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Research on Multi-Objective Optimization of Project Scheduling based on NSGA-III: Trade-off among Project Duration, Resource Allocation, and Robustness

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Abstract

As an important approach to promoting the greening and modernization of the construction industry, prefabricated buildings have been widely applied in recent years. However, current construction project management still faces issues such as decision-making reliance on experience, unreasonable resource allocation, project delays, and insufficient ability to cope with uncertainties, which affect construction efficiency and widespread adoption. Therefore, multi-objective optimization research on project duration, resource supply balance, and robustness is of great significance.This study constructs a three-objective optimization model for prefabricated building construction, comprehensively considering the impact of project duration on economic benefits, the regulatory role of resource supply balance in construction efficiency, and the criticality of robustness in addressing construction risks. The NSGA-III algorithm is employed to optimize project duration, resource balance, and robustness, with a reference point strategy incorporated to enhance algorithm efficiency. Through validation with real-world case studies, the results demonstrate that the proposed method effectively balances the three objectives and improves construction project management.

Keywords

Prefabricated Construction; Resource-Constrained Project Scheduling Problem; NSGA-III.

1. Introduction

In modern construction project management, project scheduling is a critical process to ensure smooth project execution and timely completion. As project scales expand and complexity increases, traditional scheduling methods face challenges such as imbalanced resource supply, project delays, and insufficient robustness. Therefore, multi-objective optimization techniques have been widely applied to scheduling optimization, with a particular focus on balancing project duration, resource allocation, and robustness. However, these objectives are interdependent, making it crucial to address competing demands in the optimization process, which remains a key challenge in project scheduling optimization.

In recent years, NSGA-III has been widely applied in multi-objective optimization problems due to its efficiency and stability. Particularly in resource-constrained scheduling for prefabricated construction, researchers have focused on project duration, resource allocation, and uncertainty management. Naber et al. [1] improved the RCPSP model to enhance computational performance; Wang Hong et al. [2] optimized genetic algorithms using standardized random-key representation, demonstrating superior performance in large-scale scheduling problems; Mongeau et al. [3] simplified

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mathematical expressions to improve scheduling efficiency; Siu et al. [4] combined genetic algorithms with particle swarm optimization to enhance resource allocation efficiency; Tran et al. [5] validated the accuracy of branch-and-bound methods in complex project scheduling; Kim and Lee [6] optimized genetic algorithms to improve task prioritization; Isah and Kim [7] proposed a stochastic multi-skilled resource scheduling model (SMSRS) and integrated Monte Carlo simulation for task risk assessment.

For construction site layout optimization, Yao et al. [8] improved the NSGA-II algorithm and integrated the entropy-weight TOPSIS method to optimize layout planning, improving solution quality and reducing computation time. In risk control, Song Y et al. [9] proposed a two-layer multi-objective scheduling framework using the niche genetic algorithm and the raccoon family optimization algorithm (NG-RFO), achieving superior performance in optimizing project duration, cost, and robustness. Regarding low-carbon construction, Abbasi and Noorzai [10] integrated BIM and LCA tools to reduce the life-cycle energy consumption of buildings, providing guidance for green building development.

In production scheduling and resource optimization, Wang Q et al. [11] combined NSGA-II with simulated annealing to optimize prefabricated component assembly, achieving a balance among cost, project duration, and carbon emissions. Yuan Y et al. [12] integrated fuzzy theory with the HCOEA algorithm to optimize scheduling in uncertain environments, outperforming traditional methods. Peng J et al. [13] introduced carbon emission factors and proposed an integrated optimization model to balance project duration, cost, and sustainability goals, supporting low-carbon development and cost control.

The robustness optimization of prefabricated construction projects has also received increasing attention, with various methods proposed to handle complex resource scheduling and environmental uncertainties. McAllister et al. [14] studied a model predictive control (MPC)-based closed-loop scheduling algorithm to enhance system resilience and execution efficiency. Grumbach et al. [15] incorporated regression-based machine learning methods to improve the accuracy of dynamic scheduling predictions, thereby optimizing scheduling stability. Salido et al. [16] optimized energy efficiency, robustness, and completion time in workshop scheduling, reducing energy consumption while enhancing system stability.

In scheduling evaluation and intelligent optimization, Zahid et al. [17] introduced the Float Index to assess scheduling stability, providing project managers with a basis for predicting and mitigating project delay risks. Liu et al. [18] combined reinforcement learning (RL) and meta-learning (MLR-TC-DRLS) to optimize task reward systems, improving scheduling adaptability. Palacios et al. [19] integrated fuzzy numbers with multi-objective evolutionary algorithms (MOEA) to optimize scheduling robustness, enhancing the ability to respond to uncertainties.

Overall, scheduling optimization in prefabricated construction is advancing towards multi-objective intelligent optimization, dynamic adaptability, and green sustainability. Future research should further integrate emerging technologies such as digital twins, machine learning, and artificial intelligence to enhance scheduling stability and resource allocation efficiency. Based on the NSGA-III algorithm, this study explores the trade-offs between project duration, resource balancing, and robustness in construction project scheduling, proposing optimization strategies to provide scientific decision-making support for project managers and facilitate the efficient implementation of prefabricated construction projects.

2. Model Building

2.1 Optimization Model

2.1.1 Project Duration Objective Function

This objective function represents the total project duration, which is typically defined as the completion time of the last task in the project. The goal is to minimize the project duration, i.e., to shorten the time required for project completion as much as possible.

$$T = \max(finish_i) \tag{1}$$

Task Duration Function:

$$dayi = \begin{cases} day_i, \forall j & x_{ij} = 0 \\ \dfrac{0.3day_i}{(re_{ij} - p_{ij})\hat{}2}(re'ij - pij)\hat{}2 + 0.7day_i, \exists j & x_{ij} = 1 \end{cases} \tag{2}$$

2.1.2 Resource Allocation Balance Function

To prevent excessive resource allocation, a 'peak shaving and valley filling' approach is adopted in the objective function formulation. This method provides an intuitive and efficient way to adjust project resources, ensuring maximum resource balance.

$$D = \sqrt[J]{\prod_{j=1} \max(re_{ij})} \tag{3}$$

2.1.3 Robustness Objective Function

The objective function is used to evaluate the stability and disturbance resistance of the scheduling plan when facing uncertainties. The goal is to maximize the robustness of the scheduling plan to mitigate the negative impacts of uncertainties on the project. The robustness value of the entire project is represented by the weighted sum of the free float of all activities within the project.

$$Robu = \sum_{i=1}^{n}(CIW_i \times \Delta_i) \tag{4}$$

2.2 Constraint Formulation

2.2.1 Process Constraints

When formulating the scheduling plan, it is essential to consider the overlapping relationships between tasks.

$$start_i \geq \max(finish_i), \qquad \forall i, h \in LJ_i \tag{5}$$

2.2.2 Resource Constraints

The project resource constraints require that the resource usage at any given time does not exceed the allocated upper limit.

$$\sum_{i \in At} re'_{ij} \leq re\_\max_j, \qquad \forall j, t \tag{6}$$

2.2.3 Schedule Compression Constraints

Project duration compression is subject to constraints to maintain feasibility and construction quality. The schedule compression constraints regulate the degree of duration reduction in the optimization process. To avoid excessive compression leading to an over-supply of resources, the reduced project duration must be no less than 70% of the original duration.

$$finish_i - start_i \geq 0.7 day_i, \qquad \forall i \tag{7}$$

2.3 Notation Explanation

Table 1. Variable Parameter Table

Notation	Definition
i	Activity ID
j	Resource ID
J	Resource Types
A_t	The set of active activities at time t
$re\_\max_j$	The maximum allocated amount of resource j
re_{ij}	The standard daily consumption of resource j by task i
re'_{ij}	The actual daily consumption of resource j by task i
day_i	The standard duration of activity i
LJ_i	The set of predecessor activities of activity i
$start_i$	Start time of activity i
$finish_i$	End time of activity i
x_{ij}	Whether the duration of activity i can be reduced by allocating more resource j
p_{ij}	If the duration of activity i can be reduced, the maximum deployable resource j for activity i
CIW_i	The weight of activity i, representing its importance
Δ_i	The free float of activity iii in the scheduling plan
T	Project Duration
D	Resource Allocation Balance
$Robu$	Robustness

3. Solution of Multi-Objective Optimization Model

3.1 Solution of the Multi-Objective Optimization Model based on NSGA-III

In this paper, the NSGA-III genetic algorithm is used to iteratively solve the Pareto front and search for the optimal solutions. The core idea is to generate optimal solutions through the sorting and selection of offspring in the population. The process is as follows:

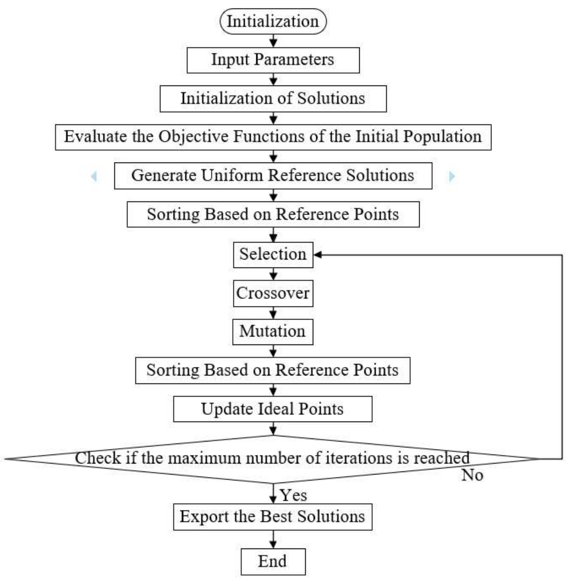

Fig. 1 Model Solving Process

The following section presents an introduction to the genetic algorithm as depicted in the flowchart:

1) Population Initialization

The population is initialized using a random method, with a predefined population size.

2) Objective Value Calculation and Constraint Handling

For each individual in the initial population, the decoding function is called to compute the corresponding project duration, resource leveling index, and robustness. During this process, constraints are handled through a scheduling adjustment algorithm (e.g., topological sorting) to ensure that generated individuals comply with task dependency constraints. Meanwhile, resource usage and task duration are dynamically updated according to the individual's genetic encoding.

3) Generating Consistent Reference Solutions

A function is used to generate a set of consistent reference points for multi-objective optimization. These reference points guide the selection process in NSGA-III by projecting the population's objective values onto them, ensuring diversity in the population.

4) Non-Dominated Sorting

After computing the objective values of the initial population, a non-dominated sorting algorithm is applied to classify individuals based on dominance levels. Individuals within the same level are further sorted based on reference points. This step prioritizes high-quality individuals for selection in the next generation.

5) Selection

A binary tournament selection method is used in the code. Each time, two individuals are randomly selected and compared. The individual with a higher fitness value (based on non-dominance rank and crowding distance) is chosen as a parent. This selection mechanism retains superior individuals while preventing premature convergence.

6) Crossover and Mutation Operations

In the crossover operation, genes of two randomly selected individuals are exchanged to generate offspring. Mutation modifies the genes of individuals randomly to introduce new search space exploration opportunities. After crossover and mutation, the offspring population undergoes recalculation of objective values and constraint handling.

7) Parent-Offspring Merging and Elite Selection

The parent and offspring populations are merged to form a combined population of double the original size. A non-dominated sorting process is applied again to select the best individuals for the next generation. This elite strategy ensures that high-quality genes from the parent population are preserved while retaining potentially superior offspring individuals.

8) Updating the Ideal Point

During each iteration, the ideal point is dynamically updated based on the current population's objective values. This guides the optimization direction and improves convergence efficiency.

9) Iteration Termination and Pareto Front Output

The above process is repeated iteratively until the predefined maximum number of generations is reached. Finally, the set of non-dominated solutions in the population is output as the Pareto front. A visualization function is used to display the three-objective results for better analysis and evaluation.

4. Example Analysis

4.1 Project Background and Data

This project involves the construction of a prefabricated residential complex in Hunan, with a total floor area of 220,000 square meters. It consists of eight high-rise residential buildings with supporting facilities, with the tallest building reaching 33 floors and an overall prefabrication rate of 52%. The primary structural system adopts a prefabricated shear wall structure.

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All prefabricated components are supplied from a factory located 60 kilometers from the construction site. The transportation follows a "just-in-time" principle, ensuring that materials for the next floor are prepared only after the previous floor's construction is completed, thereby maintaining a stable construction schedule.

In this study, a standard floor of one residential building is selected as a case example. The NSGA-III algorithm is applied to optimize the scheduling of labor, machinery, and construction materials. The objective is to enhance construction efficiency, shorten project duration, and minimize resource fluctuations. By integrating the unique characteristics of prefabricated construction, this research aims to develop a scientific and efficient scheduling strategy to ensure smooth project execution.Fig. 2 shows the AoN (Activity on Node) network diagram for this project, which includes a total of 30 activities. Activity 0 represents the virtual initial activity, and Activity 30 represents the virtual end activity.

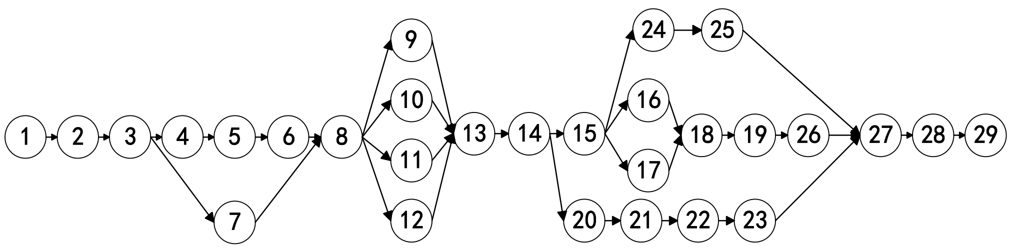

Fig.2 Project Example Network Diagram

The execution duration, resource requirements, and the weight values for each activity, determined based on experience, are provided in Tab 2.

4.2 Construction Schedule Planning

Table 2. Project Resource Availability

Activity ID	Activity Name	d	Human Resources						R_3	R_4	R_5	R_6	Weight
			R_1	x_{ij}	p_{ij}	R_2	x_{ij}	p_{ij}					
0	Start	0	0	0	0	0	0	0	0	0	0	0	0
1	Foundation Excavation	5	100	1	150	20	0	0	5	0	0	10	20
2	Formwork Fabrication and Installation	6	150	0	0	20	0	0	7	0	5	0	40
3	Rebar Processing and Tying	7	100	1	150	20	0	0	8	0	7	0	30
4	Foundation Concrete Pouring	20	150	0	0	20	0	0	9	0	0	9	40
5	Foundation Curing	14	50	0	0	25	0	0	0	3	2	0	20
6	Foundation Backfilling	10	50	1	80	10	0	0	6	0	0	7	14
7	Precast Component Ordering	40	0	0	0	2	1	3	0	0	0	0	60
8	Precast Component Reception and Placement	5	15	0	0	2	0	0	0	0	5	2	10
9	Precast Slab Installation	30	50	1	80	5	0	0	6	0	0	7	45

10	Precast Wall Panel Installation	35	50	1	80	5	0	0	7	0	0	7	30
11	Precast Wall Panel Installation	40	50	1	80	5	0	0	7	0	0	7	35
12	Precast Stair Installation	30	10	0	0	2	0	0	6	0	0	7	40
13	Precast Balcony Installation	20	30	1	50	3	0	0	5	0	0	6	40
14	Precast Exterior Wall Panel Installation	30	70	1	120	15	0	0	7	0	0	7	25
15	Precast Interior Wall Partition Installation	30	100	1	150	20	0	0	6	0	5	0	35
16	Electrical Conduit Embedding	40	100	1	150	20	0	0	0	7	7	0	40
17	Water Supply and Drainage Pipeline Installation	35	80	1	150	15	0	0	0	7	7	0	30
18	Joint Treatment and Grouting	20	80	0	0	15	0	0	5	5	4	0	35
19	Roof Waterproofing Layer Construction	25	50	0	0	10	0	0	0	6	6	0	30
20	External Wall Insulation Layer Installation	35	50	0	0	10	0	0	6	7	6	0	25
21	External Wall Cladding Installation	40	120	1	200	25	0	0	0	8	6	0	60
22	Door and Window Frame Installation	30	50	1	100	20	0	0	5	6	5	0	25
23	Door and Window Leaf Installation	25	50	1	100	10	0	0	5	6	5	0	30
24	Interior Wall Plastering	30	50	1	100	10	0	0	8	0	6	0	15
25	Interior Wall Painting	35	50	1	100	15	0	0	0	7	6	0	10
26	Floor Leveling	25	50	1	100	10	0	0	6	0	7	0	20
27	Interior Fit-Out Construction	60	150	1	300	10	0	0	7	0	8	0	10
28	Completion Acceptance	15	0	0	0	10	0	0	0	0	4	0	1
29	Construction Site Cleaning	10	15	0	0	5	0	0	0	0	4	0	20
30	End	0	0	0	0	0	0	0	0	0	0	0	0

4.3 Calculation Results

The genetic algorithm described in this paper was compiled using MATLAB R2022a, with a system configuration of 16GB RAM, an Intel(R) Core(TM) i5-8300H CPU, and Windows 10 as the operating system. Since the performance of the genetic algorithm is influenced by various parameters, a review of relevant literature was conducted and experiments were performed to select the optimal parameters. Ultimately, the population size was set to 100, the crossover probability to 0.7, the mutation probability to 0.2, and the number of iterations to 300. The results, including the project durations, resource leveling, and robustness of each schedule, are summarized in Table 3.

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Table 3. Schedule Planning Calculation Results

Schedule Options	Task Duration	Resource Allocation Balance	Robustness
1	385	30.9477	8645
2	441	28.8778	13455
3	395	30.8186	7075
4	400	31.2134	10090
5	399	30.6843	9070
6	416	28.8778	10630
7	420	29.1258	11510
8	427	28.9134	12160
9	494	27.6454	7690
10	488	28.3077	8325
11	402	29.1616	11400

By observing Table 3, it can be seen that each schedule option has its strengths and weaknesses in the three key objectives. Option 1 has the shortest project duration of 385 days, but it performs poorly in terms of resource allocation and robustness. Option 9 excels in resource allocation, with a resource leveling index of 27.6454, but it has the longest project duration. Option 2 achieves the highest robustness value of 13,455, with a moderate project duration and resource allocation. The results indicate that no single option outperforms the others across all three objectives. Decision-makers can balance the trade-offs based on their preferences and needs, selecting the schedule that best meets their requirements.

4.4 Approximate Pareto Front

To more intuitively observe the trade-off relationships between the project duration, robustness, and resource leveling objectives in the non-dominated solutions, the Pareto front is approximated based on the data from Table 3, as shown in Fig. 3.

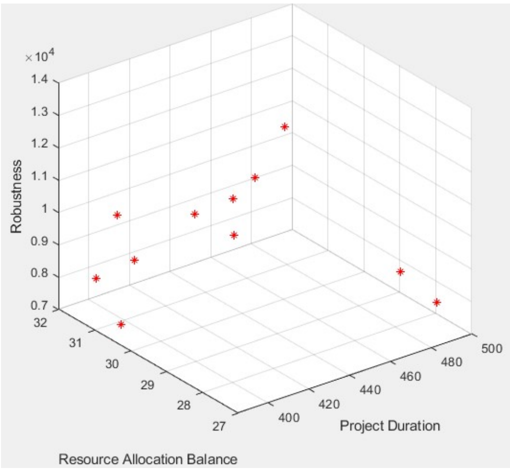

Fig.3 Pareto Optimal Solutions

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5. Conclusion

This study, based on multi-objective optimization methods, analyzes the scheduling plans for prefabricated construction projects and presents the following optimization recommendations. First, during project implementation, the optimal solution should be selected based on specific needs. For projects with tight schedules, priority should be given to plans with shorter durations, while for projects requiring higher resource utilization efficiency, solutions with better resource leveling should be considered. Secondly, there is a clear conflict between project duration and resource leveling. It is recommended to seek a reasonable balance during construction, such as choosing a plan with a moderate duration but better resource leveling to reduce hidden costs and ensure construction progress.

At the same time, the dynamic conditions on the construction site have a significant impact on the applicability of scheduling plans. Therefore, it is recommended to establish a real-time data monitoring system to dynamically adjust the construction plan in the event of unexpected situations, selecting plans that perform more stably in a dynamic environment. Additionally, resources should be reasonably allocated to avoid resource idle time or overuse, improving construction efficiency and optimizing the scheduling of key resources.

In practical applications, construction managers should comprehensively consider the results of multi-objective optimization, flexibly selecting the optimal plan by balancing the three objectives of project duration, resource leveling, and robustness. The use of NSGA-III algorithm for intelligent optimization has shown promising results, so it is recommended that construction companies adopt similar intelligent optimization tools to enhance the scientific nature and efficiency of scheduling decisions. Finally, since different optimization plans have their strengths and weaknesses, construction managers should strengthen multi-party collaboration, organize evaluation meetings, and assess candidate plans comprehensively based on the needs of various departments, ensuring the effective implementation of the scheduling plan and improving the management level of prefabricated construction projects.

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