ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0025
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Multi-objective permutation flow shop scheduling in precast production under consideration of embodied carbon emissions

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Abstract: Conventional construction methods face significant challenges in reducing carbon emissions and promoting environmental sustainability. Off-Site Construction (OSC) method is widely recognized as a low-carbon, high-efficiency alternative construction method. However, in practice, it often fails to deliver the expected benefits, leading to issues such as excessive carbon emissions, unpunctual delivery, and cost overruns in OSC projects. In order to ensure the carbon benefits of OSC and further its development,this study conducts an in-depth analysis of embodied carbon emissions in the precast production process, proposes a multi-objective optimization model based on the permutation flow shop scheduling problem, and designs an automated solution algorithm using NSGA-II to derive Pareto optimal schedules. Through the analysis of real-world case data, the proposed approach, compared to conventional scheduling methods, is estimated to reduce embodied carbon emissions by approximately 6 % while simultaneously cutting tardiness/earliness penalty by 75%. This study offers a model for precast production scheduling, effectively enhancing production efficiency and reducing carbon emissions, enabling construction component enterprises to engage in low-carbon, cost-effective, and efficient production, thereby fostering sustainable development in the construction industry.

Key words: Multi-objective optimization, Permutation flow shop scheduling, Precast production, embodied carbon emissions, NSGA-II.

1. INTRODUCTION

The traditional construction industry, responsible for over 34% of global energy demand, faces significant challenges in reducing carbon emissions [1]. As the industry embraces a broader trend towards low-carbon emissions, traditional construction practices encounter substantial hurdles. The emergence of Off-Site Construction (OSC) offers hope for a low-carbon transformation in the sector. Unlike conventional on-site construction, OSC relocates the primary carbon-intensive phases of building production to controlled, environmentally-friendly factory settings. Components are prefabricated and assembled on-site, showcasing the industrialization of construction and its natural alignment with green materials and advanced construction technologies. OSC holds the theoretical promise of reducing carbon emissions by 30% to 40% [2].

However, as OSC projects proliferate, the demand for prefabricated components surges. Coupled with the diverse requirements of contemporary building types, this poses significant challenges to the precast production process within OSC [3]. Numerous surveys reveal that the efficiency of OSC construction falls far short of expectations, especially concerning its contribution to carbon emissions reduction. This situation has garnered widespread attention from industry professionals and scholars, prompting multifaceted efforts to address the current challenges.

While technological advancements have been evident in the use of green materials, low-energy precast machinery, and lean production practices, they have not yielded the expected improvements [4].

A series of setbacks has largely been attributed to outdated precast scheduling and management methods [5]. The advanced techniques in OSC and construction bring increased efficiency and green production, but also pose significant challenges to existing rule-based or experience-based precast scheduling and management approaches [6]. Therefore, the outdated precast scheduling methods are in dire need of improvement.

The optimization of precast scheduling management has attracted considerable attention from scholars, with numerous studies focusing on metrics such as production time and cost. Summarizing past scheduling research, Wang et al. found that precast production scheduling aligns with the characteristics of the permutation flow shop scheduling problem and has seen extensive practical applications [7]. However, previous studies have primarily focused on economic benefit metrics while largely neglecting the optimization of environmental benefits, resulting in OSC's green benefits remaining largely untapped.

Achieving low-carbon efficiency in OSC precast production through scheduling optimization requires a deeper exploration of embodied carbon emissions within the precast process, a fact that previous research has not addressed [8]. In response to Wang et al.'s call [7], this study addresses the precast scheduling problem considering embodied carbon emissions. This research delves into the precast production process, quantifies embodied carbon using emission factors, considers multiple stakeholders involved in precast activities, establishes a multi-objective optimization model to minimize carbon emissions and production costs, and ultimately designs an automated scheduling method using the NSGA-II algorithm. The effectiveness of the proposed approach is demonstrated through real-world case analysis.

2. PROBLEM STATEMENT

In off-site precast production, there are typically six main processes: molding (R1), reinforcement placement (R2), casting (R3), curing (R4), demolding (R5), and finishing (R6), as shown in Figure 1. Firstly, the pallet is cleaned, and molds corresponding to different component specifications are prepared and coated with mold release oil. Once the molds are ready, pre-cut steel reinforcement and other embedded components are positioned as required. Subsequently, concrete is poured, vibrated, and initially cured. After the concrete has fully cured, demolding takes place to reuse the molds and casting beds. Finally, the components undergo finishing work to complete the process.

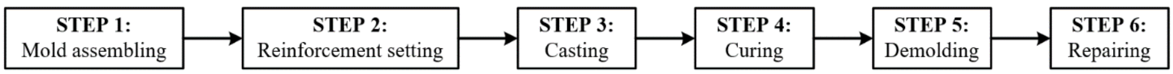

Figure 1. Precast Production Process Flow.

Efficient and sustainable precast production relies on scientific production scheduling. As previously emphasized in the literature, off-site precast production scheduling is akin to the traditional Permutation Flow Shop Scheduling Problem (PFSP), typically described as processing n components from a given set of orders in a predetermined sequence through m processing stages. Let $N = \{1,...,n\}$ represent the set of components required for orders, where $i \in N$. Each component undergoes a series of processing stages denoted as $J = \{1,...,m\}$, where $j \in J$. There are t types of components in total, denoted as $L = \{1,...,t\}$, where $l \in L$. Additionally, this study makes the following assumptions to support further problem analysis:

1) It is assumed that the component factory operates continuously, with workers on shift rotation.
2) Carbon emissions from steel production are not considered in the scope of embodied carbon calculations.
3) Machines are categorized as either fueled by gas or electrically powered. To simplify measurement, the embodied carbon emission factors for machines are calculated per processing unit, expressed in *$kgCO_2e/h$*.

3. MODEL DEVELOPMENT

3.1. Analysis of embodied Carbon Emissions in Off-Site Precast Production Scheduling

Before quantifying various carbon emissions, it is crucial to clearly define the scope and boundaries of carbon emissions. Carbon emissions encompass the release of greenhouse gases, primarily carbon dioxide (CO_2) and methane (CH_4), among others. However, in energy consumption processes, factors like technology, management, and maintenance lead to significant fluctuations in non-CO_2 gases, making them challenging to determine accurately. Hence, this study narrows its focus to CO_2 as the primary greenhouse gas for carbon accounting boundaries and calculates embodied carbon emissions associated with scheduling in the prefabricated component production process. There are three main traditional methods for carbon emission calculation: the emission factor method, the mass balance method, and direct measurement. To streamline calculations and facilitate scheduling research, this study employs the emission factor method to estimate carbon emissions related to precast production scheduling.

Carbon emissions from labor refer to the indirect emissions generated by all labor involved in the precast process, including technical workers and management personnel. Carbon emissions from machinery encompass all mechanical equipment involved in precast and support processes, including processing machinery and transportation equipment. It's important to note that carbon emissions from materials encompass items such as cement, sand, steel reinforcement, and lime used in precast and component production. However, this category falls under direct carbon emissions, and optimizing scheduling strategies offers limited benefits in reducing these emissions. Addressing such emissions requires advanced production techniques, greener raw materials, and environmental protection measures. Therefore, this study focuses on optimizing precast production scheduling to reduce carbon emissions from labor and machinery, with carbon emissions from materials excluded from consideration.

Previous research solely focused on carbon emissions during the machine processing stage, but in precast production, embodied carbon emissions from labor and machinery occur regardless of whether components are being processed. We assume the entire precast production process starts from the delivery of the first batch of components to the first workstation and continues until the final batch of components completes the last processing step. This study divides the precast production process into three stages: processing, startup, and waiting, as illustrated in Figure 2. It's important to note that both the preparation and processing stages generate carbon emissions at the same efficiency for labor and machinery. However, due to variations in the processes of different stages, we need to separately consider the calculations for processing time and preparation time, thus listing these two stages individually. Since a single production line typically handles the production of multiple components, there is often a waiting stage, where subsequent components must wait for the previous one to complete before production can commence.

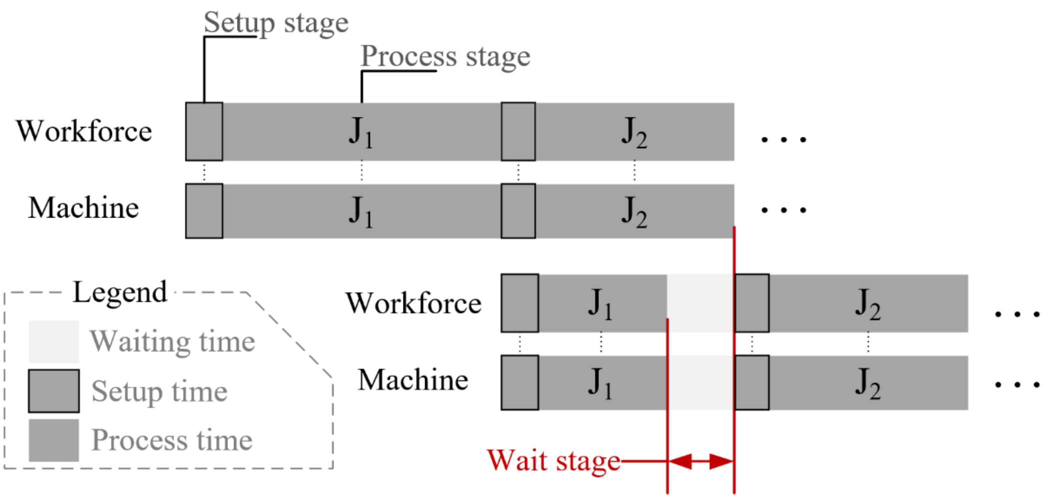

Figure 2. Embodied Carbon Emissions Stage Time Breakdown.

The processing time varies due to differences in process procedures mentioned earlier. Among these, the mold assembling, reinforcement setting, and storing processes are sequential, while the other four processes occur in parallel. Therefore, let $PT_{i,j}$ represent the processing time of component *i* in stage *j*. It is composed of the processing time $pt_{i,j}$ and preparation time $st_{i,j}$ for component *i* in stage *j*.

$$PT_{i,j} = \begin{cases} pt_{i,j} + \max\limits_{s \in i}\{st_{i,j}\} & j = 1,2,6 \\ \max\{pt_{i,j} + st_{i,j}\} & j = 3,4,5 \end{cases} \tag{1}$$

Waiting times typically result from processing bottlenecks, primarily caused by limited resources, including workstation occupancy constraints, mold resource limitations, and curing kiln capacity constraints. This study will thoroughly consider these three resource constraint conditions, as they will affect the completion time $C_{i,j}$ of component *i* in stage *j*. Therefore, the waiting time $WT_{i,j}$ for component *i* before stage *j* can be expressed as:

$$WT_{i,j} = C_{i-1,j-1} - C_{i,j-1} \tag{2}$$

1) Labor-driven carbon emissions

Labor generates carbon emissions only during processing and waiting times. Let PF_j^a represent the carbon emissions coefficient for labor during processing time in stage j, and SF_j^a represent the carbon emissions coefficient for labor during waiting time in stage j, both in units of $kgCO_2e/h$. Therefore, the embodied carbon emissions produced by labor can be expressed as E_a:

$$E_a = \sum_{i=1}^{p}\sum_{j=1}^{m} PT_{i,j} \times PF_j^a + \sum_{i=1}^{p}\sum_{j=1}^{m} WT_{i,j} \times SF_j^a \tag{3}$$

2) Machine-driven carbon emissions

In contrast to labor, machinery generates carbon emissions during transport time, and transport machines typically have different efficiencies compared to processing machines. Therefore, carbon emissions coefficients should also differ. Additionally, machines can be considered to operate at full capacity during processing, with variations in carbon emissions among different components reflected in their differing processing times. Let PF_j^b represent the carbon emissions coefficient for machinery during processing time in stage *j*, and SF_j^b represent the carbon emissions coefficient for machinery during waiting time in stage *j*, both in units of $kgCO_2e/h$. Thus, the embodied carbon emissions generated by machinery can be expressed as E_b:

$$E_b = \sum_{i=1}^{p}\sum_{j=1}^{m} PT_{i,j} \times PF_j^b + \sum_{i=1}^{p}\sum_{j=1}^{m} WT_{i,j} \times SF_j^b \tag{4}$$

3.2. A Multi-Objective Optimization Model for Off-Site Precast Production Considering Embodied Carbon Emissions

During the analysis of minimizing carbon emissions in precast production, it was observed that the essence of carbon reduction is essentially the reduction of the time that generates carbon emissions. Therefore, the goal of carbon emissions minimization can promote the minimization of makespan and idle time. However, the shortened time conflicts with the agreed-upon due dates. When components are completed ahead of schedule, the component factory inevitably incurs additional storage costs. Hence, it is necessary to strike a balance between carbon emissions minimization and Tardiness/Earliness penalty minimization, represented by W. This can be expressed using the following formula:

$$W = \sum_{i=1}^{n} \tau_i \times \max\{0, C_{i,6} - d_i\} + \sum_{i=1}^{n} \varepsilon_i \times \max\{0, d_i - C_{i,6}\} \tag{5}$$

Where τ_i represents the cost of delay per unit time, and ε_i represents the cost of earliness per unit time.

Two objectives are detailed in Eq. (6) and Eq. (7) :

$$\min f_1 = \min E = \min(E_a + E_b) \tag{6}$$

$$\min f_2 = \sum_{i=1}^{n} \tau_i \times \max\{0, C_{i,6} - d_i\} + \sum_{i=1}^{n} \varepsilon_i \times \max\{0, d_i - C_{i,6}\} \tag{7}$$

The solution space can be defined with these 5 constraints:

$$C_{i,j} \geq C_{i-1,j} + PT_{i,j} \qquad \forall i,j \; (8)$$

$$\sum_{i=1}^{p}\sum_{l=1}^{\ell} O_{t,l,i} \leq L_l \qquad \forall t \; (9)$$

$$C_{i,1} \geq C_{i',6} \times O_{t,l,i'} + PT_{i,1} \qquad \forall i' < i \; (10)$$

$$\sum_{i=1}^{p} h_{t,i,4} < H \qquad \forall t \;\; (11)$$

$$C_{i,j} \geq 0 \qquad \forall i, j \;\; (12)$$

Constraint (8) specifies that the current job cannot start before the completion of the previous job's operation. Binary variables $O_{t,l,i}$ represent the occupation of mold type l by component i at time t, where L_l represents the total number of mold type l, and component i' represents any component produced earlier than component i. Constraint (9) ensures that mold resources of each type are limited at all times, while constraint (10) indicates that molds occupied must wait for release after the previous component completes the demolding step. Variable $h_{t,i,4}$ represents whether component i is undergoing curing at time t, and constraint (11) defines the requirement to maintain a constant curing kiln capacity H throughout the production process. Constraint (12) stipulates that time variables must be non-negative.

4. ALGORITHM DESIGN

In the context of the precast production scheduling problem addressed in this study, which involves multiple resource constraints and considers the impact of production priorities and component grouping strategies on two optimization objectives, it is well-known that traditional precast production scheduling with the objective of minimizing early/tardy penalty costs is NP-hard. Consequently, employing multi-objective optimization to solve the proposed model is expected to require more computational effort. Given the complexity of the problem, this study employs heuristic algorithms to obtain solutions.

NSGA-II is one of the most effective multi-objective metaheuristic algorithms. It employs non-dominated sorting to partition the solution set into different non-dominated fronts, thus discovering Pareto-optimal solutions. NSGA-II can handle infeasible solutions or constraints through penalty functions or other methods, and its unique non-dominated sorting and crowding distance operator ensure the diversity and balance of the solution set. Therefore, in this study, algorithm design and enhancement are conducted within the framework of NSGA-II. Figure 3 illustrates the schematic process of NSGA-II.

In the precast production, n components are produced in the same processing order. In this algorithm, each scheduling scheme is represented by strings known as chromosomes. This study employs a single-layer chromosome structure for encoding, where the numbers in the string are called genes, and each gene represents a component's identifier, with its position indicating the production priority.

This paper employs a random function to generate R scheduling schemes with n components, forming an initial population of R chromosomes. Specifically, the genes on the chromosomes should include all components from the orders without repetition. Leveraging the robust global search capability of NSGA-II, this study adopts an adaptive initial population generation strategy to aid in rapid convergence.

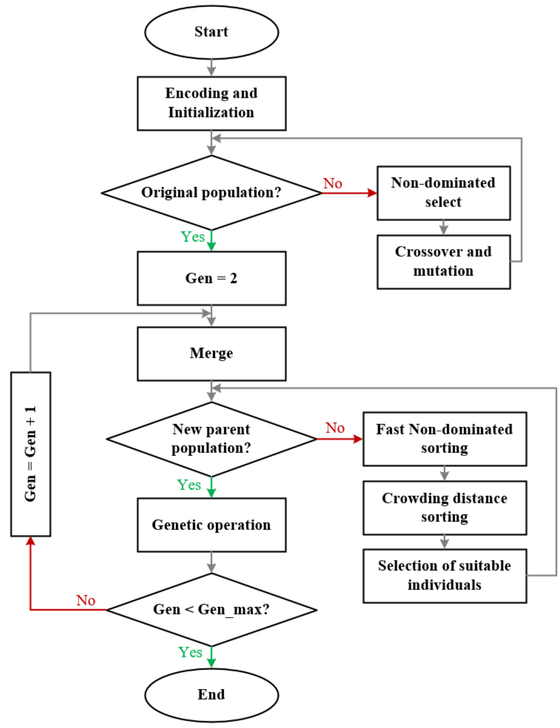

Figure 3. Algorithm flow chart.

5. PRELIMINARY VALIDATION

5.1. Data collection

This study validated the proposed multi-objective carbon-efficient scheduling optimization method using real-world case data sourced from a small to medium-sized building materials production company. The company operates a modern precast production line specializing in the production of concrete prefabricated components for various off-site construction projects (Table 1). To collect carbon emissions calculation data, information such as energy consumption of machinery in various production stages, workforce size, and component material usage was obtained. Additionally, local standards and calculations for carbon emissions were used to estimate the various carbon emission factors required for the proposed carbon-efficient scheduling model (Table 2). While the estimation method for carbon emission factors in this study may not be rigorous for precise carbon emissions measurement and control, it effectively provides carbon emissions calculation data to demonstrate the effectiveness of scheduling optimization.

Table 1. Production information of the components

Num.	Type	1	2	3	4	5	6	Due Date	Tardiness	Earliness
1	1	0.60	0.65	0.60	8.00	0.40	0.40	12	10	2
2	1	0.60	0.65	0.60	8.00	0.40	0.40	12	10	2
3	1	0.60	0.65	0.60	8.00	0.40	0.40	12	10	2
4	2	0.45	0.40	0.50	8.00	0.30	0.30	14	10	2
5	2	0.45	0.40	0.50	8.00	0.30	0.30	14	10	2
6	2	0.45	0.40	0.50	8.00	0.30	0.30	14	10	2
7	3	0.20	0.15	0.20	8.00	0.15	0.25	16	10	2
8	3	0.20	0.15	0.20	8.00	0.15	0.25	16	10	2
9	3	0.20	0.15	0.20	8.00	0.15	0.25	16	10	2
10	3	0.20	0.15	0.20	8.00	0.15	0.25	16	10	2

Note: The due date is in *h*, the Tardiness/Earliness Penalty is in *yuan*/unit-*h*.

Table 2. Carbon emissions factors

	R1	R2	R3	R4	R5	R6
PF^a	4.93	4.27	0.82	0.00	3.29	2.63
SF^a	1.41	1.41	0.09	0.00	1.03	0.75
PF^b	5.75	3.84	7.67	15.34	3.07	1.92
SF^b	1.64	0.88	6.58	1.10	0.55	0.22
st	0.05	0.10	0.15	0.20	0.05	0.05

Note: PF^a, SF^a, PF^b, SF^b are in units of *$kgCO_2e/h$*; st is in *h*.

5.2. Results and Discussions

To validate the optimization effectiveness of the proposed Multi-objective permutation flow shop scheduling, this study conducted experiments using a control group alongside the practical case analysis. The control group utilized the commonly used basic scheduling method Shortest Processing Time (SPT) to compare the improvements in carbon emissions and tardiness/earliness costs achieved by the proposed method compared to existing approaches.

The experiments were conducted on a laptop equipped with the Microsoft Windows 10 operating system and an Intel Core i7-8750H 2.20 GHz processor. Data from Tables 1 and 2 were input, and the algorithm was implemented using Pycharm Community Edition 2021.3 in Python 3.10.1.

To ensure the efficiency and effectiveness of the experiments, this study drew on successful experiences from previous research in selecting algorithm parameters. The population size was set according to the guidelines of [9], and a large number of iterations were used to terminate the algorithm. Given the complexity of the problem solution space, this study established multi-process parallel computing rules to accelerate the convergence speed of the algorithm, with an execution time of less than 2 minutes. Specific parameters were as follows: Population size: 500; Termination condition: 200; Crossover rate: 0.9; Mutation rate: 0.02.

To observe the optimization effectiveness of the proposed solution for carbon emissions and tardiness/earliness cost objectives, the study first solved the best solution based on the Smallest Processing Time (SPT) criterion using the case data: 10, 9, 7, 8, 6, 5, 4, 2, 3, 1. Subsequently, the algorithm program was executed, and the computed median-optimal solution was: 2, 3, 1, 5, 6, 4, 7, 9, 8, 10.

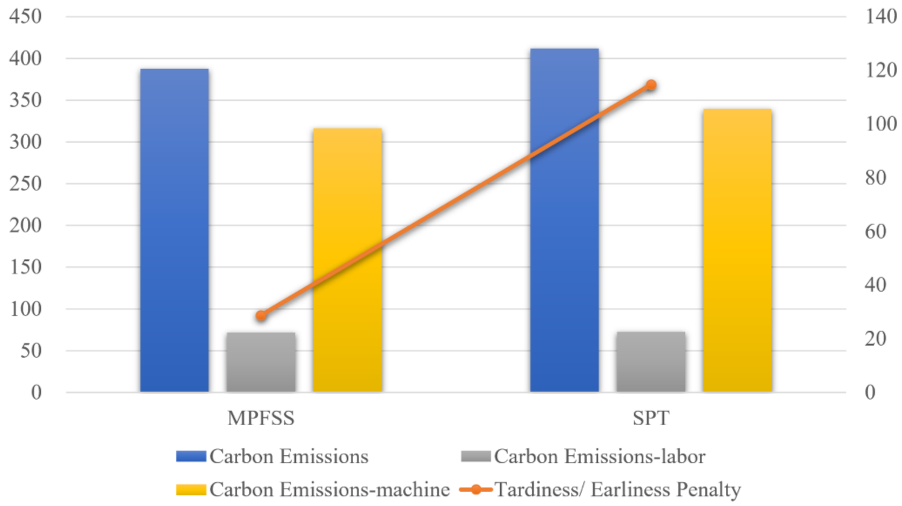

Figure 4. Comparison of Optimization Results.

The optimization solution proposed in this study resulted in a final embodied carbon emissions of 387.55 kgCO2e, while the SPT solution resulted in a final embodied carbon emissions of 411.83 kgCO2e, representing a 6% reduction. Notably, the reduction in carbon emissions caused by labor was 2%, and the reduction caused by machinery was 7%. It's important to highlight that the optimization solution proposed in this study resulted in a final early/late penalty cost of 28.70 yuan, whereas the SPT solution had an early/late penalty cost of 114.70 yuan, marking a significant 75% reduction. These experimental results demonstrate the significant effectiveness of the optimization solution proposed in this study in reducing both embodied carbon emissions and early/late penalty costs.

6. CONCLUSIONS

This study aims to explore the reduction of embodied carbon emissions in the prefabricated component production process through scheduling optimization. In response to the call by Wang et al., it provides an automated, efficient, and cost-effective decarbonization and efficiency-enhancing scheduling method, particularly suitable for small and medium-sized enterprises. Furthermore, it extends the traditional permutation flow shop scheduling problem to address the complex precast production scenarios in the construction industry. Finally, improvements to the NSGA-II algorithm, such as adaptive population initialization, are made to facilitate its wider application.

ACKNOWLEGEMENTS

The support of National Natural Science Foundation of China (NSFC) (No. 72371050 and No. 72071027) is gratefully acknowledged.

REFERENCES

[1] C. Mao, Q. Shen, W. Pan, K. Ye, "Major Barriers to Off-Site Construction: The Developer's Perspective in China", J. Manag. Eng. vol. 31, 2015.

[2] B. Qi, M. Razkenari, A. Costin, C. Kibert, M. Fu, "A systematic review of emerging technologies in industrialized construction", J. Build. Eng. vol. 39, 2021.

[3] L. Li, H. Luan, X. Yin, Y. Dou, M. Yuan, Z. Li, "Understanding Sustainability in Off-Site Construction Management: State of the Art and Future Directions", J. Constr. Eng. Manag. vol. 148, 2022.

[4] M. Arashpour, R. Wakefield, B. Abbasi, E.W.M. Lee, J. Minas, "Off-site construction optimization: Sequencing multiple job classes with time constraints", Autom. Constr. vol. 71, pp. 262-270, 2016.

[5] W. Xing, J.L. Hao, L. Qian, V.W.Y. Tam, K.S. Sikora, "Implementing lean construction techniques and management methods in Chinese projects: A case study in Suzhou, China", J. Clean. Prod. vol. 286, 2021.

[6] L. Luo, X. Liang, C. Fang, Z. Wu, X. Wang, Y. Wang, "How to promote prefabricated building projects through internet of things? A game theory-based analysis", vol. 276, J. Clean. Prod. 2020.

[7] L. Wang, Y. Zhao, X. Yin, "Precast production scheduling in off-site construction: Mainstream contents and optimization perspective", J. Clean. Prod. vol. 405, 2023.

[8] Z. Yang, Z. Ma, S. Wu, "Optimized flowshop scheduling of multiple production lines for precast production", Autom. Constr. vol. 72, pp. 321-329, 2016.

[9] J. Grefenstette, "Optimization of Control Parameters for Genetic Algorithms", IEEE Trans. Syst. Man. Cybern. vol. 16, pp. 122-128, 1986.