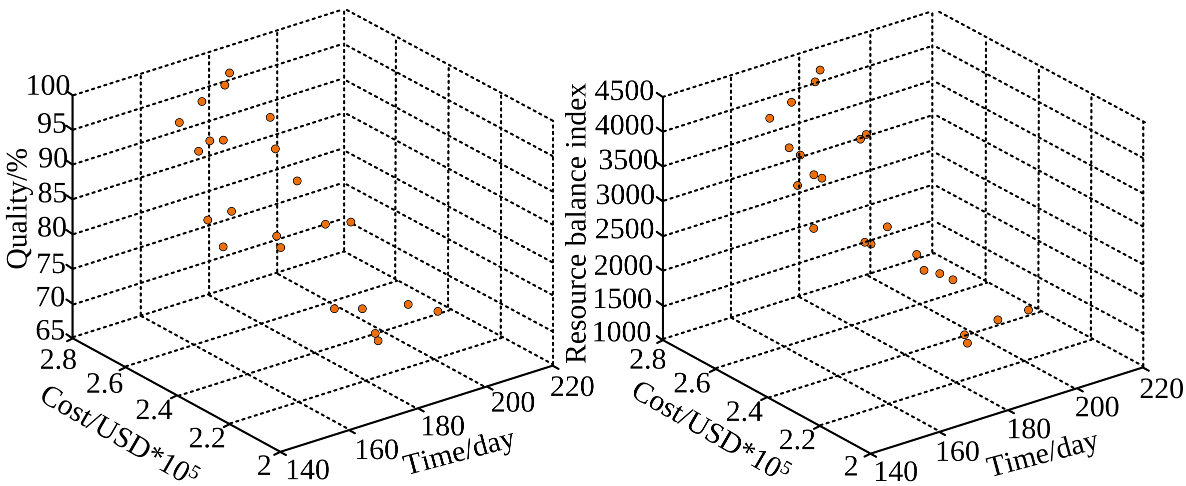
In table 1 after determining the project parameters, research is conducted on programming algorithms in Windows 7 flagship system using MATLAB 2016a software. The initial parameters are set as follows: the number of meme groups is 5, the individual number in meme group is 10, the population size is 50, and the maximum iteration number is 100. Figure 6 shows the Pareto solution set generated using improved SFLA.



(a) Duration-Cost-Quality (b) Duration-Cost-Resource balance index

Fig. 6. Improving Pareto solution set of SFLA

Figure 6 (a) shows Pareto solution set for duration, cost, and quality, while Figure 6 (b) shows Pareto solution set for duration, cost, and resource balance. After 100 iterations, a total of 132 solution sets were generated, of which 49.24% were generated in the first 15 iterations. This indicates that the initial convergence of the improved SFLA is good, and a large number of Pareto solutions can be found in a short time. The duration distribution of 132 Pareto solutions sets ranges from 150 to 250 days. The distribution of cost ranges from \$20000 to \$30000. The distribution of quality is between 70% and 100%. The resource balance level is distributed between 1500 and 4000. Due to NSGA-II being a commonly used MOP algorithm, Pareto solutions were performed using NSGA-II under the same parameter environment in Figure 7.



(a) Duration-Cost-Quality (b) Duration-Cost-Resource balance index

Fig. 7. Pareto solution set of NSGA-II

Figure 7 (a) shows the Pareto solution set for duration, cost, and quality, while Figure 7 (b) shows Pareto solution set for duration, cost, and resource balance. After completing one run, NSGA-II found a total of 23 Pareto solution sets. The minimum construction period for these solutions is 150 days, and the maximum construction period is 207 days, all of which meet the specified construction period. The minimum cost is \$212,418, the maximum cost is \$278418, the minimum quality is 69.29%, the maximum quality is 96.79%, the minimum resource balance index is

1476, and the maximum resource balance index is 4273.18. To visually compare the difference between the improved SFLA and NSGA-II in PMMOP, the study compared the operating results of improved SFLA and NSGA-II in Figure 8.

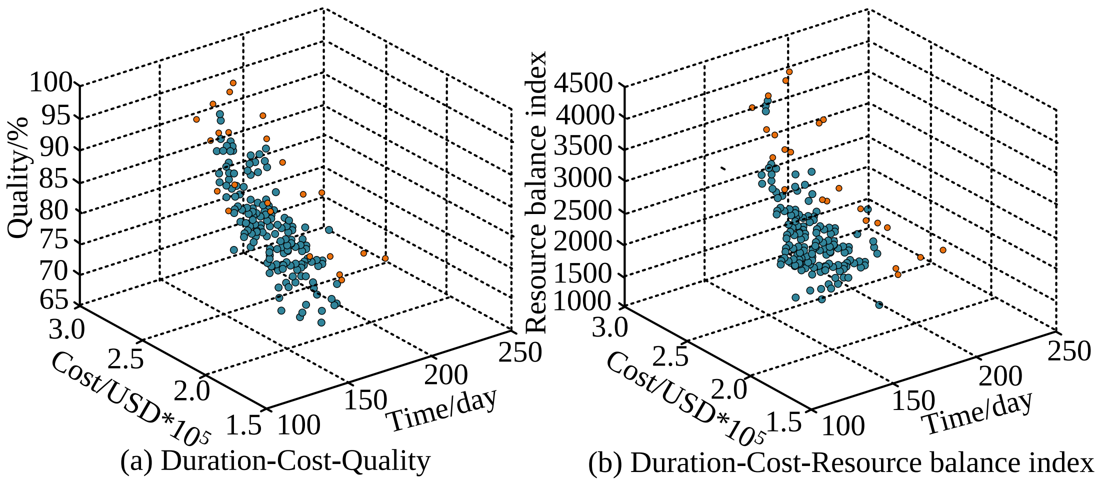


Fig. 8. Comparison of Pareto optimal solutions for improved SFLA and NSGA-II

Figure 8 (a) shows the Pareto solution set for duration, cost, and quality. The Pareto optimal solutions of improved SFLA are much higher than Pareto optimal solutions of NSGA-II. And in the distribution of scattered points, the optimal solution set distribution of the improved SFLA is closer to the optimal position. The study also listed some examples of Pareto optimal solutions for improving SFLA and NSGA-II in Table 2.

Table 2
Examples of partial pareto optimal solutions

Pareto Optimality	Execution mode selection	Time (day)	Cost (USD)	Quality (%)	RLI
				Improving SFLA	
1	(2,1,2,3,2,2,3,2,2,1,3,2,2,2,1,1,1,1)	131	216384	82.94	2441
2	(2,4,4,3,3,3,3,3,3,1,2,1,2,2,1,4,1,1)	145	199438	76.78	2218
3	(2,1,1,1,1,1,3,4,3,2,2,1,1,1,1,4,1,1)	158	260984	95.63	3766
4	(4,4,1,3,4,3,3,4,1,1,2,4,3,3,1,2,2,1)	197	225109	72.88	1532
				NSGA - Ⅱ	
1	(3,4,1,1,3,2,1,4,3,4,2,1,1,2,1,3,1,1)	152	241239	88.24	3855
2	(3,4,1,1,3,2,1,4,3,1,2,1,1,2,1,3,1,1)	152	235234	85.74	3364
3	(3,4,1,3,4,3,3,4,2,1,3,2,3,3,1,5,2,1)	179	212415	72.55	1754
4	(1,3,1,1,1,4,1,4,2,1,1,1,1,3,1,1,2,1)	154	262344	96.79	4279

In Table 1, there is a certain contradiction between duration, cost, quality, and resource balance index of PM. Construction period extension will lead to an increase in costs. The improvement of quality will extend the construction period and also increase costs. The increase in costs leads to a decrease in resource balance index. This study will compare the optimal construction period, optimal cost, optimal quality, and optimal resource balance index between SFLA and NSGA-II. Figure 9 shows the comparison between the optimal construction period and the optimal cost.

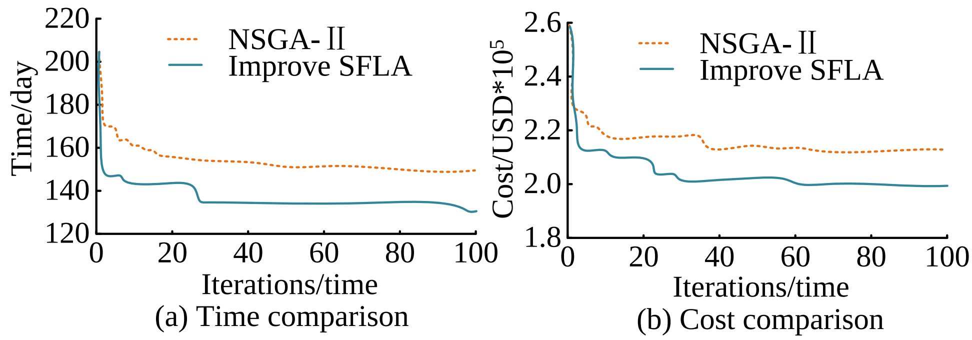


Fig. 9. Improving the comparison of the optimal construction period and cost between SFLA and NSGA-II

Figure 9 (a) shows the optimal construction period. The optimal construction period for improving SFLA is much lower than that of NSGA-II. After convergence, the optimal construction period for improving SFLA is 135 days, while the optimal construction period for NSGA-II is 150 days. Figure 9 (b) shows the optimal cost comparison between these two algorithms. The optimal cost for improving SFLA is around $20000, while the optimal cost for NSGA-II is around $21500. Figure 10 shows the comparison between optimal quality and optimal resource balance index.

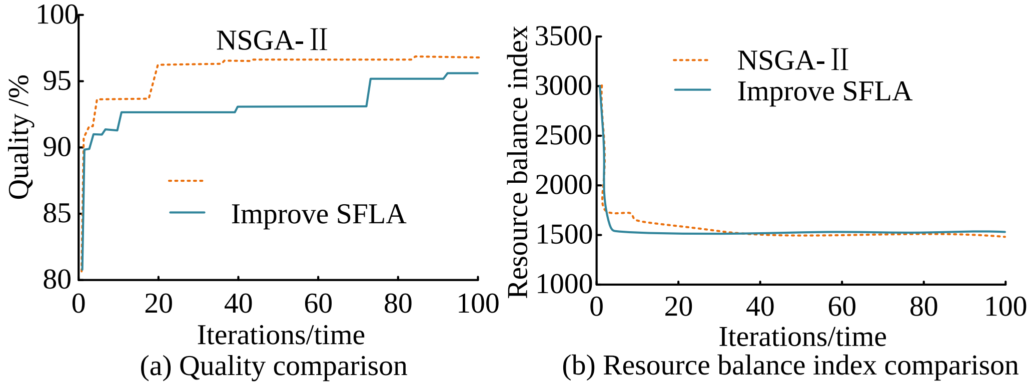


Fig. 10. Comparison of the optimal quality and resource balance index between improved SFLA and NSGA-II

Figure 10 (a) shows the comparison of the optimal quality levels. The highest quality level of improved SFLA is 95%, and the highest quality level of NSGA-II is 96%. Figure 10 (b) shows the optimal resource balance index. After the convergence of these two algorithms, the optimal equilibrium index is basically the same, around 1500.

5. Conclusion

Construction industry development has intensified competition in this industry, and various construction enterprises are facing the challenge of increasing difficulty in project management. To address this issue, a PMMOP model was constructed, which used SFLA to solve objective optimization problems. However, this algorithm cannot solve the problem of objective conflicts. Therefore, NSGA-II was proposed to improve SFLA and used the improved SFLA to solve MOP problems. The performance of improved SFLA in solving MOP problems was much higher than that of NSGA-II. In one run, a total of 132 Pareto optimal solution sets were found, with 49.24% of the solution sets found in the first 15 iterations. NSGA-II only found 23 Pareto optimal solution sets in one run. The optimization effect of improving SFLA is better, and the scatter plots of Pareto solution sets of the two algorithms show that Pareto solution set of improving SFLA is closer to the optimal position. The optimal construction period after improving SFLA optimization is lower, with an optimal construction period of 135 days for improved SFLA and 150 days for NSGA-II. The optimal cost after improving SFLA optimization is lower, with an optimal cost of around $20000 for improved SFLA and around $21500 for NSGA-II. The optimized SFLA not only shortens the construction period, reduces costs, and improves engineering efficiency, but also makes the selection of solutions more diverse and flexible.

This means that engineers can make more scientific and accurate decisions when facing various complex and ever-changing project environments. The research on resource allocation considering objective functions has not yet involved complex and diverse resource allocation situations. In the future, complex and diverse resource allocation can be considered in order to comprehensively solve optimization problems in engineering projects. At the same time, there is still room for further improvement in the SFLA algorithm, such as handling target conflict problems, making the overall optimization effect more outstanding.

Author Contributions

Conceptualization, Y.W., J.M. and Y.Z.; methodology, Y.W. and Y.Z.; software, Y.W., J.M. and Y.Z.; validation, J.M. and Y.Z.; formal analysis, Y.Z.; investigation, Y.W.; resources, J.M.; data curation, Y.Z.; writing—original draft preparation, J.M.; writing—review and editing, Y.M.; visualization, J.M.; supervision, Y.M.; project administration, Y.Z.; funding acquisition, Y.W. All authors have read and agreed to the published version of the manuscript.

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All data generated or analysed during this study are included in this published article.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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