ISSN 1330-3651(Print), ISSN 1848-6339 (Online) https://doi.org/10.17559/TV-20240720001868
Original scientific paper

Optimizing Construction Project Plan Management Using Parameter-Adaptive Improved Genetic Algorithm

Tianya JIA

Abstract: This study proposes an optimization method for construction project plan management using a parameter-adaptive improved genetic algorithm (IGA) combined with differential evolution (DE). The method addresses the challenges of inflexibility, inefficient resource allocation, and unscientific scheduling in traditional project management approaches. A multi-objective optimization model that balances project duration and resource utilization is developed. A case study demonstrated that the optimized methods reduced the project duration by up to 22.7% and the resource variance by up to 29.9% compared to the original plan. The proposed method enhances the flexibility and efficiency of construction project planning, contributing to both theoretical advancement in optimization algorithms and practical improvements in project management.

Keywords: construction engineering; genetic algorithm; parameter adaptation; project plan management

1 INTRODUCTION

The advancement of construction technology and the continuous improvement of construction project quality standards have significantly increased the complexity of construction projects. A well-formulated Construction Project Plan (CPP) that considers construction period, resource allocation, and scheduling can significantly improve project efficiency [1]. Construction Project Plan Management (CPPM) involves creating a comprehensive schedule that is continuously adjusted throughout the construction process. This adjustment accounts for various factors such as process requirements, task coordination, design, equipment, materials, tools, labor, and financial resources to ensure the project progresses smoothly [2, 3]. Reasonable CPPM can effectively reduce project costs and improve engineering efficiency. Scientific and reasonable project planning management in modern construction practice can improve the effective utilization of time and resources. Project planning management can maximize efficiency and utilization by arranging tasks and resources reasonably, avoiding resource waste and time delays. Project planning management is closely related to cost control. Through a reasonable project plan, project costs can be better controlled and the risk of cost overruns can be minimized as much as possible. A well-designed project plan facilitates the reasonable allocation and scheduling of resources, while also ensuring effective coordination between departments or processes. Such a plan helps to circumvent the potential for resource competition and waste, while simultaneously enhancing the efficiency with which resources are utilized. Effective CPPM can significantly reduce project costs and enhance efficiency. However, in current engineering practices, CPPM still faces challenges such as limited flexibility, inefficient resource allocation, and poorly designed schedules [4]. Engineering projects often involve substantial financial investments and manpower, introducing numerous uncertainties into the construction process. A lack of flexible response mechanisms in project planning can result in delays and increased costs when these uncertainties arise [5, 6]. Factors such as weather conditions, worker performance, skill levels, and on-site management further complicate the accurate estimation of process consumables during construction [7, 8]. Consequently, the construction plan must be adjusted accordingly to avoid resource surpluses or shortages. Construction projects are time-sensitive, requiring the completion of specified tasks within set deadlines. However, the numerous uncertainties and frequent changes in construction plans necessitate real-time adjustments, placing high demands on project planning and management. In summary, there are still common problems in the CPPM, such as the inability to flexibly adjust plans based on actual construction progress, serious waste of resources in the construction process, and project duration exceeding or falling below the required time for the process. The current CPPM lacks comprehensive consideration of the three important issues mentioned above, and often cannot take into account other aspects when considering one of them. Based on this, a parameter-adaptive Improved Genetic Algorithm (IGA) is proposed for optimizing CPPM. Firstly, the method optimizes the parameters of the Genetic Algorithm (GA) to improve the search efficiency of the algorithm. Subsequently, the Differential Evolution (DE) algorithm is used to solve the problem of IGA easily getting stuck in local optima. A multi-objective task model is constructed for project duration, resource allocation, and process planning. The optimized algorithm is used to solve the multi-objective building planning problem. The contribution of this study lies in the use of an IGA-based Multi-Objective Optimization (MOO) model to synergistically optimize and manage the progress, resource allocation, and project schedule of engineering construction projects. The study provides new theoretical support for improving project construction efficiency and reducing construction costs. The technical roadmap for this study is shown in Fig. 1.

In Fig. 1, the GA parameters are adjusted using parameter-adaptive methods and combined with DE to improve the search speed and global search capability of the algorithm. A multi-objective task model based on schedule setting, resource allocation, and process planning is constructed to address engineering plan management issues. The model is solved using optimization algorithms, thereby obtaining the optimal solution.

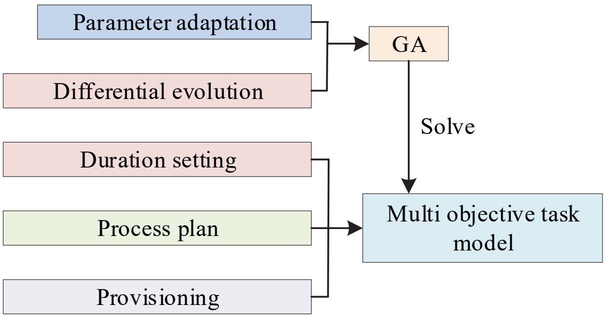


Figure 1 Technical road map

2 LITERATURE REVIEW

CPPM is crucial for the high-quality and efficient execution of engineering projects. Scholars have explored various methods to enhance prediction, data integrity, optimization, and scheduling in different fields, leveraging techniques such as GA and MOO. For instance, Dharma F proposed using a regression model based on GA to predict inflation levels, utilizing real Consumer Price Index (CPI) data from the Central Bank of Indonesia. The model achieved a mean square error of 0.1099, effectively predicting inflation rates [9]. To address data integrity and privacy issues, Tahir M et al. introduced CryptoGA, a GA-based model that can generate encryption and decryption keys and integrate them with encryption algorithms to protect cloud data [10]. In another study, Civira M et al. proposed a method based on MOO and GA to enhance the robustness of sensor configurations for damage detection after catastrophic events. The experimental verification proved its effectiveness [11]. Ashok D et al. developed Assisted Truth Enhancement GA (LGGA). This model improved the data accuracy in symbolic regression algorithms by combining logical or mathematical constraints, significantly increasing data efficiency by 61.9% with minimal data requirements [12]. To address machining challenges, Bousnina K. et al. combined PSO-ANN with GA to predict roughness, cost, and energy consumption in machining processes. This research demonstrated that appropriate process selections could notably reduce energy consumption [13]. Mohammadi S. et al. proposed an innovative construction planning framework based on intelligent simulation to address the issues of project planning and scheduling. The results indicated that by using the proposed framework, a 4D BIM model could be automatically generated, which provides a very good understanding of construction plans [14]. Afshar M. R. et al. introduced a mixed integer linear programming model to minimize project costs, focusing on the impact of subcontractor selection on scheduling. This model, when solved using a universal algebraic modeling system, reliably optimized schedules for synchronously conducted projects [15]. Liu Y. et al. proposed an improved adaptive NSGA-II to enhance the convergence, consistency, and scalability of schedule optimization results. This algorithm was effective in optimizing CP scheduling plans [16]. Additionally, Abad F. et al. developed a hybrid framework to manage the adverse effects of changes in construction projects, allowing project teams to proactively develop risk response plans [17]. For the Time-Cost-Quality (TCQT) problem, Luo D. L. et al. introduced a new optimization algorithm called adversarial multi-objective DE. This algorithm utilized adversarial learning for population initialization and generational jumps, significantly improving exploration and convergence performance [18].

In summary, while some scholars have proposed improvement methods for CPPM, these approaches often focus on only one aspect of the planning process and lack a comprehensive MOO approach. The current methods are largely confined to particular issues and are frequently optimized for a specific problem, which precludes their comprehensive coverage of all aspects of CPPM. Some methods only focus on optimizing a single objective, while in actual CPPM, it is often necessary to consider the balance of multiple objectives. Construction projects are inherently multifaceted and multi-level, involving numerous factors that interact in complex ways. Therefore, it is essential to conduct a comprehensive analysis of these influencing factors to develop more effective and holistic solutions for CPPM. The research has filled the gap in the collaborative optimization of multiple conflicting issues in the process of formulating CPPs, especially in terms of schedule setting and resource allocation. This has resulted in a reduction in the risk of corporate default and an improvement in resource utilization.

3 METHODOLOGY

Due to the strict requirements imposed by project deadlines, the construction industry often demands meticulous preparation of construction plans. However, deviations from the original schedule are inevitable, leading to frequent adjustments in the CPP. As a result, traditional CPPM methods are increasingly inadequate for the evolving demands of the construction industry [19]. In response to these challenges, this study proposes an optimization approach for CPPM based on a parameter-adaptive IGA. The study begins by introducing the parameter-adaptive IGA and its enhancements. Following this, the algorithm is applied to optimize CPPM, taking into account the current architectural characteristics and the dynamic nature of construction projects.

3.1 Optimization of Parameter Adaptive IGA

When formulating a CPP, multiple factors such as the construction timeline, materials, and payments must be considered. However, developers often struggle to balance these various indicators effectively. To address this challenge, this study proposes a MOO approach for CPP. Traditional MOO algorithms often perform poorly when processing large amounts of data, prompting this study to propose an improvement using GA. GA simulates the natural selection and genetic mechanisms found in Darwin's theory of evolution, seeking optimal solutions by mimicking the process of natural evolution. It uses mathematical methods and computer simulations to transform problem-solving into a process analogous to the Crossover and Mutation (C&M) of chromosome genes [20,21]. Nevertheless, GA presents a challenge in terms of parameter adjustment. This is due to the fact that numerous parameters require modification, including selection strategy, crossover probability, mutation probability, etc. Consequently, there is no fixed method for identifying the optimal values for these parameters. This increases the complexity of the algorithm and the difficulty of debugging. Based on this, the study introduces parameter-adaptation to improve GA. IGA greatly improves the convergence accuracy, accelerates the convergence speed, and reduces the difficulty of parameter adjustment by adaptively adjusting genetic parameters. During the execution of GA, its parameters (such as crossover probability, mutation probability, etc.) are fixed and will not be adaptively adjusted as the algorithm progresses. IGA adaptively adjusts the parameters. IGA uses roulette wheel selection method in the early stage of operation, which can achieve good selection results. In the later stage of the algorithm, the advantages of excellent individuals are insufficient. It is necessary to stretch the fitness to make the selection in GA more optimal. The standard GA uses roulette wheel selection in both the initial and later stages. The relationship between the individual fitness value in IGA and the probability of C&M is expressed in Eq. (1).

$$P_c = k_1 \frac{f_{\max} - f'}{f_{\max} - f_{\text{avg}}} \quad k_1 \le 1 \tag{1}$$

In Eq. (1), P_c represents the crossover probability in the genetic process, and k_1 is the adjustment parameter for the crossover probability. $f_{\max}$ represents the maximum fitness value of the population. f' denotes the larger fitness value between the two individuals selected for crossover. f_{avg} represents the average fitness value. For individuals with the highest fitness, the C&M probabilities are set to 0. If the condition in Eq. (2) is met for an individual, its crossover probability can then be determined.

$$f' = f_{\text{avg}} \tag{2}$$

Based on the conditions specified in Eq. (2), Eq. (3) can be derived.

$$P_c = k_1 \tag{3}$$

Similarly, if an individual satisfies the condition specified in Eq. (4), their mutation probability can be determined.

$$f = f_{\text{avg}} \tag{4}$$

According to Eq. (4), the probability of variation can be determined, as expressed in Eq. (5).

$$pm = k_2 \tag{5}$$

In Eq. (5), k_2 represents another adjustment parameter for the crossover probability. For individuals with very low fitness, the C&M probabilities might exceed 1. To prevent this from occurring, constraints are applied, and the corresponding calculation formulas are provided in Eq. (6) and Eq. (7).

$$pc = k_3, f' \le f_{avg} \quad k_3 \le 1 \tag{6}$$

In Eq. (6), k_3 represents the adjustment parameter for mutation probability. The constraint on mutation probability is defined by Eq. (7).

$$pm = k_4, f \le f_{avg} \quad k_4 \le 1 \tag{7}$$

In Eq. (7), k_4 serves as another adjustment parameter for the mutation probability. To address the issue of IGA easily falling into local optima, this study proposes optimizing it using the DE algorithm. DE is an efficient global optimization and heuristic search algorithm that operates on populations, with each individual corresponding to a solution vector. The evolutionary process of DE is similar to that of GA, including operations such as mutation and crossover, but with specific operational differences from GA [22]. DE usually converges to the global optimum faster, especially in high-dimensional and large-scale problems. Meanwhile, the DE algorithm is more suitable for optimization problems in continuous space compared to GA, so the study chooses the DE algorithm to improve GA. The flowchart for the DE algorithm is shown in Fig. 2.

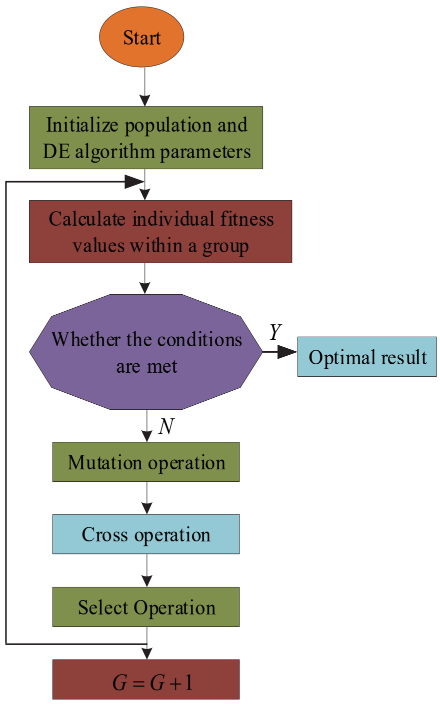


Figure 2 Differential genetic algorithm flowchart

The Improved Genetic Algorithm based on the Differential Evolution algorithm (IGA-DE) combines the strong global search capability of IGA with the robust local search ability of DE. Additionally, the structural differences between the two algorithms are relatively minor, which facilitates their integration. In the IGA-DE algorithm, handling local optimal solutions is achieved through DE search processing, which consists of three key operations: mutation, crossover, and selection. The process for differential mutation handling is illustrated in Fig. 3.

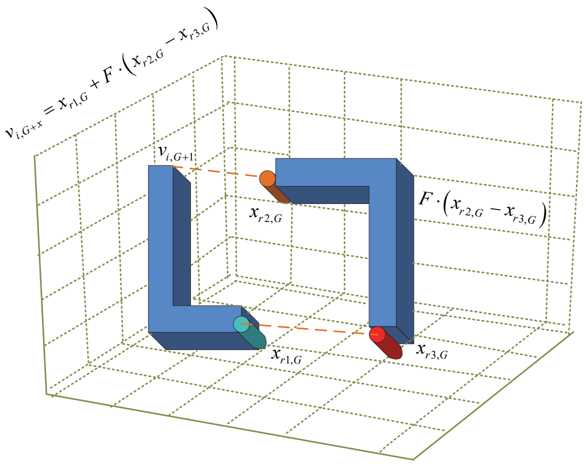


Figure 3 Schematic diagram of differential variation process

In Fig. 3, F is the scaling factor, and $v_{i,\,G+1}$ represents the intermediate individuals generated by the differential mutation operation $x_{r1,G}$, $x_{r2,G}$ and $x_{r3,G}$ correspond to different individuals within the population. The overall process of IGA-DE is depicted in Fig. 4.

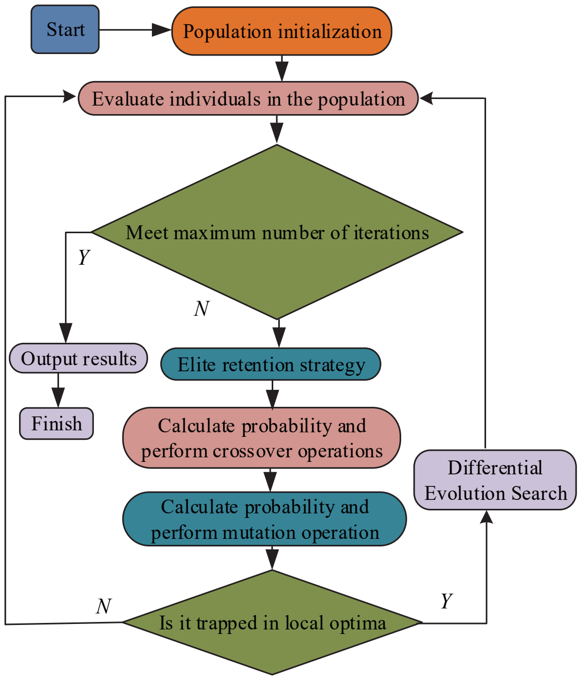


Figure 4 IGA-DE algorithm flowchart

In Fig. 4, the algorithm begins by initializing the population and evaluating its performance. It then checks whether the maximum number of iterations has been reached. If the maximum number of iterations is met, the algorithm outputs the final result. If not, it proceeds to perform C&M operations. The results obtained from these operations are then assessed for premature convergence. If the algorithm is not trapped in local optima, it returns to the evaluation step. However, if the algorithm is trapped in local optima, it applies the DE search processing to escape the local optima before continuing the process.

3.2 CPPM Optimization Based on IGA-DE Algorithm

CPPM is crucial for the successful execution of construction projects. The process of creating a construction schedule typically involves several key steps: collecting relevant information, dividing the construction project into manageable components, listing all engineering tasks, calculating quantities, and drawing construction schedule diagrams. The information collection phase primarily includes gathering drawings, contract requirements, and bills of quantities. Construction schedule diagrams are commonly presented in two formats: bar charts and network plan charts. Among these, the bar chart is the most widely used planning method [23]. The bar chart is drawn using time as the horizontal axis, with horizontal lines representing the start and end times of each project process. The entire plan is depicted as a series of horizontal lines. The advantages of bar charts include ease of preparation, simplicity, clarity, intuitiveness, and ease of understanding. They are particularly well-suited for on-site construction management, as they facilitate resource inspection and calculation. In contrast, the network planning method provides a more detailed representation of the inter-dependencies and constraints between different components of the project. This method allows for time analysis to identify key processes that impact the overall construction timeline. By highlighting these critical processes, construction management personnel can focus on resolving the main challenges in the construction process, thereby reducing uncertainty and inefficiency. The preparation of a construction schedule typically involves the following steps: determining the quantity of work, developing the operation process, selecting the construction method, planning resource allocation, preparing the overall project control schedule, and creating detailed plans for each construction milestone. The construction project scheduling process is illustrated in Fig. 5.

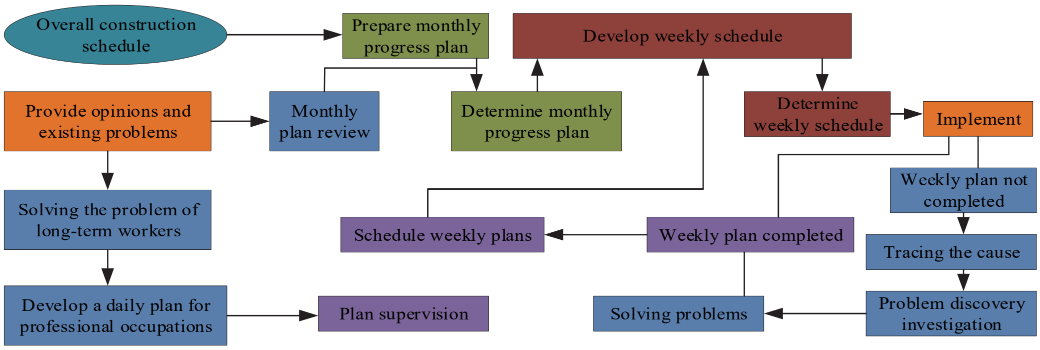


Figure 5 Construction schedule management flowchart

In Fig. 5, the project schedule is detailed from the overall construction schedule to the weekly plan, from large to small, which helps to manage project construction. CPPM involves multi-objective problems, and these issues are often difficult to coordinate uniformly. Therefore, this study proposes a CPPM MOO method grounded on the IGA-DE. The problem definition of the MOO method is generally shown in Eq. (8).

$$\min_y = f(x) = \left(f_1(x), f_2(x), \cdots\cdots, f_k(x)\right) \tag{8}$$

In Eq. (8), x represents the decision variable vector, and y is the objective function. Typically, multi-objective problems are framed as the extremum problems of multiple objective functions. In the MOO method, multi-objective values aim to find the relative optima of these functions, which are the approximate optimal solutions achieved by balancing and coordinating the various objectives. The geometric interpretation of the optima in MOO is the tangent point of the function, usually located on the boundary line of the feasible solution region, known as the optimal boundary. The diagram illustrating this optimal boundary is shown in Fig. 6.

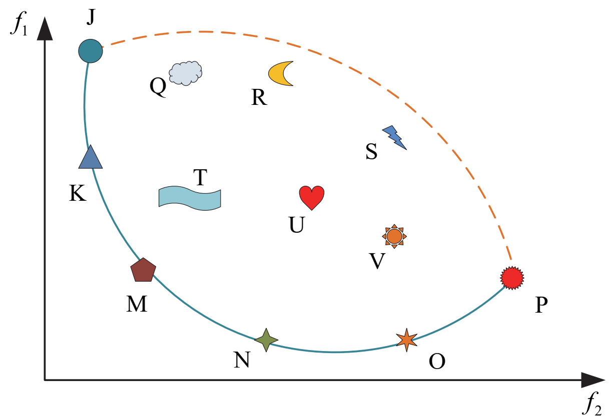


Figure 6 Optimal boundary diagram

In Fig. 6, the thick solid line represents the optimal boundary of the problem when the optimization objectives are two. This study constructs a multi-objective model for construction engineering with the goal of achieving the most reasonable planning of project duration and resource allocation. The formulation of this multi-objective model is presented in the following equation.

$$\min f = \sum_{k-1}^{k} W_k E_k \tag{9}$$

In Eq. (9), f represents the project resources. W_k and E_k denote the weight and variance of the k-th resource, respectively, where k indicates the type of resource. The expression for the total construction period is given in Eq. (10).

$$\min T = \max\left\{t_i + d_{is} \middle| i = 1, 2, \cdots\cdots, n\, s = 1, 2, \cdots\cdots, M\right\} \tag{10}$$

In Eq. (10), T represents the total project duration. i refers to the specific process, and s denotes the mode. d_s is the duration of process i under mode s, and t_i represents the time spent on process i. The average daily resource consumption of a particular resource is expressed in Eq. (11).

$$r_k = \frac{1}{T}\sum_{t=1}^{n} r_{ki} d_{is} \tag{11}$$

In Eq. (11), r_k is the average daily resource consumption of type k resource. r_{ki} is r_k under process i. n means the total amount of processes. The variance of the k-th resource demand is given by Eq. (12).

$$E_k = \frac{1}{T}\sum_{q=1}^{T}\sum_{i=1}^{n}\left(r_{kiqs} - r_k\right)^2 \tag{12}$$

In Eq. (12), q refers to a specific day of the project, and r_{kiqs} represents the consumption of resource k by process i on the q-th day under mode s. The expression for the duration of a specific process in the project is provided in Eq. (13).

$$t_j - t_i - d_i \geq 0 \quad j \in S_i \tag{13}$$

In Eq. (13), t_j represents the time spent on process j, and d_i is the duration of the process. S_i represents the set of i's subsequent work. The r_{dik}, which represents the consumption of the k-th resource during the duration of process i, is expressed in Eq. (14).

$$\sum_{t_j \in A_n} r_{dik} \leq b_k \quad \left(k = 1, 2, \cdots\cdots, m\right) \tag{14}$$

In Eq. (14), b_k represents the upper limit of the k-th resource. A_{ti} denotes the set of construction processes occurring on day t_i. m is the total number of resources. In this study, a specific construction project is selected, where each process has three construction methods to choose from. The logical relationship between the processes is illustrated in Fig. 7.

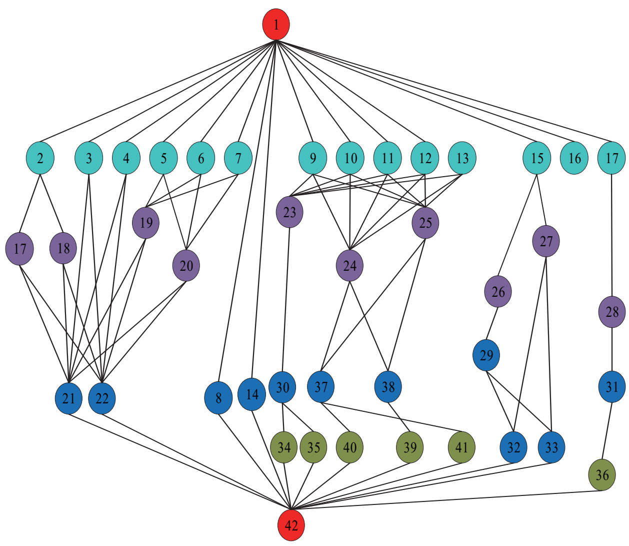


Figure 7 Project network

In Fig. 7, the project duration is set at 150 days, and the mutual constraints and dependencies between each process can be determined based on the diagram. Using the proposed MOO model, optimization management can be applied to the construction plans. This approach helps to reduce construction time and improve the overall quality of the project.

4 RESULTS

To verify the feasibility of the proposed construction project MOO plan model, the performance of the IGA-DE was first validated in the experiment to demonstrate its effectiveness in solving the target model. Following this, the effectiveness of the proposed CPPM optimization model, based on the IGA-DE algorithm, was also verified through experimental testing.

4.1 Optimization Analysis of Parameter-Adaptive IGA

This experiment was conducted using MATLAB 7.0 as the operating platform, with the evolutionary algorithm program written in MATLAB language. The study first conducted performance testing on the proposed algorithm to determine its effectiveness in optimization problems. The display of performance indicators such as search speed and global search capability could better illustrate the application significance of optimization algorithms in practical engineering projects. To develop a reasonable construction plan, and according to the construction network diagram shown in Fig. 7, the experiment collected the time and resources required for each process. Tab. 1 shows the time and resource consumption of some processes.

Table 1 The consumption of process time and required resources under different methods

Working procedure	Method 1			Method 2			Method 3		
	Time	Resource *L*1	Resource *L*2	Time	Resource *L*1	Resource *L*2	Time	Resource *L*1	Resource *L*2
2	8	4	4	10	3	3	16	7	2
4	9	20	11	12	15	9	18	10	6
6	10	6	0	13	5	0	12	3	0
7	16	33	12	25	25	9	32	17	6
9	11	10	10	16	8	8	22	5	5
11	10	16	16	15	12	12	20	8	8
14	20	56	50	30	42	37	40	28	25
16	40	65	9	60	50	7	80	33	5

In Tab. 1, the required Time and Resource Consumption (T&RC) for different processes in the project under various methods are outlined. The T&RC required for the same process varies depending on the method used, and the T&RC for different processes within the same method also differ. Consequently, the research goal is to develop a reasonable plan under the constraints of project schedule and resource allocation. To verify the performance of the IGA-DE algorithm, the experiment utilizes several test functions: Sphere, Ackley, Schwefel, and Schaffer.

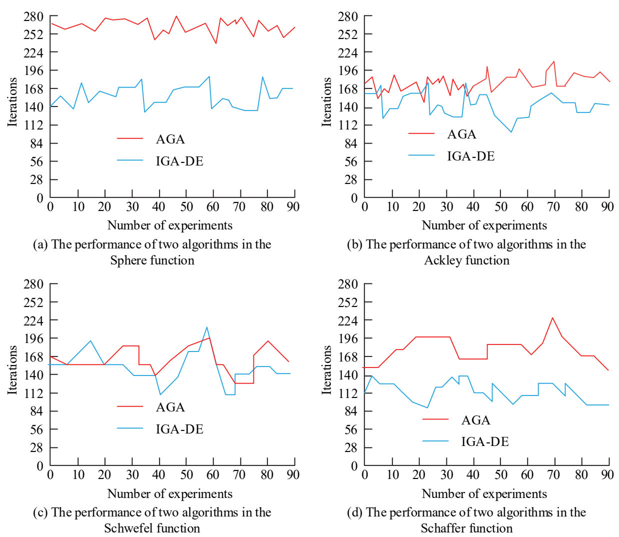


Figure 8 Comparison of algorithm convergence in different test functions

The Ackley function, characterized by multiple local minima, is useful for evaluating the algorithm's performance and convergence speed. The Schwefel function has a single global minimum point that is significantly distant from other local minima, making it challenging to escape from local optima, thus testing the algorithm's global search capability. The Rosenbrock function is employed to assess the search ability, convergence speed, and other performance metrics of the optimization algorithm. The performance of IGA-DE is compared with that of the Adaptive Genetic Algorithm (AGA) on these test functions, as illustrated in Fig. 8.

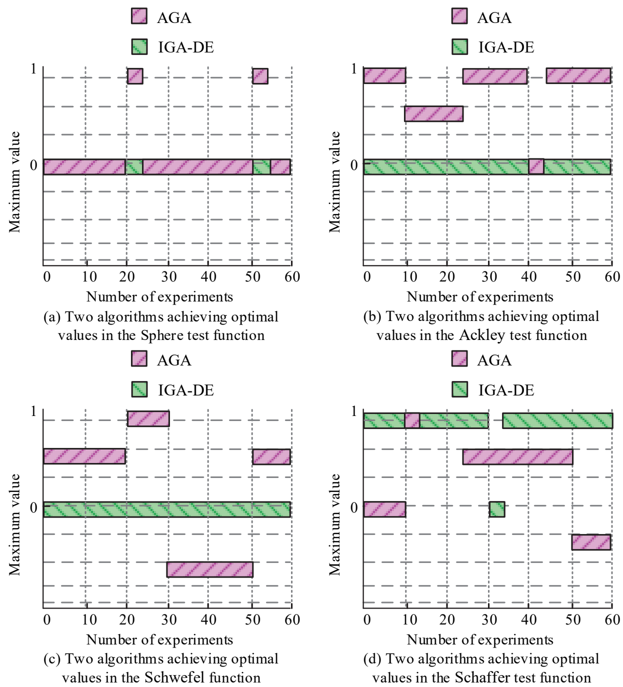


Figure 9 Comparison of algorithm optimal values in different test functions

In Fig. 8a, for the test function Sphere, the AGA converges after an average of 265 iterations, while the IGA-DE converges after an average of 115 iterations. In Fig. 8b, for the Ackley function, AGA converges after an average of 172 iterations, while IGA-DE converges after 160 iterations. In Fig. 8c, for the Schwefel function, AGA completes convergence after 160 iterations, while IGA-DE completes convergence after 154 iterations. In Fig. 8d, for the Schaffer function, the AGA completes convergence after an average of 115 iterations, while IGA-DE requires 157 iterations. The experimental data indicate that IGA-DE algorithm has a faster search speed and higher efficiency in processing large-scale data, which greatly helps to improve the efficiency of planning. To further validate the performance of IGA-DE, this study conducts a statistical analysis of the function values generated by the two algorithms across the test functions, as depicted in Fig. 9.

In Fig. 9a, for the Sphere function, both AGA and IGA-DE achieve their maximum value of 0 during the experiment. In Fig. 9b, for the Ackley function, AGA rarely reaches its maximum value of 0, while IGA-DE consistently achieves this maximum value. In Fig. 9c, AGA is unable to obtain the maximum value of 0, while IGA-DE successfully reaches it. In Fig. 9d, for the Schaffer function, the maximum value of 1 is almost impossible for AGA to achieve, while IGA-DE attains it in most experiments. These results suggest that AGA has a weaker global search ability and is prone to getting trapped in local optima. In contrast, IGA-DE demonstrates superior performance with a much stronger global search capability, allowing it to consistently find optimal solutions. The IGA-DE algorithm has a strong ability to explore and discover global optimal solutions, and can efficiently find the best solution in complex problem spaces, effectively obtaining the optimal solution for multi-objective models.

4.2 Optimization Analysis of CPPM Based on Parameter-Adaptive IGA

To verify the effectiveness of the proposed construction project MOO plan management model based on IGA-DE, an example application analysis is conducted. The optimal solution of the model in engineering projects is presented in Fig. 10.

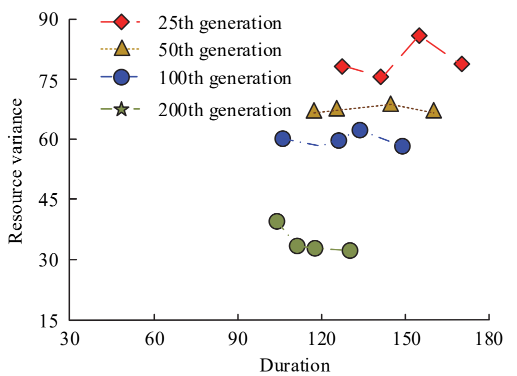


Figure 10 Evolution of the optimal solution for MOO plan management model

In Fig. 10, the experiment selects the optimal solutions for the 25th, 50th, 100th, and 200th generations, resulting in four sets of schemes. For the 200th generation, Group 1 has a duration of 116 days with a resource variance of 35.6254. Group 2 has a duration of 117 days with a resource variance of 33.5133. Group 3 has a duration of 118 days with a resource variance of 32.6195. Group 4 has a duration of 134 days with a resource variance of 30.4232. This indicates that the solution in the 25th generation is still far from optimal, both in terms of duration and resource variance. As the number of evolutionary generations increases, the target values become closer to the optimal solution, demonstrating the effectiveness of the model. This indicates that the model gradually converges to the global optimal solution during the optimization process, rather than getting stuck in local optimal solutions. The statistical significance lies in verifying the effectiveness and robustness of the model, indicating that the model can robustly converge to the optimal solution. To visually illustrate the superiority of the optimization model, a comparison is made between the original project plan and the optimized plan, as shown in Fig. 11.

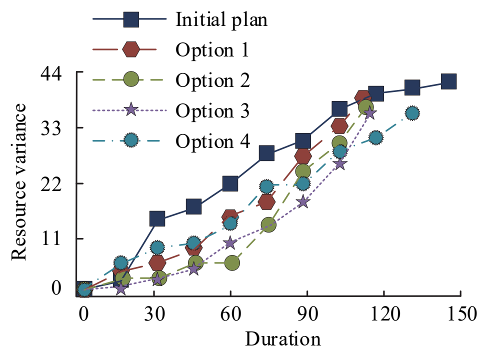
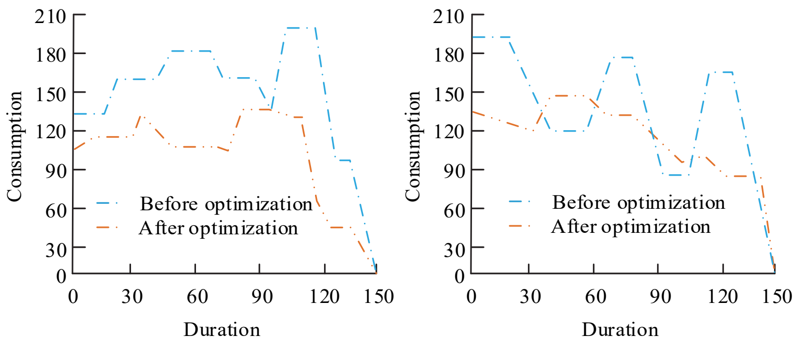


Figure 11 Comparison of project plan optimization before and after

In Fig. 11, the initial project duration is 150 days, with an initial resource variance of 43.4137. When compared to the optimized schemes 1, 2, 3, and 4, the construction period has been shortened by 22.7%, 22%, 21.3%, and 10.7%, respectively. Additionally, the resource variance has been reduced by 17.9%, 22.8%, 24.9%, and 29.9%, respectively. The data clearly show that the optimized plans not only reduce the project duration but also significantly decrease the resource variance compared to the initial plan, demonstrating the effectiveness of the optimization model. Furthermore, decision-makers can select from the four optimized options based on the specific needs of the project, thereby enhancing the flexibility of the scheme design. A comparison of the schemes before and after optimization reveals a reduction in the variance results of each group of schemes relative to the original results. This finding underscores the statistical significance ($P<0.05$) of the optimized scheme in terms of project duration and resource balance variance compared to the initial scheme, rather than pure random fluctuations. To further assess the balance in resource usage between the pre- and post-optimization plans, a comparison is made, as illustrated in Fig. 12.



(a) L1 resource weekly consumption (b) L2 resource weekly consumption

Figure 12 Comparison of weekly resource consumption before and after optimization of the plan

In Fig. 12, before optimization, the consumption of weekly resources L1 and L2 remains unstable throughout the entire construction period. In Fig. 12a, before optimization, the highest weekly resource L1 consumption is 200, with more occurrences of peak and valley phenomena. After optimization, the consumption is 180, with fewer peaks and valleys. The weekly resource L1 consumption is relatively stable. In Fig. 12b, after optimization, the stability of L2 resource consumption has significantly increased. This indicates that the optimized solution is of great help to resource allocation and can effectively reduce the instability of resource allocation. Concurrently, the optimized solution can diminish resource consumption and allocation costs throughout the allocation process by meticulously planning the resources necessary for the process.

5 DISCUSSION

Aiming at the optimization problem of CPPM, a MOO model was studied and constructed, and the model was solved using an IGA-DE-based algorithm. The experimental results demonstrated the quality and accuracy of the improvement plan. Through the proposed algorithms, CPPM could achieve more accurate and reliable project planning and resource allocation. This would help reduce project delays and resource waste, and improve overall project management efficiency. The results were beneficial for reducing time and costs, optimizing resource allocation plans and project schedules. This is of great significance for the successful implementation and budget control of construction projects. Meanwhile, the optimized scheme helped to improve the efficiency of project resource allocation. The proposed algorithm had superiority over the compared algorithms in terms of global search ability, local search ability, and convergence speed. Therefore, adopting this algorithm could improve the efficiency of project duration and resource allocation, helping to ensure timely project delivery and full utilization of resources. Regarding the comprehensive optimization problem of schedule, cost, and sustainability level in construction, Peng J et al. constructed a MOO model for the sustainability level of project duration and cost. This study obtained a series of Pareto optimal solutions using the NSGA-II algorithm. The efficiency coefficient method was used for program decision-making. The experimental results showed that the method could effectively solve the model, and at the same time, the proposed solution reduced the project duration by 8.23% and the resource variance by 14.2% [24]. In comparison, the optimization effect of this method was lower, which may be due to the stronger global optimization ability of the proposed algorithm, resulting in better solution performance for the model. It was also possible that in the construction of the problem function, the multi-objective task model proposed in the study considered more comprehensive factors and was more in line with the actual project. Tavakolan M et al. proposed a hybrid meta heuristic algorithm for MOO problems in CPP and financing. The model was first validated in a simple case study and then applied to large-scale case studies. The results indicated that the proposed model outperformed existing models in finding better project planning solutions, lower total project duration, and lower total project financing costs [25]. Compared to the proposed optimization methods, this algorithm performed worse in large-scale data processing. This may be because the research algorithm combined the advantages of DE in large-scale data processing, which is more efficient in processing and calculating large amounts of data in the project. Moreover, the research method is more conducive to decision-makers to plan goals promptly.

6 CONCLUSION

This study proposed a new method for optimizing CPPM based on parameter-adaptive IGA combined with DE. This method significantly improved project duration and resource allocation efficiency. A case study experiment showed that compared to traditional planning methods, project duration was reduced by 22.7% and resource variance was reduced by 29.9%. The MOO model provides project managers with flexible choices to balance time and resource constraints. Although the results are promising, future research should focus on testing the method on a wider range of project types and scales to improve its generality. This study has made contributions to the theoretical development and practical application of optimization algorithms in project management.

7 REFERENCES

[1] Alhijawi, B. & Awajan, A.(2024). Genetic algorithms: Theory, genetic operators, solutions, and applications. *Evolutionary Intelligence, 17*(3), 1245-1256. https://doi.org/10.1007/s12065-023-00822-6
[2] Hamdia, K. M., Zhuang, X., & Rabczuk, T. (2021). An efficient optimization approach for designing machine learning models based on genetic algorithm. *Neural*

Computing and Applications, 33(6), 1923-1933. https://doi.org/10.1007/s00521-020-05035-x

[3] Almashhadani, M. & Almashhadani, H. A. (2023). The Impact of Education on Construction Management: A Comprehensive Review. *International Journal of Business and Management Invention, 12*(6), 284-290. https://doi.org/10.24846/v29i2y202008

[4] Kaparthi, S., Mann, A., & Power, D. J. (2021). An overview of cloud-based decision support applications and a reference model. *Studies in Informatics and Control, 30*(1), 5-18. https://doi.org/10.24846/v30i1y202101

[5] Zelenka, M. & Podaras, A. (2021). Increasing the effectivity of business intelligence tools via amplified data knowledge. *Studies in Informatics and Control, 30*(2), 67-77. https://doi.org/10.24846/v30i2y202106

[6] Garud, K. S., Jayaraj, S., & Lee, M. Y. (2021). A review on modeling of solar photovoltaic systems using artificial neural networks, fuzzy logic, genetic algorithm and hybrid models. *International Journal of Energy Research, 45*(1), 6-35. https://doi.org/10.1002/er.5608

[7] Li, Z., Yu, X., Qiu, J., & Gao, H. (2021). Cell division genetic algorithm for component allocation optimization in multifunctional placers. *IEEE Transactions on Industrial Informatics, 18*(1), 559-570. https://doi.org/10.1109/TII.2021.3069459

[8] Gülmez, B. (2023). A novel deep neural network model based Xception and genetic algorithm for detection of COVID-19 from X-ray images. *Annals of Operations Research, 328*(1), 617-641. https://doi.org/10.1007/s10479-022-05151-y

[9] Dharma, F., Shabrina, S., & Noviana, A. (2020). Tahir M, Hendrastuty N, Wahyono W. Prediction of Indonesian inflation rate using regression model based on genetic algorithms. *Jurnal Online Informatika, 5*(1), 45-52. https://doi.org/10.15575/join.v5i1.532

[10] Tahir, M., Sardaraz, M., Mehmood, Z., & Muhammad, S. (2021). CryptoGA: a cryptosystem based on genetic algorithm for cloud data security. *Cluster Computing, 24*(2), 739-752. https://doi.org/10.1007/s10586-020-03157-4

[11] Civera, M., Pecorelli, M. L., Ceravolo, R., & Surace, C. (2021). Zanotti Fragonara L. A multi-objective genetic algorithm strategy for robust optimal sensor placement. *Computer-Aided Civil and Infrastructure Engineering, 36*(9), 1185-1202. https://doi.org/10.1111/mice.12646

[12] Ashok, D., Scott, J., Wetzel, S. J., Panju, M., & Ganesh, V. (2021). Logic guided genetic algorithms (student abstract). *Proceedings of the AAAI Conference on Artificial Intelligence, 35*(18), 15753-15754. https://doi.org/10.1609/aaai.v35i18.17873

[13] Bousnina, K., Hamza, A., & Ben Yahia, N. (2023). A combination of PSO-ANN hybrid algorithm and genetic algorithm to optimize technological parameters during milling 2017A alloy. *Journal of Industrial and Production Engineering, 40*(7), 554-571. https://doi.org/10.1080/21681015.2023.2243312

[14] Mohammadi, S., Tavakolan, M., & Zahraie, B. (2022). An intelligent simulation-based framework for automated planning of concrete construction works. *Engineering, Construction and Architectural Management, 29*(2), 916-939. https://doi.org/10.1108/ECAM-11-2020-0971

[15] Afshar, M. R., Shahhosseini, V., & Sebt, M. H. (2020). Optimal sub-contractor selection and allocation in a multiple construction project: Project portfolio planning in practice. *Journal of the Operational Research Society, 7*3(2), 351-364. https://doi.org/10.1080/01605682.2020.1835450

[16] Liu, Y., Cheng, H., & Liu, C. (2022). Optimization of construction program schedule plans based on multi-objective optimization theory. *Iranian Journal of Science and Technology, Transactions of Civil Engineering, 46*(6), 4763-4782. https://doi.org/10.1007/s40996-022-00865-2

[17] Abad, F. & Naeni, L. M. (2020). A hybrid framework to assess the risk of change in construction projects using fuzzy fault tree and fuzzy event tree analysis. *International Journal of Construction Management, 22*(12), 2385-2397. https://doi.org/10.1080/15623599.2020.1790474

[18] Luong, D. L., Tran, D. H., & Nguyen, P. T. (2021). Optimizing multi-mode time-cost-quality trade-off of construction project using opposition multiple objective difference evolution. *International Journal of Construction Management, 21*(3), 271-283. https://doi.org/10.1080/15623599.2018.1526630

[19] Kermanshachi, S., Nipa, T. J., & Dao, B. (2023). Development of complexity management strategies for construction projects. *Journal of Engineering, Design and Technology, 21*(6), 1633-1657. https://doi.org/10.1108/JEDT-06-2021-0324

[20] Ghorbani, A. (2023). A review of successful construction project managers' competencies and leadership profile. *Journal of Rehabilitation in Civil Engineering, 11*(1), 76-95.

[21] Obiuto, N. C., Adebayo, R. A., Olajiga, O. K., & Festus-Ikhuoria, I. C. (2024) .Integrating artificial intelligence in construction management: Improving project efficiency and cost-effectiveness. *Int. J. Adv. Multidisc. Res. Stud, 4*(2), 639-647. https://doi.org/10.62225/2583049X

[22] Luo, N., Yu, H., & You, Z. (2023). Fuzzy logic and neural network-based risk assessment model for import and export enterprises: A review. *Journal of Data Science and Intelligent Systems, 1*(1), 2-11. https://doi.org/10.47852/bonviewJDSIS32021078

[23] Mansouri Moghadam, M., Nosrati, R., & Sepidnameh, B. (2023). Evaluation of development plans with the approach of critical ethnography (Case study: Dam construction projects in Ilam province). *Community Development (Rural and Urban Communities), 14*(2), 333-351.

[24] Peng, J., Feng, Y., & Zhang, Q. (2023). Multi-objective integrated optimization study of prefabricated building projects introducing sustainable levels. *Scientific Reports, 13*(1), 2821.https://doi.org/10.1038/s41598-023-29881-6

[25] Tavakolan, M. & Nikoukar, S. (2022). Developing an optimization financing cost-scheduling trade-off model in construction project. *International Journal of Construction Management, 22*(2), 262-277. https://doi.org/10.1080/15623599.2019.1619439

Contact information

Tianya JIA
(Corresponding author)
Intelligent Construction College,
Dazhou Vocational and Technical College,
Dazhou, Sichuan, 635001, China
E-mail: jiatianya9011@163.com