



Dynamic Production Scheduling for Prefabricated Components Considering the Demand Fluctuation

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ABSTRACT

A dynamic optimized production scheduling which takes into account demand fluctuation and uncertainty is very critical for the efficient performance of Prefabricated Component Supply Chain. Previous studies consider only the conditions in the production factory and develop corresponding models, ignoring the dynamic demand fluctuation that often occurs at the construction site and its impact on the entire lifecycle of prefabricated construction project. This paper proposes a dynamic flow shop scheduling model for prefabricated components production, which incorporates demand fluctuation such as the advance of due date, insertion of urgent component and order cancellation. An actual prefabrication construction project has been used to validate the proposed multi-objective genetic algorithm model. The experimental results show that the proposed model can achieve a cost saving of up to 43.2%, which shows that the proposed model can cope well with the occurrence of demand fluctuation. This research contributes to the dynamic decision support system for managing prefabricated components.

KEY WORDS: Production Scheduling, Demand fluctuation, Multi-objective genetic algorithm, Prefabricated components.

1 INTRODUCTION

PREFABRICATED construction projects have developed rapidly in China in recent years due to the advantages of resource saving, environment friendliness and labor saving. In a prefabricated construction project, a large number of wet works from the construction site are transferred to the offsite prefabricated components (PC) production factory, which can greatly reduce the labor required at the construction site and the stacking of raw materials (Yang, et. al. 2016). Although prefabricated buildings have many advantages, they have not achieved the desired results in practice, this is mainly caused by the untimely delivery of PCs (Wang and Hu 2017). For example, the early or late delivery of PC during the production stage will lead to change in planning for the following stages and finally cause time and budget overrun (Wang, et. al. 2018). Considering the efficiency of the whole prefabricated construction

project, decision makers in the factories need to find a suitable and adaptive method to generate the complex dynamic production schedule.

Currently, producers mainly perform the production scheduling based on their experience (Chan and Hu 2001) and it is difficult for the decision maker to obtain an optimal solution when different factors have to be considered. Moreover, the demand fluctuation at the assembly stage will affect PC production scheduling significantly. Some unpredictable events may occur during the assembly stage, which will lead to the delivery date of some components being advanced or delayed by several days. If producers are unable to provide an appropriate response to these unpredictable events, this will result in an increase in cost. So, it is very important to take into account the demand fluctuation while creating the PC production schedule.

Based on the above discussion, this paper proposes a scenario-based dynamic production scheduling

model for the production of PC. In the planning stage, the paper integrates the existing literature (Chan and Hu 2001, Yang, et. al. 2016) and generates a standard production schedule considering the normal PC production processes. Then, during the execution stage, a dynamic model responds considering the contingency factors that may occur at the construction site. For example, it will re-optimize the schedule according to the impact of the demand fluctuation. In addition, a genetic algorithm is used to optimize the model and the optimization objective is to minimize the make span and extra cost and finally realize on-time delivery. The model has been verified using the data collected from an actual project.

The main contributions of this paper are as follows:

(1) The proposed approach integrates the three main processes of a PC project, namely, production, transportation, and assembly; it focuses on the dynamics and interactivity in the production scheduling of prefabricated components and proposes an optimization model based on different scenarios.

(2) Three types of demand fluctuations are considered and optimization measures are proposed to deal with these demand fluctuations. A multi-objective genetic algorithm is used to achieve the dynamic scheduling optimization with the goal of shortest completion time and the minimum additional cost. The experimental results show that the proposed model achieves a cost saving of up to 43.2%.

2 RELATED WORK

2.1 Prefabricated Production Optimization

THIS section briefly summarizes the prior research in prefabricated component production optimization.

Chan and Hu (2001) proposed a flow shop scheduling model to minimize delays and early delivery and make a distinction between normal working hours and overtime hours. Leu and Hwang (2002) consider the number of cranes, the size of the steam curing space and the storage space of rebar cage as resource constraints. Li et al. (2010) integrate resource constraints, including molds, labor, inventory, and workspace, into the model and developed a scheduling model to realize minimum production costs. Khalili and Chua (2014) integrate two new ideas into mixed integer linear programming (MILP) optimization model to achieve optimization of resources and cost for the precast production of complex configurations. The model is validated using two examples with different scenarios. The results show that employing the idea of prefabrication configuration and component grouping in production planning for prefabricated structures can reduce total costs by up to 13% compared to the existing planning approach. Prata et al. (2015) propose an integer linear programming model for the precast concrete beams production problem. The objective function is the minimization of the production loss of a production

order. The results indicate that significant gains may be achieved in terms of reduction of planning time through the application of the proposed model.

2.2 Dynamic Scheduling

The production scheduling is a dynamic and interactive process. In addition to the internal factors in the production stage that influence the scheduling, other stages in the prefabricated construction project lifecycle also have an interactive impact on the production scheduling.

Liu and Tang (1999) applied an adaptive optimization framework and developed a dynamic flow shop scheduling model with the goal of minimizing the average flow time of jobs arriving as Poisson process. The static heuristic algorithm is embedded in the control model as a scheduling controller. Yuan and Yang (2013) argue that local search can be embedded in genetic algorithms to improve their performance in dynamic environments. Local search can help the algorithm track the optimal trace. Yazdani et al. (2015) used the mixed integer linear programming model to solve the problem of cross-dock vehicle scheduling with multiple entrance and exit doors, aiming to find the sequence that minimizes the maximum completion time. They proposed a new search element heuristic algorithm for large search examples. Wang, Choi and Lu (2015) consider the random uncertainty in the actual manufacturing environment and present a two-stage simulation-based hybrid estimation of distribution algorithm to schedule the permutation flow shop under stochastic processing times. Mousavi & Zandieh (2016) proposed a genetic algorithm and a local search algorithm to solve the mixed flow shop scheduling problem with maximum completion time and total delay as objective functions. Lin et al. (2017) studied the scheduling problem of reentrant replacement pipelining. They used genetic algorithms to embed the solutions obtained by heuristic algorithms into the initial solutions. The results show that GA algorithm has the best effect on large scale problems. Shoval and Efatmaneshnik (2018) consider the probability for success (or failure) of a manufacturing job and its effect on other jobs. Moreover, they present a mathematical model for determining the expected manufacturing cost and proposes heuristics for reducing that cost.

2.3 Literature Analysis

Bases on the recent literature in production scheduling of prefabricated component, several research gaps need to be addressed. First, recent literature focuses only on the production phase of PCs so the proposed models are not well applied in practice, especially when faced with fluctuations in demand. Secondly, prior work in production scheduling primarily focuses on random processing time and machine failures. Although these factors

impact the performance of scheduling, the other stages also need to be considered. Especially, the demand fluctuation due to uncertain events at the assembly site has a major impact on production scheduling.

In order to address the issues discussed above, this paper innovatively integrates three processes of PC project, including production stage and assembly stage. Then, three types of demand fluctuations are considered and optimization measures are proposed to deal with the demand fluctuations. Chan and Hu (2001) used genetic algorithms to optimize the flow shop scheduling problem and compared the results with other heuristic algorithms. The comparison shows that the GA can obtain good schedules for the model, giving a family of solutions that are at least as good as those produced by the heuristic algorithms. They also proved that GA is reliable and stable, and is able to produce good results under a wide variety of operating conditions. Thus, we use the multi-objective genetic algorithm to achieve the dynamic scheduling optimization with the purpose of achieving the shortest completion time and the minimum additional cost.

3 DYNAMIC SCHEDULING MODEL

3.1 Proposed Model

The proposed model consists of two scenarios as shown in Figure 1.

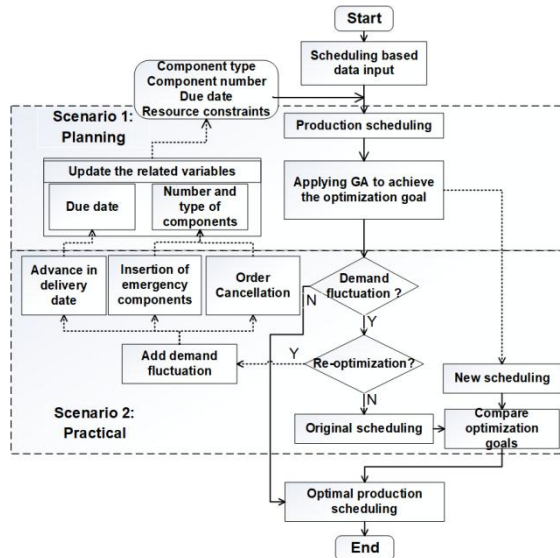


Figure 1. Framework of Proposed Model

In the planning stage, production scheduling mainly considers information regarding existing orders, production processes and resource constraints.

The first scenario of the model focuses on model-based scheduling optimization. The order information is input into the model and optimized using a genetic algorithm. Then, an optimal schedule with shortest completion time and minimum extra cost is obtained if there is no demand fluctuation.

However, during the implementation of the project, some incidents may cause the production plan generated during the planning stage to be out of sync, and the original optimization process needs to be revised. Thus, the second scenario represents the execution stage and three types of demand fluctuation are considered in the production process. When demand fluctuation occurs, the production would be interrupted and some related variables will be changed. Then, the model checks the current information and inputs this information into scenario 1 of the model for re-optimization. Finally, the new production schedule and the original schedule will be compared and the optimal schedule under the influence of demand fluctuation is obtained.

3.2 Production Scheduling

The production process of prefabricated components is divided into 9 steps: Mold manufacturing; mold assembling, reinforcement setting, concrete casting, curing, mold removal, cleaning and repairing, storing, and transportation. The PC production scheduling could be viewed as a multi-objective flow shop scheduling problem [9]. The optimization problem could be abstracted as: n components need to be processed by m workstations, each component has to be processed by all workstations and the sequence of workstation cannot be changed.

The production process can be divided into four types of operations. The first type is interruptible operation such as mold manufacturing, mold assembling, reinforcement setting, mold removal, cleaning and repairing. The calculation of the completion time for this type of process is given by equation (1). The second type is non-interruptible operation such as concrete casting; the calculation of the completion time for this process type is given by equation (4). The third type is called parallel operation such as curing and storing. The calculation of the completion time for this type is given by equation (5). The fourth type of operation is transportation and its completion time is expressed by equation (6).

Thus, the time taken by the production process is calculated from equations (1) to (6), and these equations have been adopted from the existing literature (Yang, et.al. 2016, Wang and Hu 2017). The notations used in this article and their meanings are shown in Table 1.

Table 1. Notations in this paper

Notations	Meaning
J_i	The i th component
k	The k th workstation
$C(J_i, k)$	the completion time of component J_i at the workstation k
$t_{i,k}$	the operation time of the component J_i at the workstation k
T, T^*	the cumulative completion time
D	number of days used from the start of production to this step
H_w	the normal working hours per day, $H_w = 8$
H_o	the overtime hours, $H_o = 4$
H_N	the non-working hours, $H_N = 16$
d_i	Due date of component J_i
d_{randn}	due date of a randomly selected component
Δd	The number of days the delivery date changes
C_i	the completion time of component J_i
α_i	the unit storage fee due to early completion
β_i	the unit penalty due to delay
$rand$	a random number between 0-1
n	The number of components need to be product
Δn	The number of urgent component or cancelled components

$$C(J_i, k) = \begin{cases} T & , \text{if } T \leq 24D + H_w \\ T + H_N & , \text{if } T > 24D + H_w \end{cases}, k = 1, 2, 3, 6, 7 \quad (1)$$

The calculation of T and D can be expressed as:

$$T = \max\{C(J_{i-1}, k), C(J_i, k-1)\} + t_{i,k} \quad (2)$$

$$D = \text{int}(T / 24) \quad (3)$$

$$C(J_i, k) = \begin{cases} T & \text{if } T \leq 24D + H_w + H_o \\ 24(D+1) + t_{i,k} & \text{if } T > 24D + H_w + H_o \end{cases}, k = 4 \quad (4)$$

$$C(J_i, k) = \begin{cases} 24(D+1) & \text{if } (24D + H_w) < T^* < 24(D+1) \\ T^* & \text{if } T^* \leq 24D + H_w \text{ or } T^* \geq 24(D+1) \end{cases}, k = 5, 8 \quad (5)$$

$$C(J_i, k) = \begin{cases} 24(D+1) + t_{i,k} & \text{if } T^* > 24D + H_w + H_o \\ T^* & \text{if } T^* \leq 24D + H_w + H_o \end{cases}, k = 9 \quad (6)$$

3.3 Modelling of Demand Fluctuation

The production process of precast components is often affected by uncertain factors. In general, the influencing factors are mainly divided into on-site factors and off-site factors. The on-site factors are problems caused by the factory itself, such as changes in processing time due to the skill proficiency of workers, and machine breakdown. The off-site factors are mainly derived from the assembly side, such as the arrival of new components, change of delivery date, etc. Due to the complexity of the construction site, the demand fluctuation becomes the most important factor. Many scholars have studied the changes in processing time, machine breakdown and the arrival of new components. However, the impact of these factors is not very significant due to the long production time of PC. Therefore, this paper mainly deals with the impact of demand fluctuations of components on scheduling.

In order to simplify the representation of fluctuations in demand, this paper mainly considers three types of demand fluctuation, such as the advance of due date (equation 7), insertion of urgent component (equation 8), and order cancellation (equation 9).

$$d_{randn} = d_{randn} - \Delta d \quad (7)$$

$$n = n + \Delta n \quad (8)$$

$$n = n - \Delta n \quad (9)$$

3.4 Optimization Objective

(1) Total completion time

$$f_1 = C(J_n, 9) \quad (9)$$

where $C(J_n, 9)$ is the completion time of the last component.

(2) Extra costs

Delays in the completion of components will result in an increase in penalty, while early completion will require additional sites for stacking. This will also result in additional costs, which can be expressed as:

$$f_2 = \sum_{i=1}^n [\alpha_i \cdot \max(0, C_i - d_i) + \beta_i \cdot \max(0, d_i - C_i)] \quad (10)$$

where α_i is the unit storage fee due to early completion; β_i is the unit penalty due to delay. In this paper, $\alpha_i = 2$, $\beta_i = 10$, C_i is the completion time of component J_i ; d_i is the delivery time of component J_i in contract.

4 APPLICATION

4.1 Case Introduction

In order to test the performance of the model, data from an actual project was used to verify the feasibility and practicability of the proposed model. The project is a prefabricated residential project in Pudong Area, Shanghai, which began in December 2018. The participants of the project are all affiliated to Shanghai Urban Construction Group, in which the producer is Shanghai Xiasha Prefabricated Component Factory, the transporter is Shanghai Urban Construction Materials Company, and the assembler is the Longdong Avenue Prefabricated Residential Project Department. The project used prefabricated concrete components, which are highly standardized. The types of components include stairs, balconies, façade panels, PCF exterior wall panels, air conditioning panels, beams, columns, laminated floors, thermal insulation wall panels, and Interior wall panels. Table 2 shows the data used in this experiment. S1-S9 represent the production time required for the prefabricated components at each stage, where S1 represents mold manufacturing, S2 represents mold assembly, S3 represents reinforcement setting, S4 represents concrete cast, S5 represents curing, S6 represents mold removal, S7 represents repairing, S8 represents storing, and S9 represents transportation. Due date indicates the time required (in hours) from the signing of the order to the delivery of the component at the construction site, as specified in the order. These data are summarized by the production manager based on previous production conditions.

In this project, because the number of molds is sufficient and the production site is also relatively spacious, there are no restrictions on the number of molds and the storage space between workstations. Therefore, these two restrictions are not considered in the experiment.

4.2 Stage 1: Scheduling Optimization Using GA

1) Application of Genetic Algorithm

First, the order information of the prefabricated components is input into the model and optimized using a genetic algorithm to obtain a near optimal production schedule. The process of executing the genetic algorithm is shown in Figure 2 and the application of the genetic algorithm in this paper involves the following steps:

(1) Generate the initial population

The population is represented by a matrix of $m \times n$, where n is the number of components and m is the number of individuals in the population, each element in the matrix is an integer number between 1 to n . Each row of the matrix represents a production sequence, called a chromosome. Each element of the matrix represents the number of the component, called a gene.

The initial population of chromosomes is determined by randomly generating the aforementioned matrices. As an example, Figure 3 is a typical chromosome in the initial population. It represents the production sequence of components as follows J1-J5-J7-J8-J3-J4-J6-J9-J10-J2.

(2) Calculate individual fitness values

For each individual in the population, the fitness value needs to be calculated. The fitness function should be set according to the model's objective equation. The paper uses the weights to convert the multi-objective equation into a single-object equation:

$$f = 1 / (w_1 \cdot f_1 + w_2 \cdot f_2)$$

where w_1, w_2 are the weights of the two optimization goals, $0 < w_i < 1, i = (1,2)$ and $w_1 + w_2 = 1$.

(3) Select

According to the fitness value of each individual, the paper adopts the roulette method to perform the selection operation. The select probability for individuals with high fitness values will be higher, and the select probability of each individual can be

$$P_i = f_i / \sum_{i=1}^m f_i$$

expressed as:

(4) Crossover

This study adopts two-point crossing, as shown in Figure 4. Two individuals are selected randomly from the population and two intersection points are selected randomly from them. The genes outside the two intersections are retained, and the genes between the two intersections are replaced by non-repetitive genes.

(5) Mutation

This study adopts Shift mutation, as shown in Figure 5. It works as follows: select two points at random, the latter point is inserted ahead of the former point. The genes between two points are then shifted backwards.

(6) Termination condition

As the number of iterations increases, the individual's fitness value will gradually increase and eventually reach the local optimal or optimal solution. By setting the number of iterations to terminate the algorithm, a series of near optimal solutions can be obtained.

Table 2. Input data

type	Processing time of each work station(h)									Due time(h)
	S1	S2	S3	S4	S5	S6	S7	S8	S9	
STA	8	0.5	1	0.4	7	0.5	0.5	10	2	168
BALC	4	2	2	0.5	7	1	1	10	2	144
FAC-P	5	1.5	1.5	0.5	7	1	1	10	2	168
PCF-P	6	1.5	2	0.5	7	1	1	10	2	144
AC-P	4	0.5	1	0.2	7	0.5	0.5	10	2	168
BEAM	9	0.7	2	0.5	7	0.6	0.5	10	1.5	168
COLU	7	2	2.5	0.5	7	1.5	0.5	10	1.5	144
LA-F	10	1.0	1.5	0.5	7	0.5	0.5	10	3.0	168
TI-P	8	3.5	3	1	7	1	1	10	1.5	144
IW-P	4	1.5	1.5	0.5	7	1	1	10	2	144

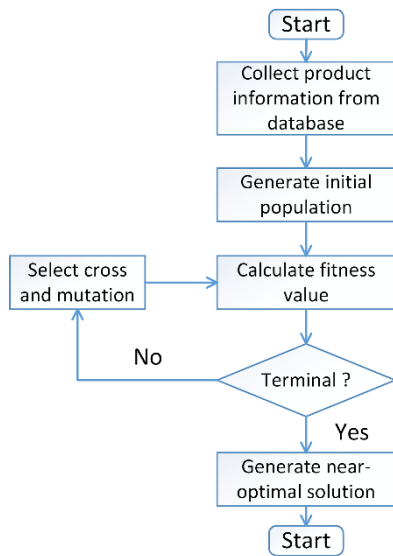


Figure 2. Process of applying the genetic algorithm

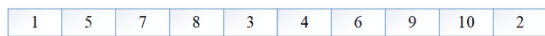


Figure 3. Initial population

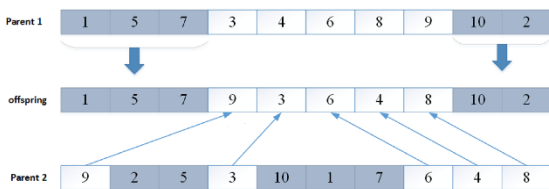


Figure 4. Crossover operation

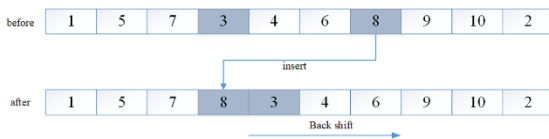


Figure 5. Mutation operation

(7) Improvement of the algorithm

Because the solution space is too large, the fitness value of the population often fluctuates and eventually falls into local optimum. In order to ensure that the

population evolves towards increasing the fitness, the worst 10% individuals of the new generation are replaced by the best 10% individuals of the old generation.

2) Results of Stage 1 of the Model

For our simulation experiment, the proposed model was programmed using Matlab R2016a. The parameters of the genetic algorithm were set as follows: population size $m=100$, genetic algebra: 300, crossover probability: $P_c=0.8$, and mutation probability: $P_m=0.02$.

First, assuming the factory receives an order, the producer inputs the order information, as shown in Table 2, into the proposed model. Scenario 1 of the model will use the genetic algorithm to optimize the production schedule to achieve the shortest completion time and minimum extra cost. Figure 6 and Figure 7 show that, as the number of iterations of the algorithm increases, the completion time and the extra cost gradually decrease and eventually reach convergence. Finally, the optimal production schedule obtained by the model is 9-1-4-7-2-10-3-5-8-6. The required completion time is 241.5 hours and the additional cost is \$1665.

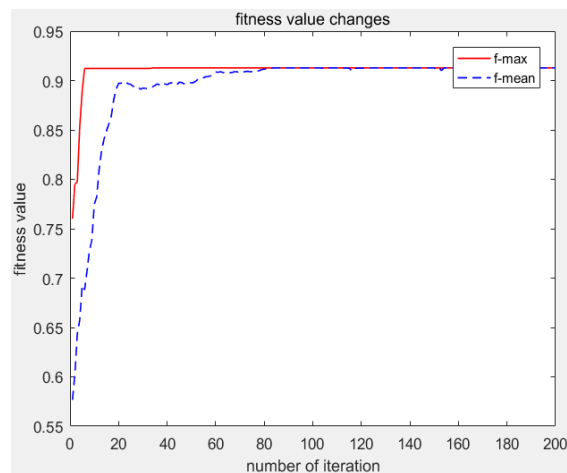


Figure 6. Convergence curve

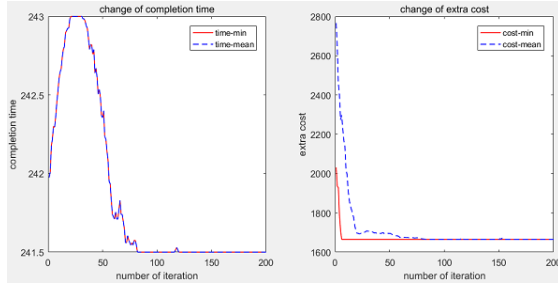


Figure 7. Time and extra cost change

4.3 Stage2: Dynamic Scheduling for Demand Fluctuation

In order to better cope with the influence of uncertain factors in the production process, the scenario 2 of the model sets the following three types of demand fluctuations in the production process: change of delivery date, insertion of emergency components, and cancellation of orders. The type and impact of these uncertainties are shown in Table 3. The change in the delivery date will cause the delivery date of some components to be advanced or delayed by a few days. The insertion of emergency components will result in an increase in the number of components, and these emergency components have a higher production priority; order cancellation will cause some components to cancel production.

Table 3. Type and impact of demand fluctuation

No.	Type	Impacted variables	Impact mode
1	Change of delivery date	d_i	Equation (7)
2	Insertion of emergency components	n	Equation (8)
3	Cancellation of orders	n	Equation (9)

In addition, as shown in scenario 2 of Figure 1, when demand fluctuates, production schedules need to be revised due to the change in production information. In practice, the producer only implements the original plan in advance or later through simple empirical judgment. In our approach, we check the production information when demand fluctuations occur and use the genetic algorithm to re-optimize the schedule according to different types of demand fluctuation events, and the optimal scheduling with respect to the current state is obtained to achieve cost savings.

In order to test the ability of the model to cope with demand fluctuations, let us assume that demand fluctuations occur when component No. 7 starts production. At this time, scenario 2 of the model will generate a new production schedule based on the current production state using the genetic algorithm.

The optimal production schedule is selected in comparison to the previous production schedule.

(1) Advance in delivery date: Assume that the delivery date of component No. 6 is advanced from 168h to 144h. Due to change in production information, the model will re-optimize the remaining components (2-10-3-5-8-6). In normal practice, the producer simply produces the advanced components first based on experience, so the schedule is 6-2-10-3-5-8, and the completion time is 243h, and the additional cost is \$2525. The proposed model uses genetic algorithm to achieve dynamic optimization. The optimized schedule is 2-3-10-5-6-8, the completion time is 243h and the extra cost is \$1805. As shown in Table 4, although the completion time was not shortened, the extra cost was reduced $(2525-1805)/2525=28.5\%$.

Table 4. Result comparison (advance in delivery date)

Optimize method	Production scheduling	Completion time	Extra cost
Experience method	6-2-10-3-5-8	243	2525
Dynamic scheduling	2-3-10-5-6-8	243	1805

(2) Insertion of emergency components: Assuming that components No. 1 and No. 4 are required to be added to the order, the traditional method will set the priority of these two components to be the highest. As shown in Table 5, the production schedule is 1-4-6-2-10-3-5-8, the completion time is 290h, and the additional cost is \$4725. The optimized schedule generated by the proposed model is 4-10-3-2-5-1-8-6, the completion time is 289.5h and the additional cost is \$3765, saving $(4725-3765) / 4725 = 20.3\%$ of the cost.

Table 5. Result comparison (insertion of emergency components)

Optimize method	Production scheduling	Completion time	Extra cost
Traditional method	1-4-6-2-10-3-5-8	290	4725
Dynamic scheduling	4-10-3-2-10-5-8	289.5	3765

(3) Cancellation of order: Assume that components No. 3 and No. 8 cancel production. As shown in Table 6, the schedule obtained by the empirical method is 2-10-5-6, the completion time is 194h, and the additional cost is \$555. The optimized schedule generated by the model is 10-6-5-2, the completion time is 193.5h, and the extra cost is \$315, which results in cost savings of $(555-315)/555=43.2\%$.

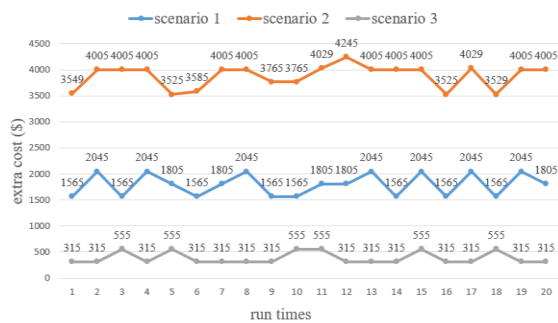
Table 6. Result comparison (cancellation of order)

Optimize method	Production scheduling	Completion time	Extra cost
Experiment method	2-10-5-6	194	555
Dynamic scheduling	10-6-5-2	193.5	315

From the above experimental results, although there is no improvement in the completion time, the production schedule generated by the model has a smaller additional cost, which proves the effectiveness of the proposed model in response to demand fluctuations.

4.4 Sensitivity analysis

In order to validate the stability of the proposed model, a sensitivity analysis experiment has also been carried out. 20 consecutive runs of the model under the three scenarios discussed in Section 4.3 were performed. The extra cost of each run is depicted in Figure 8. The results show that the proposed model is quite stable.

**Figure 8. Results of sensitivity analysis experiment**

5 CONCLUSION

THE production of prefabricated components is a crucial stage in a prefabricated construction project, and the production stage is affected by other stages. Therefore, the production schedule of prefabricated components needs to fully consider the possible impact of other stages. This study presents a dynamic flow shop scheduling model for the production of prefabricated components, which considers the impact of demand fluctuations during the assembly stage. The dynamic scheduling model proposed in this paper is not only applicable to PC production, but also applicable to the scheduling problems with similar characteristics. The risks that affect production scheduling come not only from the production stage, but also from outside. External risks have an important impact on production scheduling, and in order to achieve better project performance, it is necessary to make timely feedback on these risks.

The proposed methodology consists of two scenarios: Scenario1 uses genetic algorithm to obtain the optimal solution in a static environment. Scenario 2 considers three types of demand fluctuations, including advance of delivery date, insertion of urgent components, and cancellation of order. Experiment results show that the proposed model not only provides production scheduling with shortest completion time and minimum extra cost, but also responds well with demand fluctuation.

It is clear that the production of prefabricated components is a complex process and is affected by many factors. Our future research will take into account the requirements of various participants of the entire prefabricated component supply chain and comprehensively consider the impact of risks from other participants. The optimization must also take into account the cooperation and competition between the various parties. Moreover, some factories have installed multiple production lines to increase productivity. However, multiple production line scheduling problem is more sophisticated, and the dynamic scheduling strategy is more complex. We will attempt to solve the problem of multi-production line dynamic scheduling in our future work.

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7 REFERENCES

- Chan, W. T., & Hu, H. (2001). An application of genetic algorithms to precast production scheduling. *Computers & Structures*, 79(17), 1605-1616.
- de Athayde Prata, B., Pitombeira-Neto, A. R., & de Moraes Sales, C. J. (2015). An integer linear programming model for the multiperiod production planning of precast concrete beams. *Journal of Construction Engineering and Management*, 141(10), 04015029.
- Khalili, A., & Chua, D. K. (2013). Integrated prefabrication configuration and component grouping for resource optimization of precast production. *Journal of Construction Engineering and Management*, 140(2), 04013052.
- Leu, S. S., & Hwang, S. T. (2002). GA-based resource-constrained flow-shop scheduling model for mixed precast production. *Automation in construction*, 11(4), 439-452.
- Li, S. H., Tserng, H. P., Yin, S. Y., & Hsu, C. W. (2010). A production modeling with genetic algorithms for a stationary pre-cast supply chain. *Expert Systems with Applications*, 37(12), 8406-8416.

- Lin, W. C., Wu, C. C., Yu, K., Zhuang, Y. H., & Liu, S. C. (2017). On the Use of Genetic Algorithm for Solving Re-entrant Flowshop Scheduling with Sum-of-processing-times-based Learning Effect to Minimize Total Tardiness. *Intelligent Automation & Soft Computing*, 1-11.
- Liu, J., & Tang, L. (1999). The new algorithms for the dynamic flowshop scheduling. *IFAC Proceedings Volumes*, 32(2), 307-312.
- Mousavi, S. M., & Zandieh, M. (2016). An efficient hybrid algorithm for a bi-objectives hybrid flow shop scheduling. *Intelligent Automation & Soft Computing*, 1-8.
- Shoval, S. & Efatmaneshnik, M. (2018). A probabilistic approach to the stochastic job-shop scheduling problem. *Procedia Manufacturing*, 21, 533-540.
- Wang, K., Choi, S. H., & Lu, H. (2015). A hybrid estimation of distribution algorithm for simulation-based scheduling in a stochastic permutation flowshop. *Computers & Industrial Engineering*, 90, 186-196.
- Wang, Z., & Hu, H. (2017). Improved precast production-scheduling model considering the whole supply chain. *Journal of computing in civil engineering*, 31(4), 04017013.
- Wang, Z., Hu, H., & Gong, J. (2018). Framework for modeling operational uncertainty to optimize offsite production scheduling of precast components. *Automation in Construction*, 86, 69-80.
- Yang, Z., Ma, Z., & Wu, S. (2016). Optimized flowshop scheduling of multiple production lines for precast production. *Automation in Construction*, 72, 321-329.
- Yazdani, M., Naderi, B., & Mousakhani, M. (2015). A Model and Metaheuristic for Truck Scheduling in Multi-door Cross-dock Problems. *Intelligent Automation & Soft Computing*, 21(4), 633-644.
- Yuan, Q., & Yang, Z. (2013). On the performance of a hybrid genetic algorithm in dynamic environments. *Applied Mathematics and Computation*, 219(24), 11408-11413.

8 NOTES ON CONTRIBUTORS



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