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Research paper

Construction scheduling optimization in the prefabricated buildings through multi-objective GA on the principle of sustainable development

Chuanguang Yang[1]

Abstract: To save resources and protect the environment to the maximum extent, green buildings came into being. Among them, prefabricated building is the only way for traditional buildings to transform into green buildings. The construction scheduling of traditional buildings is mostly focused on the control of on-site resources, which cannot scientifically and reasonably complete the construction goal of prefabricated building. In response to the above issues, a resource constrained scheduling model based on genetic algorithm is designed by sustainable development, and an improved non dominated sorting genetic algorithm with elite strategy is introduced. It is used to solve the time cost weight balance scheduling model and the low-cost low-carbon scheduling model. The research results indicated that this algorithm had a reverse generation distance value of 0.35 when evaluated 4000 times, and a super volume value of 0.43 when evaluated 10000 times. In the application of a certain affordable housing project, the resource constrained scheduling model based on genetic algorithm can shorten the assembly phase to 8 days, and the low-cost low-carbon scheduling model using proposed algorithm can reduce the transportation cost and carbon emission duration of transportation vehicles to 22501 yuan and 93.75 h, respectively. Resource constrained scheduling models based on genetic algorithms and low-cost low-carbon scheduling models have potential in the field of green buildings, which can achieve significant results in saving time, cost, and reducing carbon emissions. These research results can provide reference for the promotion and practice of green buildings, and guide the formulation and implementation of relevant policies.

Keywords: non-dominated sorting genetic algorithm, prefabricated building, prefabricated component, resource constraints, sustainable development principles

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1. Introduction

To address multi-objective optimization in PB construction scheduling, researchers often use the NSGA-II algorithm. This is a multi-objective optimization algorithm that utilizes non-dominated sorting and crowding comparison to tackle conflicting objectives [1–3]. The NSGA-II algorithm generates multiple Pareto solutions, offering decision-makers more choices to balance trade-offs. It surpasses traditional genetic algorithms with its superior global search and diversity preservation, making it ideal for multi-objective optimization. Its applications span engineering, machine learning, production scheduling, etc. Given the benefits and challenges of prefabricated building (PB) projects, traditional scheduling methods may prove inadequate [4–6]. To address the aforementioned issues, this article constructs three stages of the construction process of prefabricated buildings (PB) based on the principles of sustainable development: assembly, production, and transportation. On this basis, two new scheduling models were proposed: a resource constrained (RC) scheduling model based on genetic algorithm (GA), a time cost length (TCT) based on non dominated sorting genetic algorithm II (NSGA-II), and a minimum total completion time (LCLC) scheduling model. The above two scheduling models were implemented using mathematical algorithms and computational methods. Firstly, genetic algorithm (GA) was used for construction scheduling under resource constraints during the assembly phase; Then, during the production phase, a TCT scheduling model based on NSGA-II was adopted and optimized in terms of cost and time; Finally, an LCLC scheduling model based on NSGA-II was used during the transportation phase, aiming to minimize transportation costs and carbon emissions.

This article's novelty lies in its in-depth exploration of prefabricated building (PB) projects, emphasizing their unique benefits like material savings, waste reduction, faster progress, and labor efficiency. Furthermore, it constructs innovative scheduling models tailored for PB projects, recognizing the limitations of traditional methods. Using genetic algorithms and non-dominated sorting genetic algorithm II, it develops RC, TCT, and LCLC models. Notably, it also integrates environmental considerations like transportation costs and carbon emissions, enhancing the model's real-world applicability.

The research framework consists of four main parts. The first part is a summary of the relevant research results. The second part proposes a resource constrained construction planning model based on genetic algorithm. The design of this model aims to address the trade-off between time cost and low-cost low-carbon models. The third part introduces an improved non dominated sorting genetic algorithm that combines elite strategies. This algorithm can more effectively handle multi-objective optimization problems and has a reverse distance value of 0.35 when evaluated 4000 times, and a super volume value of 0.43 when evaluated 10000 times. The fourth part mainly verifies the effectiveness of the proposed model and applies it in a specific affordable housing project.

2. Related works

The production and transportation scheduling problem of prefabricated components is an indispensable and important material in the PB construction field, which can be regarded as a resource constrained project scheduling problem. Wang et al. established a rescheduling model for prefabricated production to minimize the maximum completion time of prefabricated component production plans, and designed an improved grey wolf scheduling model. The results showed that the rescheduling model can effectively improve the stability of prefabricated component production systems [7]. Du et al. proposed a dynamic mobile workshop scheduling model to address the impact of frequent dynamic demand fluctuations on prefabricated component production systems in construction sites. Simulation experiments have shown that the model can effectively cope with the occurrence of demand fluctuations [8]. Yi et al. optimized the transportation plan for prefabricated components to minimize truck transportation and inventory holding costs. The research results indicate that the model is superior to traditional transportation schemes [9], and has a lower cost to generate the optimal transportation scheme. Zhang and Yu designed an elastic cost trade-off optimization model based on prefabricated component supply chain planning, addressing the potential disruption of delivery due to low productivity and various traffic restrictions. The simulation results have verified the feasibility of the model [10]. Manman et al. developed a single factor measurement model based on production, storage, transportation, and lifting, and used this model to measure the factors that affect the quality of PB construction. The research results indicate that the transportation and storage stages have a greater impact on the quality of prefabricated components [11].

GeneGA is an algorithm that seeks global optimal solution by simulating natural evolutionary processes and is usually used to solve project scheduling problems. Shooohyar and Amiri designed a combination of a genetic algorithm and a simulated annealing algorithm to address the increased difficulty of multimodal resource-constrained project scheduling due to multimodal resource requirements. The experimental results show that the proposed algorithm can effectively reduce the difficulty of project scheduling [12]. Marri and Rajalakshmi aim to propose optimization schemes for maximum completion time, energy consumption and data transmission time, and design a hybrid algorithm based on genetic algorithm and multi-target energy perception model. The simulation results show that the hybrid algorithm has good performance [13]. Kazemi et al. proposed a mixed integer linear planning model, discussed the comprehensive production and distribution scheduling of different parallel machines on the production line, and used the genetic algorithm to solve the model based on the optimization attribute mechanism. The results confirm the feasibility of GA [14]. Nikselisht and Raji design a task mapping and scheduling method based on multi-objective genetic algorithm problems in the design stage of the embedded system. Experimental results show that the proposed method has a higher speed-up ratio compared to other task scheduling methods [15]. A hybrid genetic algorithm based on the packaging strategy to minimize the maximum completion time of the working group was proposed by Su et al. The results demonstrate the effectiveness of a hybrid genetic algorithm in working group scheduling optimization studies [16]. Biermann et al. analyzed more than 3000 scientific studies published between 2016 and 2021 and showed that these targets influenced the understanding and communication of sustainable from local to global levels [17]. Welland et al. investigated the impact of 17 SDGs in the United Nations 2030 Agenda, analyzed the integrated and integrated approaches needed to achieve these goals, they proposed 11 thematic contributions around integration, governance challenges and implementation of [18].

In summary, there are many research achievements on the scheduling problem of prefabricated components and GA, but most of the research achievements are in the production and transportation stage, with little involvement in the assembly stage; GA is often applied to the optimization of work scheduling in flow shop, and rarely applied to the construction scheduling of PB. In response to the above issues, a construction scheduling model for the production, transportation, and on-site assembly is constructed during the PB construction process. GA and NSGA-II algorithm are used to solve the scheduling models for these three stages.

3. PB construction scheduling optimization model by GA and NSGA-II

PB construction scheduling has the characteristics of being in different locations and at different times. This study aims to optimize the established goals of PB construction projects from the perspectives of time and resources. This chapter focuses on the RC scheduling model in the assembly stage, the TCT scheduling model in the production stage, and LCLC in the transportation stage of PB construction. GA and NSGA-II are used to solve these three scheduling models.

3.1. PB construction process and construction of RC scheduling model based on GA

PB is a building assembled from prefabricated components, which are processed and produced in the factory and transferred to the construction site through transportation equipment, and then assembled on-site through reliable connections. Based on the principle of sustainable development, the PB construction process mainly consists of determining the construction plan, producing prefabricated components, transporting and storing prefabricated components, and assembling prefabricated components, as shown in Fig. 1 [19–21].

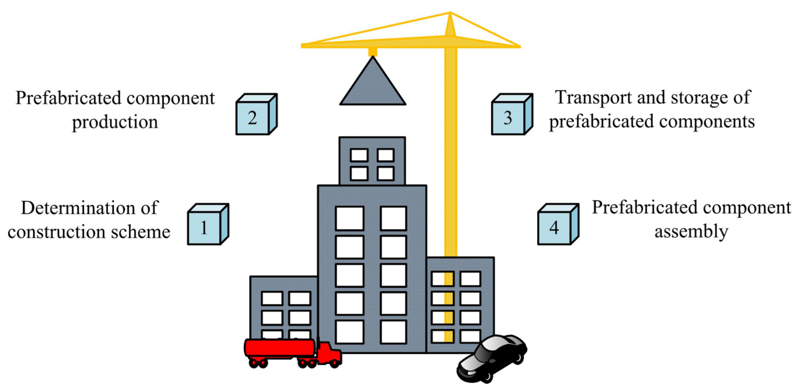

Fig. 1. PB project construction process

During construction, determining the production and transportation plan precedes the on-site assembly plan, as it impacts efficiency and quality. This plan considers prefabricated component production, transportation, and assembly, requiring manufacturers with appropriate capacity and technology. Professional transportation vehicles are needed for safe delivery due to component size and weight. Adhering to sustainable development, the construction process is divided into assembly, production, and transportation stages. The assembly stage, crucial for determining overall duration and efficiency, involves solving a resource-constrained scheduling problem. Finding the shortest scheduling model satisfying various constraints requires algorithms and models, ensuring smooth progress and high-quality completion. The RC scheduling model is outlined in Eqs. (3.1) and (3.2).

$$\begin{cases} \min S_{n+2} \\ st.S_q + d_q \leq S_l, \quad S_l \in P(l) \end{cases} \tag{3.1}$$

In Eq. (3.1), $\min S_{n+2}$ represents that the objective function is the minimum chemical period, where $n+2$ represents the virtual work at the end of the activity. $st.S_q + d_q \leq S_l, S_l \in P(l)$ is the tight pre-activity constraint relationship between activities l and q, where $P(l)$ is l's tight pre-activity set. The expression of activity resource constraint $\sum\limits_{l \in A(t)} r_{lk} \leq R_k$ is shown in Eq. (3.2).

$$\begin{cases} \sum\limits_{l \in A(t)} r_{lk} \leq R_k \\ t = 0, 1, \ldots, S_{n+2} \\ S_l \geq 0, \quad l = 1, 2, \ldots, n+2 \end{cases} \tag{3.2}$$

In Eq. (3.2), r_{lk} and R_k represent the number of resources k and the upper limit of resource capacity used by the activity l in time t. $t = 0, 1, \ldots, S_{n+2}$ refers to the discrete value of time, while $S_l \geq 0, l = 1, 2, \ldots, n+2$ represents the non negative start time of all activities. Based on the fact that the RC scheduling model only has one objective function, GA is studied to solve it. The five elements of GA are population size, chromosome encoding, fitness function, genetic operation, and stopping criterion, among which chromosome encoding is the encoding of the scheduling model using natural numbers [22, 23]. In order for the fitness value of each chromosome to represent the solution quality, research needs to convert the minimization goal into the maximization goal, as shown in Eq. (3.3).

$$fit = \frac{1}{F(x)} \tag{3.3}$$

In Eq. (3.3), $F(x)$ is the minimum completion time. The study generates different sorting methods for processes through the constraint relationship of tight before tight after and resource upper limit. If fit is greater than fit_0, process fit is updated until all processes in the chromosome sequence are processed and $fit_{\max}$ is obtained. The selection strategy for the study is the roulette wheel strategy, which designs a roulette wheel with the same number of sectors as N by calculating the probability $p(x_i)$ of each fitness value, and the sector area is proportional to the $p(x_i)$ value, as shown in Eq. (3.4).

$$p(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_i)} \tag{3.4}$$

In Eq. (3.4), $f(x_i)$ is the fitness value of each individual. The crossover operation in GA adopts a partial mapping crossover method for operation, and the crossover process is shown below. First, the parent chromosome is selected from the population selected based on the roulette wheel strategy, and then a random number is obtained that satisfies $0 \le k_1 \le k_2 \le l$, where l represents the chromosome length. Then, the chromosome is cut into two segments and position swapped to facilitate the resolution of the final coding duplication conflict problem. The mutation operation uses the mutation probability p_m to exchange two randomly selected gene positions. If p_m is too high or too low, it is not conducive to the algorithm's operation.

3.2. TCT and LCLC scheduling models construction based on NSGA-II algorithm

After determining the assembly progress of the assembly stage, the study needs to determine the production cycle of prefabricated components for subsequent work to ensure that they can be produced and delivered to the construction site during the construction process. The production process of prefabricated components is shown in Fig. 2.

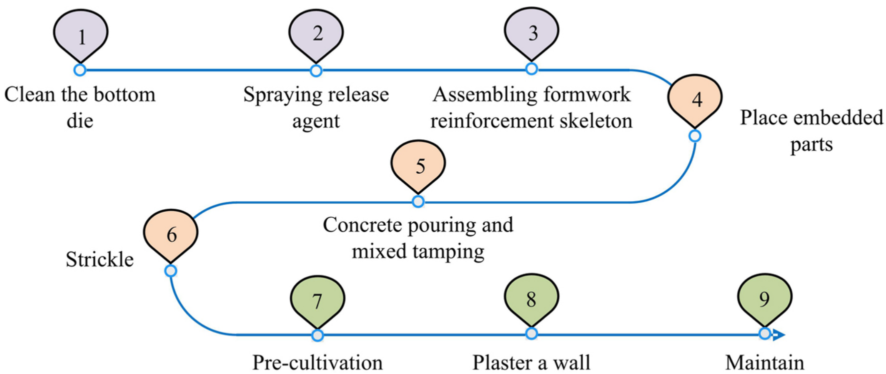

Fig. 2. Production flow chart of prefabricated components

In Fig. 2, the production of prefabricated components first requires cleaning of the bottom formwork, followed by spraying release agent and assembling the formwork reinforcement framework. Then, embedded parts are placed, concrete pouring and vibration are carried out, followed by scraping and pre curing the surface. Finally, time is used for curing. Under the requirements of meeting the construction period, the production stage scheduling problem is a deadline discrete TCT problem, finding a scheduling optimization model with the shortest production time and the lowest cost. The establishment of the TCT scheduling model is shown in Eqs. (3.5) to (3.8).

$$\begin{cases} \min \sum_{j=1}^{n+2} d_{jz} \\ \min \sum_{j=1}^{n+2} \sum_{z \in M_j} c_{jz} \times x_{jz} + \sum_{j=1}^{n+2} r \times d_{jz} \end{cases} \tag{3.5}$$

In Eq. (3.5), $\min \sum_{j=1}^{n+2} d_{jz}$ and $\min \sum_{j=1}^{n+2} \sum_{z \in M_j} c_{jz} x_{jz} + \sum_{j=1}^{n+2} r \times d_{jz}$ represent the minimum chemical period and the minimum project cost, where jz refers to the j virtual activity with z execution modes, d is the duration, and $c_{jz} \times x_{jz}$ and $r \times d_{jz}$ represent the production cost and indirect cost of prefabricated components. The expression of decision variable x_{jm} is shown in Eq. (3.6).

$$s.t \sum_{m \in M_j} x_{jm} = 1, 2, \ldots, n+2 \tag{3.6}$$

Eq. (3.6) indicates that non virtual activities have multiple execution modes to choose from. If virtual activities choose execution mode m, then the decision variable x_{jm} takes a value of 1, otherwise it is 0. The expression of the tight constraint relationship of virtual activities is shown in Eq. (3.7).

$$S_i + \sum_{m \in M_j} d_{jm} \times x_{jm} \le S_j, \quad \forall < i, j > \in A(t) \tag{3.7}$$

In Eq. (3.7), S_j is the start time of virtual activity m_j. The expression for the project completion time meeting the deadline χ is shown in Eq. (3.8).

$$\begin{cases} S_{n+2} \le \chi \\ S_j \ge 0, & \forall j \in V \\ x_{jm} \in \{0, 1\}, & \forall m \in M_j \end{cases} \tag{3.8}$$

In Eq. (3.8), $S_j \ge 0, \forall j \in V$ indicates that the start time of each activity is non negative, while $x_{jm} \in \{0, 1\}, \forall m \in M_j$ indicates that the decision variable x_{jm} has a value of 0 or 1. The transportation stage links assembly and production, requiring pro transportation to the site. Its scheduling aims to minimize costs and carbon emissions via the LCLC model (Eqs. (3.9)–(3.12)), with emissions tied to total transport time.

$$\begin{cases} P_j = \alpha \dfrac{L_j \times H \times r_c}{100} & (j = 1, 2, \ldots, n) \\ T_{ij} = \mu \dfrac{2H}{v_j} & (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n) \end{cases} \tag{3.9}$$

In Eq. (3.9), i and j represent the type of prefabricated components and the number of transportation vehicles, P_j and T_{ij} represent the round-trip freight and time of the transportation vehicles, L_j represents the fuel consumption of the transportation vehicles, H, r_c, and v_j represent the transportation distance, diesel price, and transportation speed of the vehicles, and α and μ are the adjustment coefficients for transportation costs and speed. The time T_{yj} of transportation vehicles for prefabricated components is shown in Eq. (3.10).

$$T_{yj} = T_j + t_z + t_u \tag{3.10}$$

In Eq. (3.10), t_u, t_z, and t_u represent the transportation round-trip time, loading time, and unloading time. The transportation volume of each type of prefabricated component should meet the demand of the construction site for that type, and the transportation vehicles at any time should not exceed the total number of transportation vehicles of that model, as shown in Eq. (3.11).

$$\begin{cases} st.\sum_{j=1}^{n} x_{ij} \geq M_i \\ \sum_{i\in A(t)} x_{ij} \leq R_j \end{cases} \tag{3.11}$$

In Eq. (3.11), M_i is the required quantity of prefabricated component. R_j is the total number of transportation vehicles. The weighted evaluation score $W(n)$ is shown in Eq. (3.12).

$$W(n) = \xi f_1(n) + \lambda f_2(n) \tag{3.12}$$

In Eq. (3.12), $f_1(n)$ and $f_2(n)$ represent the objective functions with the shortest production time and the lowest production cost. To reflect the order and mode selection of work execution, NSGA-II uses double-layer encoding to represent individuals, and the final NSGA-II flow is shown in Fig. 3.

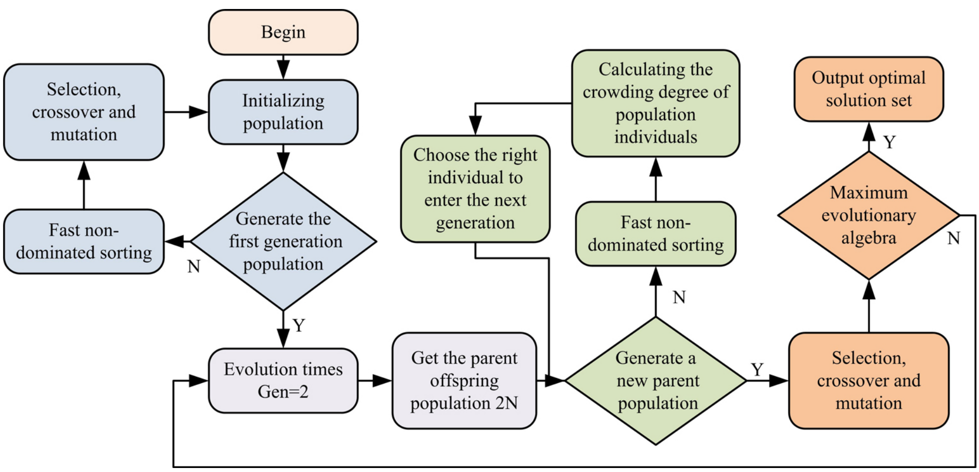

Fig. 3. NSGA-II flow diagram

By GA flow, NSGA-II in Fig. 3 approximates the Pareto optimal solution by fast non dominated sorting. Then, the population crowding degree *nd* is calculated and a suitable individual is selected to generate a new parent population. After selection, crossover, mutation, and other operations, the maximum evolution algebra is determined to obtain the final Pareto optimal solution set.

4. PB construction scheduling model result analysis based on GA and NSGA-II

To better validate the three scheduling models by GA and NSGA-II, the study first compared and tested the three algorithms with NSGA-II, and then applied the three scheduling models to a certain affordable housing project for analysis. This chapter focuses on NSGA-II performance and the scheduling optimization of the three scheduling models during the construction process of the project.

4.1. Performance analysis of NSGA-II

In order to verify the effectiveness of NSGA-II in multi-objective situations, MATLAB 2017a programming was used to conduct comparative experiments on the PSO-BP algorithm, NGSA algorithm proposed in reference [24], and Improved Particle Swarm Optimization (IPSO) algorithm proposed in reference [25]. The experimental parameters for NSGA II are set to have a crossover probability of 0.8 and a mutation probability of 0.2. The performance indicators are moderate value, inverse distance (IGD), and hyper volume (HV) evaluation indicators (Fig. 4).

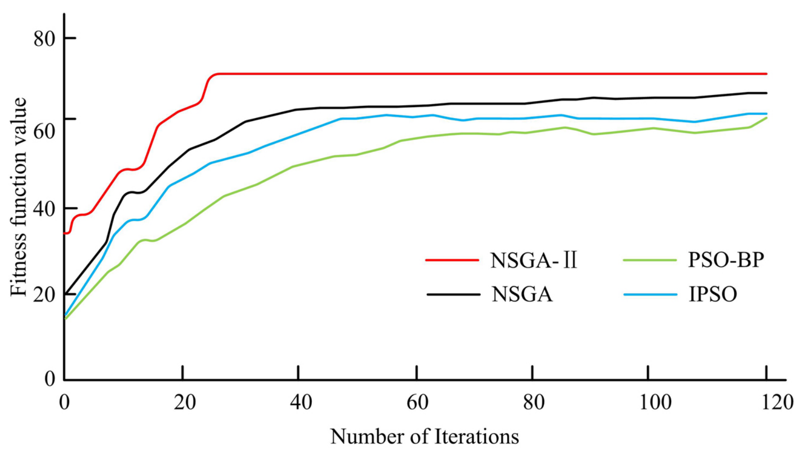

Fig. 4. Fitness results of four algorithms

Among them, NSGA II achieved a high fitness rate of 74.44 after only 24 iterations, showing a strong optimization ability. NGSA also performed well, reaching a fitness of 58.77 after 32 iterations. The IPSO and PSO-BP algorithms are slightly behind, but still have optimization potential, with a fitness value of 56.85 for 46 iterations and of 52.21 for 60 iterations. In conclusion, all four algorithms are effective in optimization, and NSGA II and NGSA have stronger performance. These findings provide valuable insights for further understanding and optimization of the algorithms.

Fig. 5 compares four algorithms on IGD and HV metrics. NSGA-II excelled, having the lowest IGD at 4000 evaluations and outperforming on HV, finding high-quality solutions early and improving consistently. NGSA, IPSO, and PSO-BP also improved but were slightly inferior. In summary, NSGA-II was superior on both metrics in multi-objective optimization, offering valuable insights for algorithm understanding and enhancement.

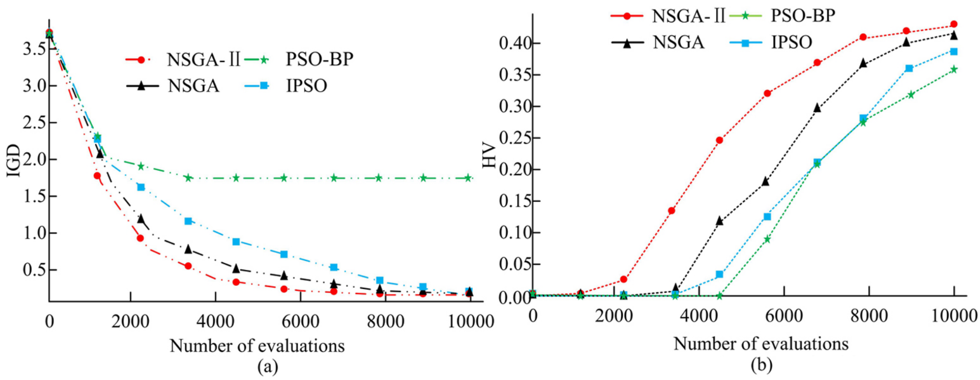

Fig. 5. IGD and HV results of four algorithms; (a) IGD results of four algorithms, (b) HV results of four algorithms

4.2. Scheduling model application analysis by GA and NSGA-II

To verify the practicality of scheduling model, a model analysis was conducted using a certain affordable housing project. The affordable housing project consists of two units, with a total of 18 floors. Starting from the third floor roof, the project entered the PB construction phase, with a distance of approximately 80 km between the prefabricated component production factory and the project site. A certain affordable housing project's construction process involved various resources. During assembly, a 6517B-10 tower crane, 2 surveyors, 11 formwork lifting, 4 general, 10 steel reinforcement, and 6 concrete workers were used. For production, 58 prefabricated exterior wall panels, 20 PCF panels, 84 composite panels, 24 composite beams, 4 stairs, and 8 balconies were required. Additionally, 2 heavy-duty semi-trailer tractors and three 35 t and 25 t trucks were essential for transportation. To assess the RC scheduling model's performance during assembly, GA was employed for 130 iterative calculations, yielding the final target construction period. This summary condenses the original information while preserving key details.

Fig. 6 is a Gantt chart chart of the schedule in the assembly phase based on the RC scheduling model. The numbers 14 to 26 were the same as above. The homework time for sequence numbers 1, 4, 6, 8, 9, 10, 12, 14, 17, 19, 21, 22, 23, and 25 was 0.5 days, the homework time for sequence numbers 2, 5, 7, 11, 15, 18, 20, and 24 was 1 day, and the homework time for sequence numbers 3, 13, 16, and 26 was 1.5 days. From Fig. 7, the shortest assembly phase $T_{\min}$ based on the RC scheduling model was 8 days.

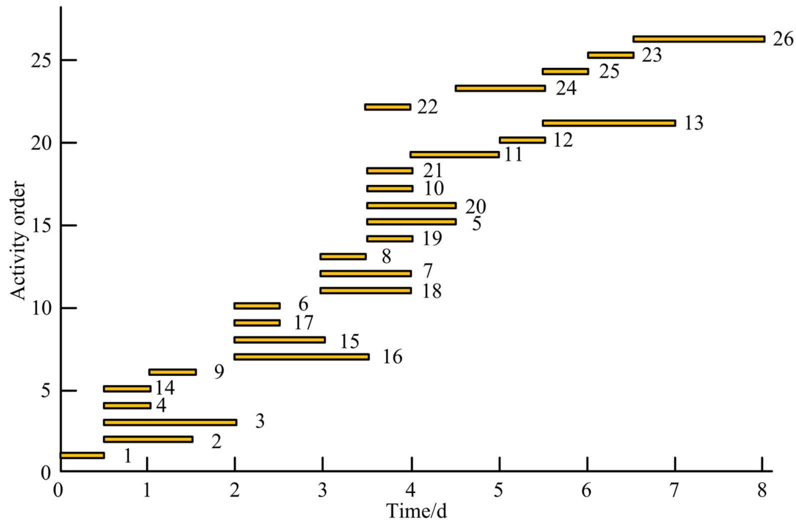

Fig. 6. Gantt chart of assembly stage based on RC scheduling model

Fig. 7 shows the optimal solution obtained by the TCT scheduling model using NSGA-II, where F_1, F_2, and $W(n)$ represent the time, cost, and final weighted score of prefabricated components, respectively. Fig. 7(a) shows the results of F_1 and F_2 for prefabricated components

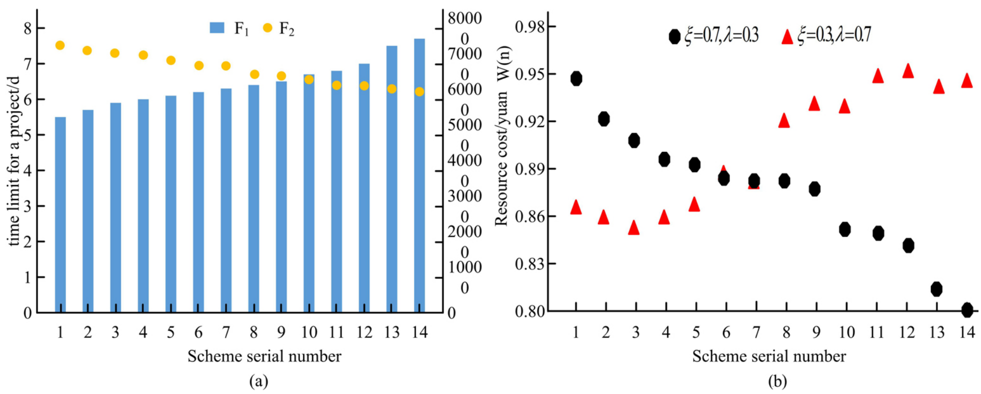

Fig. 7. Optimal solution of TCT scheduling model based on NSGA-II algorithm; (a) F_1 anf F_2 values of 14 schemes, (b) $W(n)$ results of 14 schemes

under different schemes, with F_1 and F_2 for scheme 1 being 5.5 days and 74858 yuan, respectively. The F_1 and F_2 of Plan 12 are 7 days and 63360 yuan respectively. Fig. 7(b) shows the results of prefabricated components at $\xi = 0.7$, $\lambda = 0.3$ and $\xi = 0.3$, $\lambda = 0.7$ under different schemes. When $\xi = 0.7$, $\lambda = 0.3$ is used, the $W(n)$ value of Scheme 1 is 0.948; When $\xi = 0.3$, $\lambda = 0.7$, the $W(n)$ value of Scheme 12 is 0.918. From the Fig. 7, it can be seen that Scheme 1 (5.574858) is the optimal scheduling scheme for $\xi = 0.7$, $\lambda = 0.3$, and Scheme 12 (763360) is the optimal scheduling scheme for $\xi = 0.3$, $\lambda = 0.7$.

Fig. 8 shows the variation curve between the carbon emission duration and transportation cost of the LCLC scheduling model under NSGA-II. Fig. 8(a) shows the iterative curve of carbon emission duration. When the number of iterations was 30, the shortest carbon emission time was 93.75 h. Fig. 8(b) shows the iteration curve of transportation cost. When the number of iterations was 30, the minimum transportation cost was 22501 yuan.

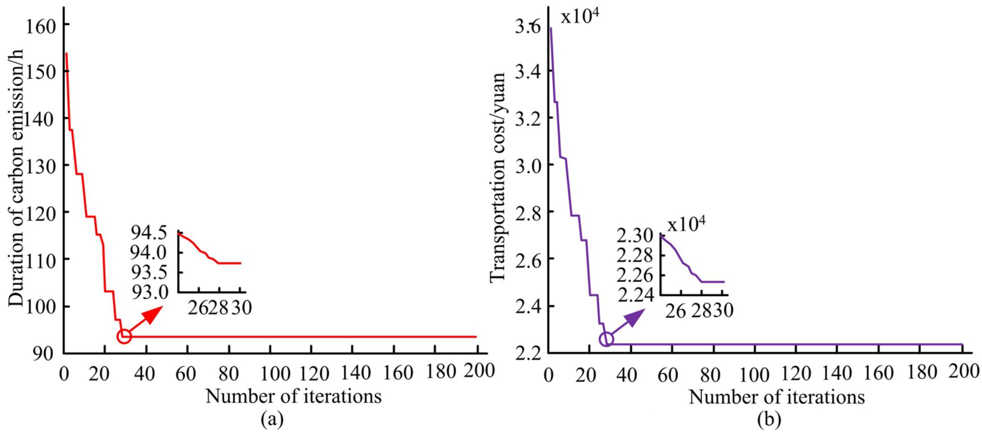

Fig. 8. Results of carbon emission duration and transportation cost based on NSGA-II algorithm; (a) Iterative curve of carbon emission duration, (b) Transportation cost iteration curve

5. Conclusions

The traditional construction scheduling methods are no longer applicable to the heterogeneity and timeliness of prefabricated building projects (PB). This study is based on the principle of sustainable development and constructs RC scheduling models based on genetic algorithm (GA), as well as TCT and LCLC scheduling models based on non dominated sorting genetic algorithm II (NSGA-II). Research has found that NSGA-II has an IGD value 0.29 lower than NGSA at an evaluation frequency of 4000, and a HV value higher than NGSA at 10000 evaluations. Meanwhile, the newly proposed PSO-BP algorithm outperforms NGSA and Improved Particle Swarm Optimization (IPSO) algorithms in both IGD and HV metrics. Application analysis shows that the GA based RC scheduling model can shorten the assembly stage to 8 days. When using the TCT scheduling model based on NSGA-II during the production phase, scheduling scheme 12 is preferred in terms of cost, while scheduling scheme 1 is preferred in terms of duration. When using the LCLC scheduling model during the transportation phase, the transportation cost and carbon emission duration are 22501 yuan and 93.75 yuan, respectively. In summary, the proposed scheduling model based on GA and NSGA-II has superior performance and can be applied to PB projects. But in the future, we need to consider the impact of environmental changes on construction progress.

Acknowledgements

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