Multi-Objective Optimization of Construction Project Management Based on NSGA-II Algorithm Improvement

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***Abstract*—In the building industry, one of the key components to ensuring a project's successful completion is multi-objective project management. However, due to its own limitations, the traditional multi-objective management approach for projects is no longer able to meet the requirements of building construction and urgently needs to be improved. This is because the construction industry is becoming more competitive and construction standards are improving. Traditional methods for multi-objective optimization typically involve simply summing multiple objectives with weights, overlooking the interdependencies among these objectives. These methods often get trapped in local optimal solutions and rely heavily on predefined models and parameters, limiting their adaptability to sudden changes during the construction process. Therefore, a multi-objective management approach based on multi-objective genetic algorithm for construction projects is proposed. It enables in-depth analysis and comprehensive optimization of the complex relationships between objectives, leading to more informed decisions. By facilitating rapid iteration and adaptation, it enables timely adjustments and optimizations to ensure that project goals remain consistent in complex and dynamic environments. In the experimental validation, the NSGA-II algorithm achieved a significant accuracy of 0.642 and success rate of 0.504 on the VOT dataset, both of which improved by about 1.0% and 0.6% compared to the comparison algorithm. Experimental results on the TrackingNet dataset revealed that the algorithm achieved an accuracy of 0.791 and a success rate of 0.763, while it still maintained an accuracy of 0.542 and a success rate of 0.763 in the face of occlusion. The enhanced multi-objective genetic algorithm had higher accuracy and success rates. This demonstrates the efficiency and excellence of the multi-objective management optimization approach suggested in this study for building projects. The research results have some application value in the multi-objective optimization of engineering projects.**

Keywords—NSGA-II algorithm; improvement strategy; construction engineering; project management; multi-objective optimization

I. INTRODUCTION

With the development of the economy and the continuous acceleration of urbanization, the construction industry has gradually become an important part of the national economy. When carrying out construction, project management is extremely important, which involves the economic benefits of the project, quality, safety, environmental protection and other aspects of the requirements [1]. Current construction project management often adopts the traditional method of single objective or simple weighting for optimization, which makes it difficult to effectively balance the trade-offs between different objectives, and lacks the flexibility to respond to dynamic changes in demand. This limitation not only affects the overall efficiency and sustainability of the project, but also renders the project inadequate in the face of emergencies. Therefore, it is particularly important to propose a multi-objective optimization (MOO) method with strong adaptability and high computational efficiency in a dynamic construction environment. Consequently, it offers enhanced scientific and comprehensive decision support for construction project management, thereby promoting the coordinated development of resource utilization, economic benefits, and environmental protection in the construction industry. This area of research is of particular interest to experts and scholars in the industry. The research structure is divided into five sections. Section I outlines the importance of MOO in construction project management, as well as the problems and challenges in the current research. Section II is to construct and introduce the construction and solution of MOO model of construction engineering project, and discuss the objective function model of construction time, cost, quality and environment management. Section III shows the empirical test of the algorithm, including experimental design, data set selection and performance evaluation. Section IV discusses the experimental results and analyzes the performance and advantages of the algorithm in different application scenarios. Finally, Section V is the conclusion, which summarizes the main findings, practical application value, and future research direction.

In related research, Hamidreza et al. created a novel machine learning (ML) model to address the issue that current labor estimation algorithms often only take particular construction project types or specific influencing factors into account. At the work package level, the model could forecast the labor resource use time series. The results of the study indicated that the model could be used to predict the utilization of labor resources in construction projects, which could help in resource allocation. It was also able to prioritize the available resources to improve the overall performance of the project [2]. To dynamically manage the preliminary costs of a construction project, Zhouxin et al. proposed an artificial intelligence-driven analytical model for estimating and controlling construction costs. ML had the potential to enhance cost estimation during the construction process' procedural stage. The study's findings demonstrated that the ML model could be used to optimize workflow for cost savings and the useful outcomes of data-driven management [3]. Ghoroqi et al. proposed a

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computational model for a multi-objective (MO) whale optimization algorithm (WOA) based on the Pareto profile to minimize the overall project delay time and associated costs. A comparative study revealed that the MO WOA-supported scheduling technique and solution approach were implemented, and this led to notable gains [4]. The process of cost optimization in construction projects requires maximizing value through effective resource management, cost control and achieving project goals within budget. Therefore, MAJDI Bisharah et al. identified the variable aspects that had significant impact on project cost (PC) through feature selection method. The outcomes revealed that it could effectively allocate resources to achieve project success and improve profitability [5]. In the construction project management mentioned above, the model improves resource management under a single objective, but it primarily focuses on cost control and lacks consideration of other key factors such as quality and environmental impact. The primary motivation of the research is to incorporate additional objectives, such as project quality and environmental impact, to construct a more comprehensive MOO model. The objective is to achieve labor optimization and the balance between time and cost.

Van et al. constructed an analytical model based on both exploratory factor analysis and validation factor analysis. The study's findings showed that the model helped create the theory behind the variables affecting how effective the materials management process is. The key findings about the influencing factors could be used to measure the effectiveness of the materials management process [6]. Simon et al. classified elements into major underlying determinants that caused the majority of the performance deviations, so reducing the scope of construction cost and time management to a few concrete, important areas of attention. This improved the management of the variables influencing time and cost overruns in public construction projects. This supported and improved the rapid decision making required in a variable environment such as construction [7]. Aiming at the problem of efficiency improvement in construction project management, Si et al. put forward the application method of self-organizing digital concept in data mining and intelligent planning. Therefore, it could achieve the improvement of efficiency in construction management practice stage. The study showed that the use of intelligent self-organizing data mining systems in this process could optimize the design and construction complexity, and evaluate the effectiveness of the model by integrating digital twin-driven intelligent construction and basic theoretical method. The results confirmed that the self-organizing model had a direct impact on time prediction planning [8]. Lawal et al. addressed the sustainability challenges facing the Nigerian construction industry by proposing ways to achieve better economic, social and environmental sustainability outcomes through resource optimization and reduced rework practices. Complex relationships between variables were assessed using a structural equation model based on covariance. Path analysis revealed a significant positive correlation between resource optimization and rework reduction and the social and environmental outcomes of construction firms [9]. Due to the identified conflict between efficiency and environmental impacts in off-site construction, Zheng et al. proposed a MOO framework. The framework incorporated a grouping technique for hybrid flow prefabricated production scheduling, aiming to minimize carbon emissions and reduce late/early departure penalties. The proposed approach reduced carbon emissions by an average of 37.5% through real case studies, while late/early penalties were reduced by more than 10% [10]. A simulation-based method was presented by Sensenses et al. to maximize the cost-time trade-off for project planning issues in the face of uncertainty. Several project schedule collapse scenarios that produced equally plausible realizations were taken into consideration during this approach. The suggested approach has a considerable deal of potential to improve project management, according to experimental data [11]. While the construction project management approach outlined above provides a basic management theory, it lacks a discussion of the joint optimization of multiple objectives. In addition, insufficient consideration of factors affecting project quality and the environment leads to a one-sidedness in optimization results. It also provides no empirical verification for navigating dynamic and complex project environments. The research motivation is to develop a MOO framework that incorporates the relationship between material management and other objectives, along with a more flexible and adaptive algorithm to address dynamic changes in the construction environment. Research models include weighted sum, particle swarm optimization, and MO genetic algorithms. The weighted sum method can be subjective in weight selection and may not capture nonlinear relationships between objectives. Particle swarm optimization can suffer from premature convergence in complex problems, while MO genetic algorithms often have long convergence times and lack flexibility. In contrast, NSGA-II is chosen for this study because of its ability to effectively discriminate between high and low quality solutions. By utilizing crowding distance (CD), it maintains solution diversity and delivers high-quality results quickly. Additionally, it adapts well to both linear and nonlinear relationships among objectives, making it suitable for various MOO challenges, including construction projects.

In summary, most of the existing studies only consider the coordination and optimization of two objectives in the construction project. However, the existing research on MOO mostly focuses on the coordination of single or limited objectives, such as duration and cost, quality and environment. Many studies tend to ignore the complex relationships between them, which leads to the lack of applicability and comprehensiveness of optimization results in practical decision-making. Many models in the existing literature make the simplifying assumption that the environment and parameters remain static. This approach fails to adequately address the dynamic adjustment requirements that arise during project execution. Despite the prevalence of the MOO algorithm, it exhibits suboptimal efficiency, particularly in complex MO scenarios where the computational complexity is substantially elevated. In view of the above gaps, this study proposes a MO management method based on the improved NSGA-II algorithm. This method aims to comprehensively optimize project duration (PD), cost, quality, and environment, and to solve the problem of insufficient treatment of multiple interactive objectives in the current literature. The enhancement of the NSGA-II algorithm has been demonstrated to improve the adaptability of the algorithm in dynamic, changing environments. This enhancement enables the algorithm to respond to changes in the project in real time, thereby ensuring the effectiveness of the optimal solution. An algorithm efficiency optimization strategy is proposed to improve computational efficiency and reduce execution time. The research innovation is mainly reflected in the improvement of NSGA-II, including the pre-computation of the dominant relationship between individuals to reduce the computational complexity of non-dominant sorting. The sorting strategy has been demonstrated to expedite the identification of congestion distance. Rather than employing the conventional adjacent calculation, local information is utilized to expedite the calculation process and enhance the diversity and velocity of selecting high-quality solutions. The shared fitness mechanism is adopted to make the lower level individuals get higher priority in the selection. The main contribution of this research is to improve the responsiveness and computational efficiency of the model in project management in the face of complex dynamic environments, realize real-time adjustment and optimization of the actual construction, provide important reference value for the sustainable development of the construction industry, and fill the management efficiency gap of the current MOO technology.

II. EP Multi-Objective Model: Construction and Solution

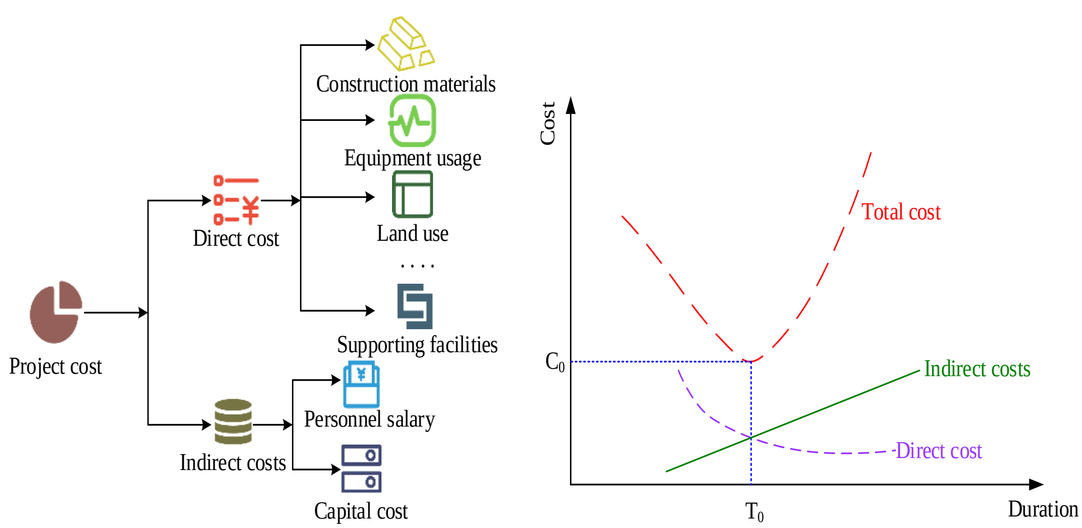
A. MOO Model Construction for EPs

In construction projects, time, cost, quality, and environment are key interrelated management objectives that influence outcomes. A well-structured schedule is essential for smooth progress, which has a direct impact on operating costs and customer satisfaction. Effective cost control addresses both DCs (such as materials and labor) and IDCs (such as management fees). MOO helps managers reduce costs while maintaining quality and schedules. High-quality buildings reduce maintenance costs and safety risks, improve customer satisfaction, and require rigorous quality control to meet relevant codes and standards. In addition, managing the environmental impacts of construction - such as dust, wastewater, and noise pollution - enhances a company's corporate social responsibility and market competitiveness, especially in the context of green building certification. Reasonable arrangement of PD is an important prerequisite for MO management of EPs, which is also one of the main objectives of management. To guarantee that the project can be finished in the allotted time with both quality and quantity, management of PD necessitates dynamic adjustment of the construction time of each step in accordance with the plan. The general OF model of PD management is shown in Eq. (1) [12].

$$B = \max_{L \in Lm} \left(\sum_{(i,j) \in L_m} t_{ij} \right) \tag{1}$$

In Eq. (1), B denotes the PD. Lm denotes the set of feasible paths. (i, j) denotes the project process. t_{ij} denotes the time required for a single process. Cost management of a project is a dynamic control process. The structure of its components and its relationship with the duration are shown in Fig. 1.

In Fig. 1(a), the PC of the project is mainly composed of two parts: direct cost (DC) and indirect cost (IDC). The DC project construction is directly related to the project, including land use, machinery, construction equipment, etc. IDC are not directly related to the construction of the project but must be spent on the part of the project, mainly for personnel wages, management fees and so on. The purpose of PC management is mainly to carry out reasonable planning for all costs in the whole process of project construction. Furthermore, the project schedule is guaranteed to control the costs required for the project as far as possible, to maximize the economic benefits. The OF model of PC management is shown in Eq. (2) [13].



(a) Project cost composition (b) The relationship between project duration and cost

Fig. 1. Schematic diagram of construction project duration cost optimization model.

$$C = \sum_{(i,j)\in L_m} \left(C_{ij}^d + C_{ij}^i \right) \quad (2)$$

In Eq. (2), C represents the total PC. C_{ij}^d denotes the DC required to complete the process. C_{ij}^i denotes the IDC required to complete the process. The DC of the project is declining in Fig. 1(b) as the project's duration rises. This is because the shorter the project duration, the more labor and machines are used per unit of time, which increases the DC of the project. However, a reduction in PD also reduces the cost of labor, project management, etc., thus reducing the IDC of the project. The total cost (TC) of a project decreases and then increases as the PD increases. When the PD increases to a certain level, there will be a minimum value (MinV) of the TC of the project. This MinV can be solved using the OF optimization model of PD-cost to obtain the optimal solution between PC and duration, as shown in Eq. (3) [14].

$$C = \sum_{(i,j)\in L^m} \left[c_{ij}^d + a_{ij} \left(t_{ij}^n - t_{ij} \right)^2 \right] + \sum_{(i,j)\in L^m} b * t_{ij} \quad (3)$$

In Eq. (3), a_{ij} denotes the marginal cost factor of the process. t_{ij}^n represents the planning time needed to finish the procedure. The real time needed to finish the process is indicated by the letter t_{ij}. b denotes the project overhead cost required for a single day. The established quality standards in each stage of the building process serve as the foundation for the project's quality management. This enables the quality of the project (QOP) to meet the requirements of the contract, the industry and other parties. The main influencing factors of project quality and its relationship with PD are shown in Fig. 2.

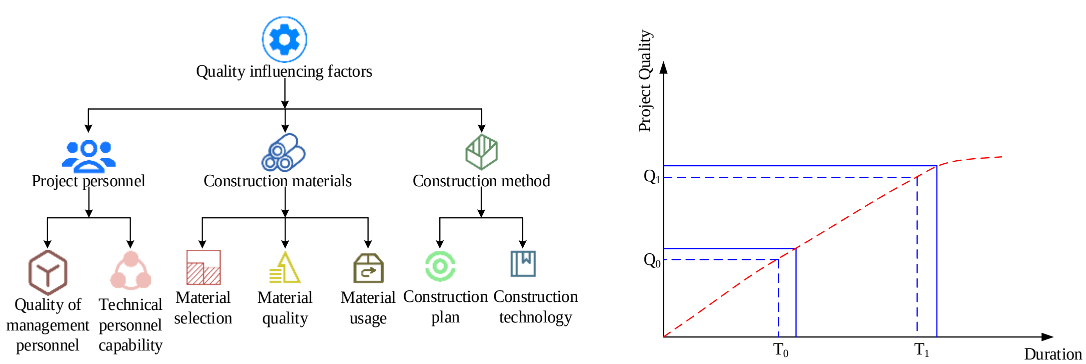
In Fig. 2(a), the factors affecting the QOP are multifaceted, mainly including the technical ability of the personnel, the quality of construction materials, construction technology, etc., which affect the quality of each process of the project. When managing the QOP, it is necessary to find out the deficiencies in these factors according to the actual situation of the project and take corresponding measures to improve [15]. Unlike calculating the duration and cost of a project, the quality of a project is highly subjective. It is difficult to calculate directly. It is necessary to quantify it in an attempt to establish the OF model. The study set different weights according to the impact of different factors on the overall QOP to establish the OF model of project quality, as shown in Eq. (4).

$$D = \sum_{(i,j)\in L_m} w_{ij} q_{ij} \quad (4)$$

In Eq. (4), D denotes the project quality. w_{ij} denotes the impact weight of project quality. q_{ij} denotes the actual quality level. To build the objective function model of project quality, it is essential to quantify and weight each factor affecting the overall quality, which has a significant impact on the model performance. Key influencing factors include the technical ability of construction personnel, material quality, construction standards and technologies, project management and supervision processes, and the external environment. To quantify these factors and set their weights, the expert scoring method can be applied, followed by the weighted average method to calculate the weight for each factor. In Fig. 2(b), there is a roughly positive correlation between project quality and its required duration. The longer the duration of the project, the more construction time for each process, and theoretically the overall QOP will be better. However, the duration of a project obviously cannot be infinitely long, so the QOP can only fluctuate within a given duration. As the PD continues to increase, the improvement of project quality is also more and more limited, gradually converging to a fixed value. The OF optimization model of PD-quality is shown in Eq. (5).

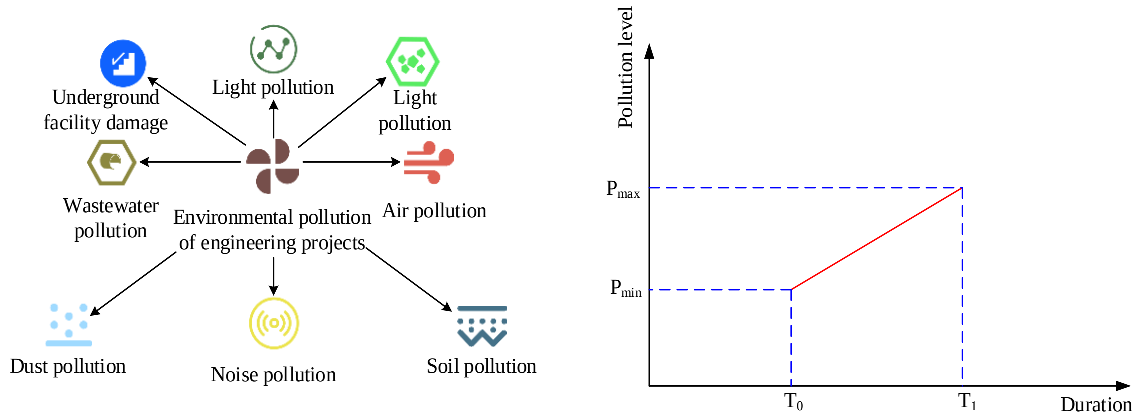
$$\beta_{ij} = \frac{q_{ij}^n - q_{ij}}{\left(t_{ij}^n - t_{ij} \right)^2} \quad (5)$$

In Eq. (5), q_{ij}^n denotes the level of quality to be achieved. The environmental management of the project is one of the key elements of project management nowadays, this is because all EPs will inevitably pollute the surrounding environment during the construction process and must be controlled [16]. The types of environmental pollution from projects and their relationship with PD are shown in Fig. 3.



(a) Factors affecting the quality of engineering projects (b) Relationship diagram between project quality and schedule

Fig. 2. Schematic diagram of project duration quality optimization model construction.



(a) Types of environmental pollution caused by engineering projects

(b) Relationship diagram between project environment management and construction period

Fig. 3. Schematic diagram of construction period environment optimization model construction.

In Fig. 3(a), in the construction process of EPs, the pollution to the environment mainly includes dust pollution, light pollution, garbage pollution, water pollution, noise pollution and so on. All these pollution are unavoidable for engineering construction. The environmental management of the project is to minimize the degree of pollution of the building construction on the surrounding environment under the condition of meeting other requirements. The study uses factor analysis to assess the impact of different types of pollution on the environment. Factor analysis is a multivariate statistical technique used to identify latent variables that influence observable variables, help understand relationships among factors, and reduce data dimensionality for improved modeling. First, several measures of environmental impact are selected as inputs to the analysis using accurate and valid data. The correlation coefficient between these variables is calculated to assess their interrelationships. Principal component analysis is then performed to extract the underlying factors, followed by factor rotation to ensure that each factor is significantly loaded by only a few variables. The factor load matrix is analyzed to determine which variables most influence each factor. Finally, an objective function model for environmental management is established, as presented in Eq. (6).

$$f(x) = \min E = (L \times W) \times \sum_{ij \in L} \left(t_{ij} \times e_{ij} \right) + K \tag{6}$$

In Eq. (6), E indicates the degree of environmental pollution. L denotes the distance between the project site and the residential area. W denotes economic indicators. e_{ij} denotes the evaluation value of pollution factors. K denotes the proportion of resource consumption. In Fig. 3(b), PD and environment are interacting with each other. The PD will affect the environment, and at the same time, the environmental factors will also affect the planning of the PD and the actual completion time of the process. Fig. 3(b) shows a positive correlation between project environmental management and PD. As PD increases, the need for environmental management increases, as does its complexity. Longer construction periods lead to more activities, greater environmental impacts, and higher management costs to comply with environmental standards. The environmental impacts of prolonged construction may vary at different stages, and the diversification and complexity of activities require more stringent management measures to address emerging environmental risks. Since it is not possible to quantitatively calculate the various types of pollutants, the study obtains the OF optimization model of PD-environment from the time that each process lasts, as shown in Eq. (7) [17].

$$e_{ij} = e_{ij}^{n} - \varpi_{ij} \left(t_{ij}^{n} - t_{ij} \right) + e_{ij}^{s} \tag{7}$$

In Eq. (7), e_{ij} denotes the actual degree of environmental pollution from the project. e_{ij}^{n} denotes the degree of environmental pollution during the planning period. ϖ_{ij} represents the rate of change of environmental pollution. e_{ij}^{s} represents the estimable part of environmental pollution during the planning period. Eq. (8) illustrates how a comprehensive optimization model of PD-cost-quality-environment may be created by combining the aforementioned OF optimization models between PD and PC, quality and environment.

$$\begin{cases} \min T = \max \left(\sum_{(i,j) \in L^{m^m}} t_{ij} \right) \\ \min C = \sum_{(i,j) \in L^{L^m}} \left[c_{ij}^{n} + a_{ij} \left(t_{ij}^{n} - t_{ij} \right)^2 \right] + \sum_{(i,j) \in L^m} b^{*} t_{ij} \\ \max Q = \sum_{(i,j) \in L^m} \lambda_{ij} \left[q_{ij}^{n} - \beta_{ij} \left(t_{ij}^{n} - t_{ij} \right) \right] \\ \min E = \sum_{(i,j) \in L^{L^m}} \left[e_{ij}^{n} - \varpi_{ij} \left(t_{ij}^{n} - t_{ij} \right) + e_{ij}^{s} \right] \end{cases} \tag{8}$$

In Eq. (8), β_{ij} denotes the marginal coefficient of project quality. λ_{ij} represents the influence coefficient of the process on the overall QOP. By solving the MOF optimization model of the project, the duration of the project can be reduced as much as possible within the standard requirements. This can result in lower cost, higher quality and less pollution to the environment. In real-world projects, pollution is assessed in four dimensions: actual pollution levels, pollution levels during the design period, the rate of change in pollution levels, and projected pollution levels for the design period. The actual level of pollution is measured by on-site monitoring of pollutant concentrations, including particulate matter, noise levels, and water quality. Pollution during the design phase is assessed using environmental impact assessment reports or predictive models that identify potential sources of pollution at various stages of construction. Statistical models using historical data from similar projects help predict pollution levels. The rate of change in pollution is quantified by analyzing time series data, comparing pre- and post-construction levels of pollutants, and calculating annual rates of change. During the design phase, pollution can be managed through established environmental goals and regulations, with ongoing monitoring to assess actual emissions against allowable standards.

B. Project MOO Model Solution Based on NSGA-IIA

The NSGA-IIA is a type of genetic algorithm, which simulates the optimization method of biogenetic mechanism in nature, and is used to solve the MOF optimization model. Therefore, the research utilization will use this algorithm to solve the MOF model of the process project. Fig. 4 illustrates the algorithm's flow.

In Fig. 4, the first step of the NSGA-IIA is to generate an initialization population. The initialization population consists of a set of individuals. Each individual represents a feasible solution to the model. A non-dominant sorting is performed on these individuals, and then crossover and mutation are used to generate a new generation of a sub-population. This sub-population represents a subset of the solution space. The second step is to merge these two populations, the current population and the newly generated subpopulation, to form a new population. Non-dominated sorting (NDS) of the merged population identifies multiple Pareto fronts. The purpose of NDS is to classify individuals into different ranks based on their dominance relationships. Individuals known as the first rank are optimal because no other individual dominates them. Individuals in the second rank are dominated by individuals in the first rank and so on. Diversity among individuals in the same rank is assessed by calculating the CD. For each goal, individuals are ranked according to the value of that goal. The distance between individuals is calculated and the crowding of the bordering individuals is recorded as infinite. The CD for intermediate people is the total of the differences between two adjacent persons on that target. The right people counts will be chosen to make up the next generation of the population, taking into account the CD and the outcomes of NDS [18-19]. Loop the above steps and stop running the algorithm when a predetermined number of iterations is reached. It also outputs the final result as the optimal solution of the MOF model. Due to the need for fast NDS and CD calculation, the NSGA-IIA has a high computational complexity and requires a long running time, especially when there are more optimization functions in the objective model [20]. Therefore, as shown in Fig. 5, improving the algorithmic process is required to lower the computational complexity and running time and optimize the MOF of EPs utilizing the NSGA-II method.

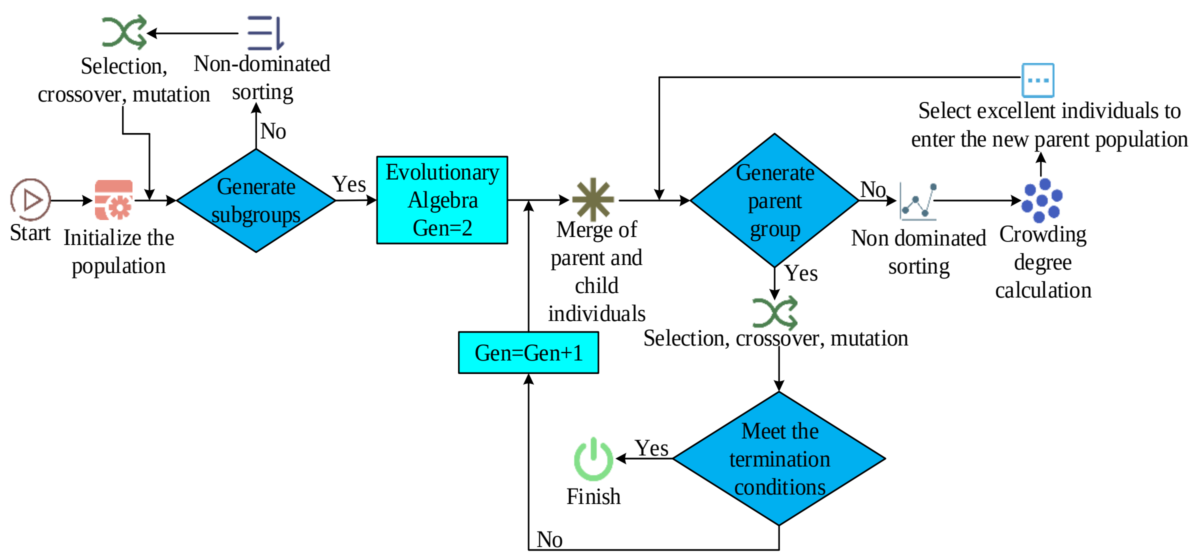


Fig. 4. Schematic diagram of SGA-II algorithm flow.

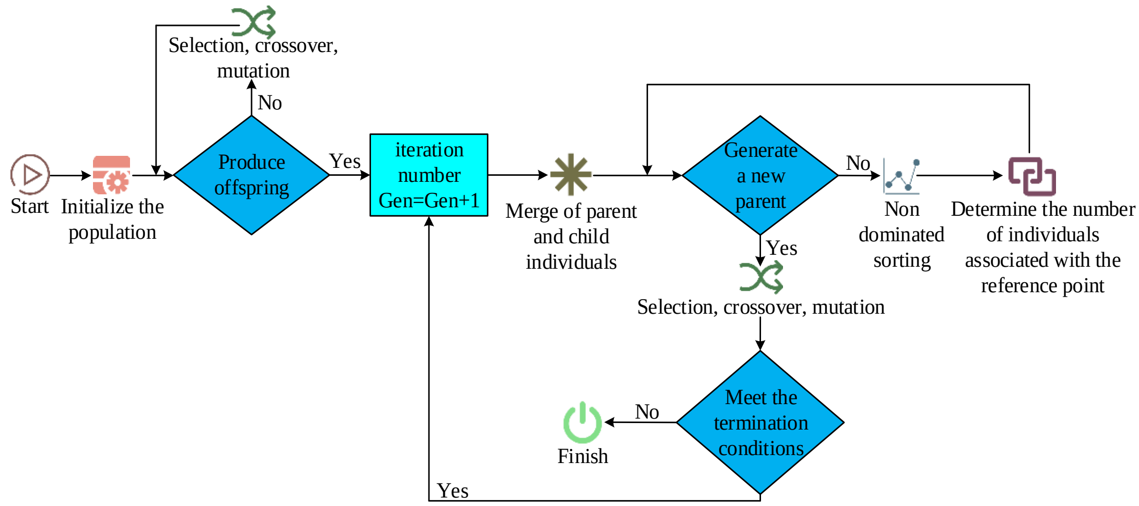


Fig. 5. Schematic diagram of the improved NSGA-IIA flow.

In Fig. 5, the improved NSGA-IIA is first optimized for fast NDS and CD calculation. The computational complexity of NDS can be reduced by pre-computing the dominance relationship between individuals. A more efficient sorting strategy is used to find the CD quickly. Secondly, NDS is used to rank the new population. Hierarchical management of populations is done through shared fitness. Among them, the value of shared fitness decreases accordingly with the increase of the rank, thus guaranteeing the priority of the lower ranked individuals in the selection process. The third step is to utilize the method of reference points, which are evenly arranged on the standard hyperplane. The individuals in the population are also uniformly divided so as to calculate the number of reference points, as shown in Eq. (9).

$$P = \binom{M+H-1}{H} \tag{9}$$

In Eq. (9), P denotes the number of reference points. M denotes the dimension. H denotes the number of copies. Then the OF in the optimization model needs to be quantized to facilitate the association of the set reference points, as shown in Eq. (10).

$$f_i^{'}(x) = f_i(x) - Z_i^{\min} \tag{10}$$

In Eq. (10), $f_i^{'}(x)$ denotes the quantized function. $f_i(x)$ denotes the original OF. $Z_i^{\min}$ denotes the MinV of the function. After the quantization of the function is completed, it is also necessary to find the extreme point of the function, as shown in Eq. (11).

$$\mathrm{ASF}(X,W) = MAX_{i=1:m}\left(f_i^{'}(x)/W_i\right) \tag{11}$$

In Eq. (11), $\mathrm{ASF}(X,W)$ denotes the ASF function. Based on the extreme points of the function, the corresponding function values can be obtained. The function values of each individual are unified into a plane of the same dimension as the established reference point, as shown in Eq. (12).

$$f_i^{n}(x) = \frac{f_i^{'}(x)}{ai} = \frac{f_i(x) - Z_i^{\min}}{ai} \tag{12}$$

In Eq. (12), ai represents the distance of each function value to the plane coordinate axis. The position at which each function value is placed is linked to the reference point, and the person represented by the function value with the smallest distance between them is found and linked to the reference point. Finally, the selected individuals are iterated until the optimal solution of the target model is achieved. The core of the improved NSGA-IIA for solving the MOF optimization model of an EP is the cross-variation process of the population individuals, as shown in Fig. 6.

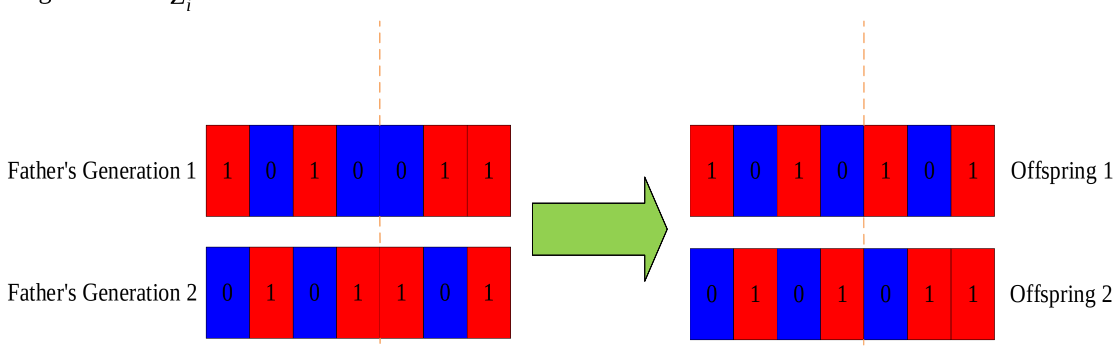


Fig. 6. Schematic diagram of BX crossover operator.

In Fig. 6, the improved NSGA-IIA utilizes the SBX for the simulation of the single-point crossover operator, which ensures that useful information can be obtained from the newly generated populations, as shown in Eq. (13).

$$\begin{cases} x_{1j}(t) = 0.5*\left[\left(1-\gamma_j\right)x_{2j}(t)+\left(1+\gamma_j\right)x_{1j}(t)\right] \\ x_{2j}(t) = 0.5*\left[\left(1+\gamma_j\right)x_{2j}(t)+\left(1-\gamma_j\right)x_{1j}(t)\right] \end{cases} \tag{13}$$

In Eq. (13), x_{1j} and x_{2j} denote individuals of the parent population. γ_j denotes the degree of mixing of individual characteristics of the parent population. The formula for the degree of mixing is shown in Eq. (14).

$$\gamma_j = \begin{cases} \left(2\mathrm{u}_j\right)^{\frac{1}{\eta+1}} & , \ \mathrm{u}_j \leqq 0.5 \\ \left[\dfrac{1}{2\left(1-u_j\right)}\right]^{\frac{1}{\eta+1}} & , \ \mathrm{u}_j > 0.5 \end{cases} \tag{14}$$

In Eq. (14), u_j denotes a constant between 0 and 1. η denotes the distribution index. Due to the minimal population variety at the beginning of the algorithm, the search process may settle on locally optimal solutions. It is investigated that the diversity of the population can be enhanced by dynamically increasing the crossover probability and mutation probability. This raises the likelihood that a globally optimal solution will be found by enabling the algorithm to search a larger solution space. As the number of iterations increases, the mutation probability is gradually reduced, which can effectively reduce the occurrence of "catastrophic mutation". Catastrophic variation refers to the fact that in the later stages of the search, a large number of sudden changes may destroy the good solutions that have been found. By controlling the diversity of the algorithm at a later stage, the algorithm is stabilized. This facilitates convergence to high quality potential solutions as shown in Eq. (15).

$$\begin{cases} p_c^{'} = p_c \times \left(1-\dfrac{\text{gen}}{\max \text{gen}}\right) \\ p_m^{'} = p_c \times \left(1-\dfrac{\text{gen}}{\max \text{gen}}\right) \end{cases} \tag{15}$$

In Eq. (15), p_c denotes the adaptive crossover probability. gen denotes the current iteration number. max gen the maximum number of iterations. While the MOO model presented in this study focuses on construction projects, it has broader applicability in other fields. For example, in manufacturing, key objectives such as schedule, cost, and quality must be balanced, with production adjustments made according to market demand. Similarly, public infrastructure projects must navigate complex codes and standards while addressing schedule, cost, quality, and environmental concerns. Using this MOO approach, project managers can better manage stakeholder relationships and effectively meet multiple project objectives.

III. Analysis of NSGA-II and its Improved Algorithms

A. Performance Analysis of NSGA-IIA

To verify the effect of the proposed method, the implementation environment in the study is mainly focused on the actual construction scene of the construction project, including project planning, resource allocation, and construction management. The improved NSGA-II algorithm will be applied to a typical construction project that must meet multiple objectives such as time reduction, cost control, quality assurance, and environmental protection within a limited time and budget. By monitoring and analyzing real-time data from all phases of the project, such as construction progress, resource consumption, and environmental impact, the algorithms will dynamically adjust optimization strategies to cope with unforeseen changes and challenges. Furthermore, the study will address the distinct requirements of various construction projects (e.g., residential, commercial, public facilities, etc.) during the implementation phase. These unique implementation environment factors will subsequently encourage the refinement and optimization of the algorithm, thereby ensuring the efficacy and relevance of the final decision. To verify the success rate and accuracy of MO genetic algorithm in solving item function model, a series of systematic evaluation measures and tools are adopted. In terms of algorithm implementation, based on Python programming language, NumPy and SciPy libraries are used for numerical computation, and the results are visualized with Matplotlib library. To verify the success rate (SR) and accuracy of the MO genetic algorithm in solving the item function model, the study will conduct comparative analysis experiments on two different datasets. The super-parameters of the model are set as follows: The population size is 100, and the larger population size can provide a better diversity of solutions, avoid premature convergence, and help find the global optimal solution. The mutation probability is set to 0.1, which is mainly used to keep moderate changes and prevent the algorithm from falling into the local optimal solution. The crossover probability is set to 0.9, which is mainly used to speed up the convergence rate of solutions, and can effectively produce high-quality descendant solutions in MOO. The number of iterations is set to 500 to ensure that the algorithm converges in the right time and obtains the best solution. The experiment uses the VOT and TrackingNet datasets. The VOT dataset is a benchmark for evaluating various visual target tracking algorithms, while TrackingNet focuses on efficient performance evaluation, providing various scenarios, video sequences, tagging boxes, and metrics for measuring algorithm accuracy and robustness. The validation measures adopted in this study include key performance indicators such as accuracy, success rate, and center position error. Moreover, the effect of the improved algorithm is comprehensively evaluated through comparison and analysis with existing MOO algorithms. The analysis compared the SiamRPN, SiamFC and SiamRPN18++ algorithms. SiamRPN demonstrated high accuracy through its regional proposal network, effectively selecting from multiple candidate regions, strong positioning capabilities, and a MOO process. The SiamFC algorithm processes target features with consistent convolution operations and retrieves them by calculating feature similarity. SiamRPN18++, on the other hand, uses a deeper network architecture to enhance feature extraction, improving adaptability and accuracy for multiple tracking targets. Firstly, the study conducts overlap rate and center position error analysis on VOT dataset. The results are shown in Fig. 7.

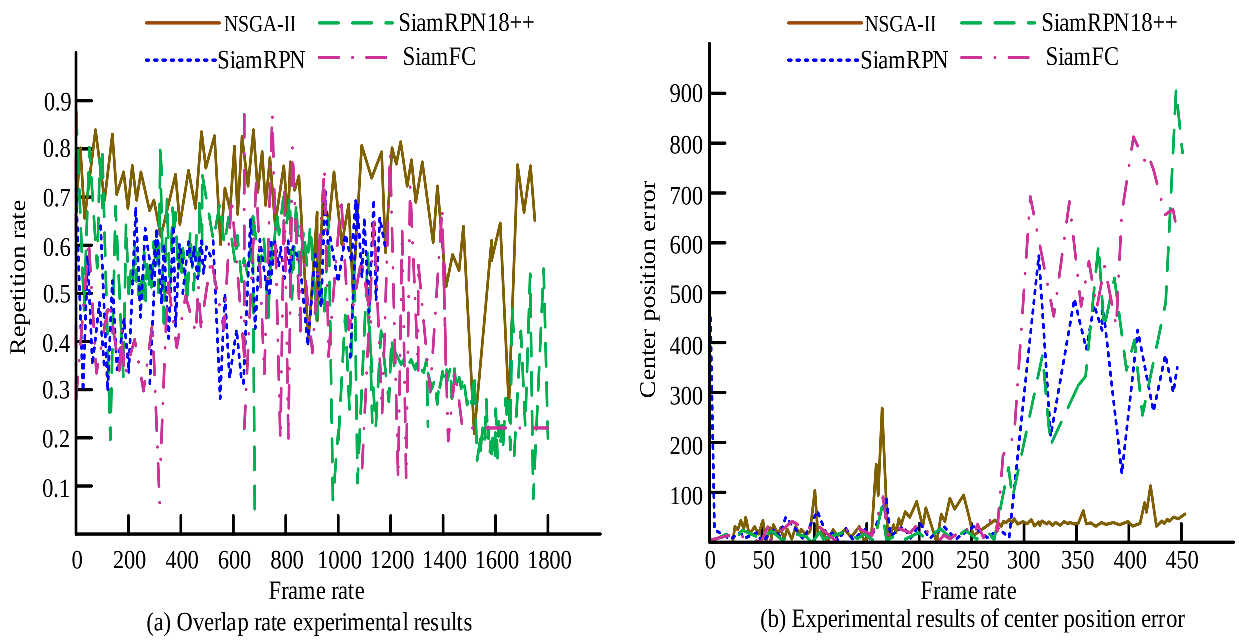


Fig. 7. Comparison analysis curve of overlap rate and center position (I).

In Fig. 7, the NSGA-IIA has the optimal overlap rate of 0.75, which is the best. Compared with other algorithms, the average overlap rate increases by 0.156%, which effectively optimizes the efficiency of solving the target features. This lays the foundation for the improvement of the solving performance in the case of multiple objectives. The NSGA-IIA performs well in the tracking error of the sequence center position with minimal error. Compared with other basic algorithms, NSGA-II algorithm is able to reduce the center position error by 5.84, 30.63, and 43.42 pixel points, respectively. When the number of objective model functions is too many, NSGA-II algorithm significantly reduces the center position error. The proposed algorithm makes full use of the evaluation mechanism of non-dominant sorting and congestion distance to maintain the diversity of solutions and obtain better solutions in a short time. In target tracking tasks, the algorithm can more accurately capture the location information of the target, thereby improving the positioning accuracy and reducing the error. To better show the performance of NSGA-IIA, the study conducts comparative experiments on the VOT dataset. The SR and accuracy change graphs are shown in Fig. 8.

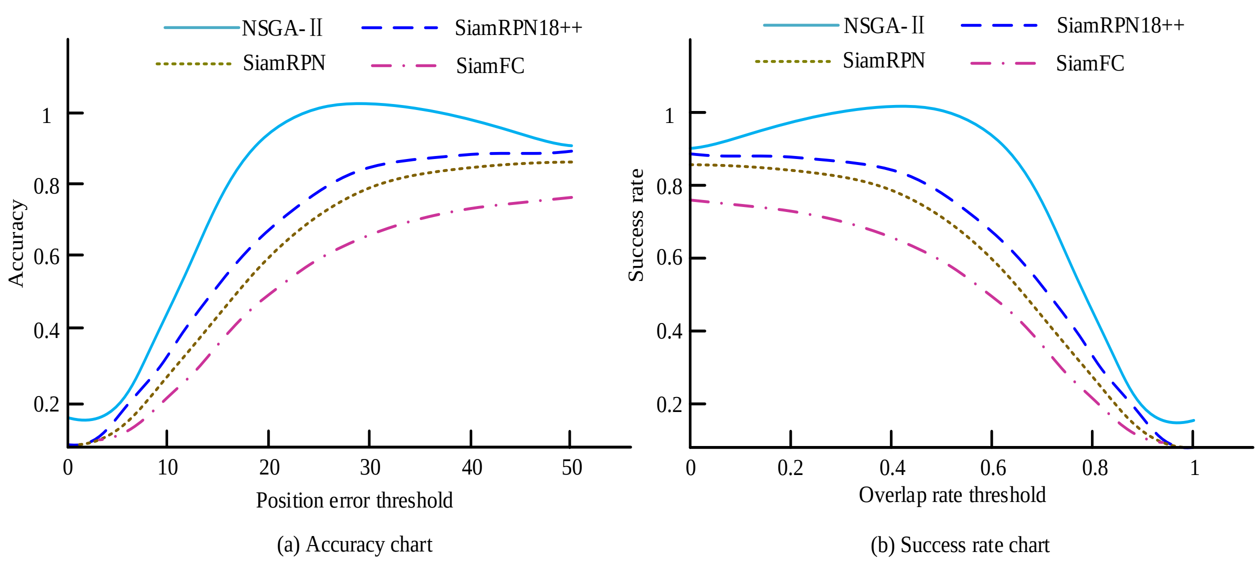
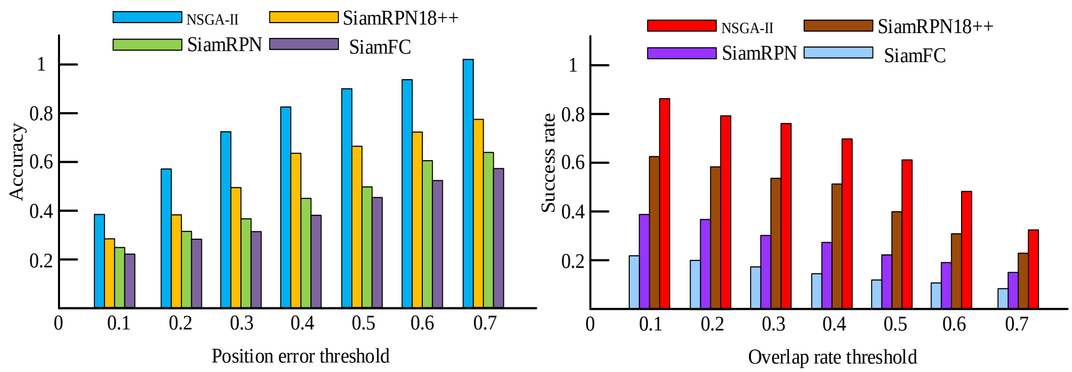


Fig. 8. Success rate and accuracy chart on the VOT dataset (I).

Fig. 8(a) represents the accuracy results of different algorithms in the validation of VOT dataset. The results display that the NSGA-IIA proposed in the study has an accuracies of 0.642. Its overall improvement in accuracy over SiamRPN18++, SiamRPN, and SiamFC algorithms is about 1.0%. Fig. 8(b) represents the SR results of different algorithms in the validation of VOT dataset. The findings show that, in comparison to the other three algorithms, the NSGA-IIA suggested in the study has a SR of 0.504, indicating an overall improvement in accuracy of roughly 0.6%. The results indicate that NSGA-II has higher localization accuracy in tracking the target and can capture the actual position of the target more efficiently with less error. In specific scenarios, it can maintain its reliability in a variable environment. Considering the relatively limited size of the VOT dataset, the effectiveness of the algorithm needs to be examined more comprehensively. The obvious improvement in the results in Fig. 8 shows the effectiveness of the algorithm in dealing with complex multi-target problems, which can better detect and identify target features and reduce the number of false tracks. This enhancement in performance provides a robust technical foundation for dynamic management and decision-making in construction projects, thereby enabling timely responses to unexpected situations and strategic adjustments in a changing construction environment. Therefore, the research conducted further experiments on the TrackingNet dataset to verify the success rate and accuracy of NSGA-II algorithm under different environmental conditions, including the availability and price fluctuations of construction materials, the availability and cost of labor, as shown in Fig. 9.



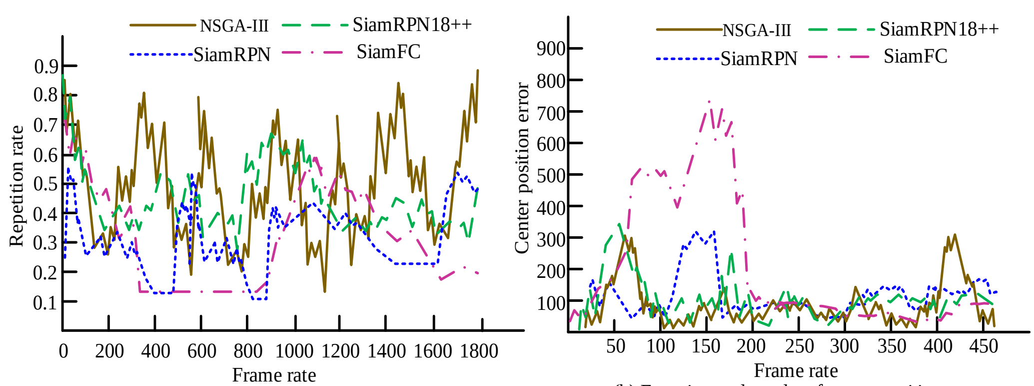
(a) Accuracy chart (b) Success rate chart

Fig. 9. Success rate and accuracy graph on the TrackingNet dataset (I).

Fig. 9(a) represents the accuracy results of different algorithms on TrackingNet dataset. The results display that the accuracy of the proposed algorithm has 0.791, which is an overall improvement of about 1.2% compared to the accuracy of SiamRPN18++, SiamRPN, and SiamFC algorithms. In the performance detection under occlusion attribute, the accuracy of the proposed algorithm has 0.542, which is an overall improvement of 0.4% compared to the comparison algorithms. Fig. 9(b) represents the SR results of different algorithms in TrackingNet dataset. The results display that the SR of the proposed algorithm of the study has 0.763, which is a 1.8% improvement compared to the SR of the comparison algorithms. Similarly, in the performance detection under occlusion attribute, the proposed algorithm has a SR of 0.763, which is an improvement of 3.3% compared to the SR of the comparison algorithm. The results indicate that NSGA-II still exhibits relatively strong robustness in dealing with complex and challenging tracking situations, proving its applicability and reliability in real application scenarios.

B. Performance Analysis of the Improved NSGA-IIA

To verify the overlap rate and center position error of the improved NSGA-IIA, the study will conduct a comparative analysis experiment on the VOT dataset, as shown in Fig. 10.



(a) Overlap rate experimental results (b) Experimental results of center position error

Fig. 10. Comparison analysis curve of overlap rate and center position (II).

In Fig. 10, the overlap rate of the improved algorithm is optimal. Compared with other algorithms, the average overlap rate of the algorithm is improved by 0.126. This indicates that the improved algorithm can obtain more accurate optimal solutions of the objective model, which improves the accuracy and robustness of the algorithm in solving the MOF optimization model. The improved algorithm is ranked first with the minimum error in the center position of the sequence. Compared with other algorithms, its average center position error is reduced by 23.450 pixel points. This indicates that the improved method has a smaller center position error and is able to solve the best solution of the MOF model more accurately. The study uses the VOT dataset for a comparative experiment to confirm the enhanced algorithm's tracking performance, as illustrated in Fig. 11.

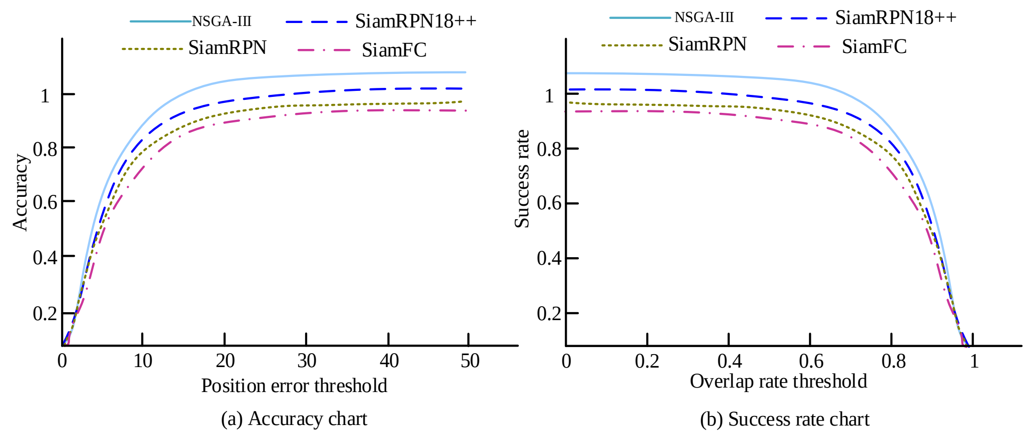


Fig. 11. Success rate and accuracy graph on the VOT dataset (II).

In Fig. 11, the SR and accuracy of the improved algorithm are 0.690 and 0.845, respectively. Compared with other algorithms, the average improvement is 1.5% and 1.2%. This indicates that the algorithm performs optimally among the tested algorithms and fully proves its effectiveness. In the performance test under the occlusion attribute environment, the accuracy and SR of the proposed algorithm are improved compared with the comparison algorithms. Among them, the research algorithm improves about 2.1% in accuracy, and the final accuracy is 0.918. It improves about 2.7% in SR, and the final SR is 0.691. The enhancement in the success rate signifies the algorithm's capacity to effectively address occlusion and variations in the target, leveraging its adaptive characteristics and dynamic adjustment mechanism to ensure uninterrupted target tracking. In the context of complex construction projects, this advantage enables project managers to make faster and more accurate decisions in a highly dynamic construction environment. Consequently, this improves the overall project management efficiency and effectiveness. Fig. 12 displays the enhanced algorithm's validation findings using the TrackingNet dataset.

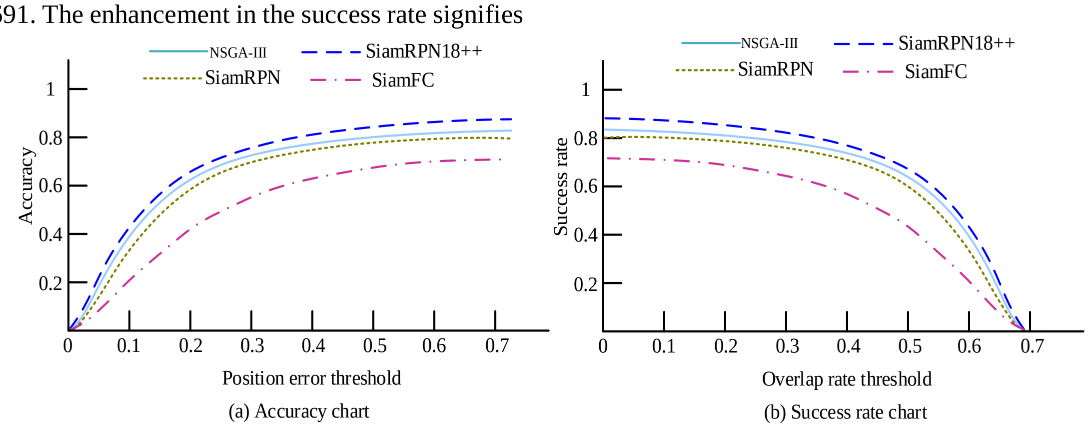


Fig. 12. Success rate and accuracy graph on the TrackingNet dataset (II).

In Fig. 12, the overall SR and accuracy of the improved algorithm under the TrackingNet dataset are 0.490 and 0.572, respectively, which are improved by 1.2% and 0.6% on average compared to other algorithms. By improving the algorithm, it shows good performance in the test of the dataset, which verifies the effectiveness of the improvement measures. In the presence of occlusion, the algorithm achieves an SR of 0.454%, which is 4.2% higher on average than other algorithms. It also achieves an accuracy of 0.536%, which is 1.5% higher than other algorithms on average. This further confirms the effectiveness of the algorithm in performing MOO. The specific construction project is a sub-division project of a comprehensive commercial plaza. The total budget cost of the project is 5 million yuan, and the planned construction period is 120 days. The project management team is challenged to coordinate multiple objectives, including optimizing construction cost, ensuring construction quality, and reducing environmental impact while meeting the deadline. The results of MOO in construction projects are shown in Table I.

TABLE I. RESULTS OF MULTI-OBJECTIVE OPTIMIZATION IN CONSTRUCTION PROJECTS

Goal	NSGA-II	Improved NSGA-II	Change
Duration (days)	120	110	-10
Total cost (ten thousand yuan)	500	480	-20
Quality Score (0-1)	0.75	0.85	0.1
Environmental impact score (score)	30	25	-5

Table I shows that based on the improved NSGA-II algorithm, the PD is reduced by 10 days from 120 days to 110 days. The TC is reduced from 5 million yuan to 4.8 million yuan, saving 200,000 yuan. The quality score of the project increases by 0.10 from 0.75 to 0.85. The environmental impact score is reduced by five points from 30 to 25. The findings indicate that the model effectively realizes the multiple objectives of reducing the construction period, minimizing costs, enhancing quality, and decreasing environmental impact. It also provides robust algorithmic support and a scientific foundation for the management of construction projects.

IV. RESULTS AND DISCUSSION

This study used the improved NSGA-II algorithm to analyze the MOO model for construction projects, focusing on the effective coordination of PD, cost, quality, and environmental impact. The simulation results showed a reduction in PD from 120 days to 110 days, indicating improved construction efficiency and less time wasted, facilitating earlier project delivery. On the cost front, total spend decreased from 5 million yuan to 4.8 million yuan, highlighting the significant savings achieved through optimized resource allocation while maintaining quality requirements. The quality score improved from 0.75 to 0.85, ensuring better overall project quality while reducing duration and cost. In addition, the environmental impact score decreased from 30 to 25 points, demonstrating algorithm's commitment to sustainable practices. Unlike traditional optimization methods, the improved NSGA-II could manage multiple objectives simultaneously, allowing project managers to adjust the weights of objectives based on situational needs to achieve optimal balance in complex environments. This flexibility was of paramount importance for contemporary construction projects, which frequently encountered rapid changes and unforeseen risks. The enhanced algorithm facilitated real-time updates to objectives and constraints, enabling timely strategy adjustments to ensure project effectiveness. In the same type of research, compared with the research in literature [2], this study used particle swarm optimization algorithm, and the average cost reduction was only 150,000 yuan. The study in reference [3] used a MO WOA, and the quality score was improved by 0.05. The research in literature [4] showed that the algorithm could achieve environmental quality improvement while reducing the score by only about 3 points. Compared with other relevant studies, the results of this study showed that the improved NSGA-II algorithm achieved more significant time reduction, cost saving, quality improvement, and environmental impact reduction in the MOO of civil engineering projects.

V. CONCLUSION

The research built a MOO model that incorporated the project schedule, cost, quality, and environment in an attempt to address the issue of MO management optimization of construction projects. Moreover, the improved NSGA-IIA was utilized for solving and validation. Through experiments on the VOT and TrackingNet datasets, the NSGA-IIA performed well on the VOT dataset. The accuracy reached 0.642 and the SR was 0.504, which were 1.0% and 0.6% better than the comparison algorithm, respectively. On the TrackingNet dataset, the accuracy was 0.791 and the SR was 0.763. Moreover, the accuracy under occlusion was 0.542 and the SR was 0.763, demonstrating the robustness of the algorithm in complex environments. The improved algorithm exhibited a high accuracy and SR of 0.690 and 0.845 in the VOT dataset, which provided a more reliable solution for selecting the target model. This research contributed to the knowledge system by expanding MOO theory and proposing a model based on the improved NSGA-II algorithm, focusing on the duration, cost, quality, and environmental impact of construction projects. This model enriched the theoretical framework of MOO and offers new insights for researchers in architecture. For the AEC industry, the model enhanced project management efficiency, promotes sustainable development, and informed industry policies and standards. By facilitating better coordination of multiple objectives, the approach emphasizes the importance of balancing economic benefits with environmental protection, ultimately providing sustainable solutions that help organizations achieve their green building goals. However, the research is not without its limitations. The computational efficiency and stability must be improved in the face of extreme dynamic changes and high-dimensional targets. The presence of decision bias, stemming from incomplete or inaccurate data, is a notable concern. Consequently, future research endeavors will prioritize the further optimization of the algorithm's performance, the exploration of more adaptive mechanisms, and the development of parallel computing methods to enhance the prediction and analysis of data.

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