Article | Received 4 November 2024; Accepted 28 January 2025; Published 17 February 2025
https://doi.org/10.55092/sc20250002

Swarm-intelligence collaboration based regular scheduling and dynamic rescheduling of precast component production: in prefabricated building project management

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Highlights:

- Swarm-intelligence collaboration model in precast concrete production.
- The dynamic-interval distribution cooperation strategy is proposed.
- The genetic algorithm based on Tchebycheff decomposition is used to obtain schemes.
- Less production time and rescheduling cost compared with the traditional method.

Abstract: The production of precast concrete (PC) component in factory is a very influential and complex work for the construction of the project. The rhythm of production is often delayed because the production process in most PC component factories is discrete at present. This study focuses on the production process of PC components and aims to propose regular scheduling and dynamic rescheduling models in prefabricated building project management. Based on the swarm-intelligence (SI) collaboration mechanism, the dynamic-interval synergy auction (DISA) strategy is proposed to improve contract net protocol (CNP). The genetic algorithm based on Tchebycheff (TCH) decomposition strategy is used to obtain the optimal production scheduling schemes. In addition, this model designs a coding mechanism for components based on Omniclass classification standard and the attributes of components are extended based on IFC extension mechanism. This model was verified in a PC factory. The experimental results showed that the decentralized negotiation mode with dynamic time window mechanism can avoid local optimization of schemes. Compared with traditional calculation method, this method could obtain more comprehensive and lower cost schemes. Based on the collaboration mechanism, with improved CNP and TCH strategies introduced, the dynamic model can improve the integrity and intelligence of PC factory.

Keywords: swarm-intelligence collaboration; precast concrete; IFC based on BIM; mathematical model; dynamic rescheduling

1. Introduction

Prefabricated concrete structure is the fastest developing building form at present due to low construction cost, low environmental pollution, and convenient operation, so the output of precast concrete (PC) components is also showing obvious growth trend [1]. The number of PC components with different types and complex production processes in some large factories is enormous. Some research in the Architecture, Engineering, and Construction (AEC) field indicates that intelligent approaches can enhance management efficiency and reduce costs [2,3], so the production scheduling management is necessary for PC factories.

The management task in PC factory is multi process, multi objective and multi constraint. Nowadays, many factories adopt enterprise resource planning (ERP) [4,5] or manufacturing execution system (MES) to improve the production efficiency [6,7]. However, unlike the general factory management for producing small products, because of the large volume and long production cycle of concrete products in PC factory, with more difficult to coordinate and manage, many optimization or management methods cannot comprehensively consider production scheduling management from the global and dynamic perspectives in the actual application process, whose response to the dynamic environment changes in PC factories is slow. Therefore, there is still space for improvement in the scheduling management of PC production.

Many PC factories still adopt the fixed production line mode at present, which obviously cannot meet the current industry development needs. By comparison, the dynamic assembly line mode is one of the most effective ways to increase the profits of PC factories, which can be more effective in space and machinery utilization, reduce the conflict of production resources, saving more than 20% of production time [8]. However, due to the backwardness of management methods, most PC factories are still using inefficient and simple scheduling methods for order arrangement and production management of assembly lines, whose production often fall into dilemma when the number of orders or component types become large, or some abnormal events occur.

PC factories involve multiple interdependent processes such as production, storage, transportation, and on-site delivery. Swarm intelligence (SI) models mimic decentralized decision-making, enabling each process to operate autonomously. For unpredictable events like order changes, machine breakdowns, or material delays, SI models are inherently adaptive, capable of quickly responding to such dynamic disruptions. Like how swarms of insects or flocks of birds coordinate their actions, SI models facilitate effective collaboration among different "agents" (e.g., workstations, transport vehicles, or storage facilities). This ensures smoother synchronization of production schedules and on-site delivery [9].

Based on the model of swarm-intelligence (SI) collaboration, this study maps the entities and processes involved in order integration, scheduling decisions, and anomaly handling in the PC factory to eight agents, and then constructs their respective definition and collaboration modes. The dynamic-interval synergy auction (DISA) strategy and weighted Tchebycheff approach (TCH) concept are used, under multi-objective and multi-constraint conditions, to generate optimal conventional scheduling schemes and dynamic rescheduling schemes respectively. Finally, this model was simulated and analyzed in a component factory, and the scheduling schemes were obtained under different conditions. In addition, the special notations appearing in this paper are shown in Figure 1 as follows for convenience.

Notations			
$j_{l,j}$	The jth component entering assembly line l.	f^*_{WI}	Sort descending of f^l_{WI}.
$N_{l,k}$	Component in kth workstation of assembly line l.	Q	The number of selected assembly lines.
$S(J_{(l,j)}, N_{(l,k)})$	Start time of component j in workstation k of assembly line l.	t_s	Start time of the equipment fault.
$P_{(l,j,k)}$	Production time of jth component in kth workstation of lth line.	t_e	End time of the equipment fault.
$C(J_{(l,j)}, N_{(l,k)})$	Completion time of jth component in kth workstation of lth line.	L_r	The number of assembly lines changed after rescheduling.
H_w	Normal working hours.	φ	Component type in rescheduling.
H_n	Anormal working hours.	t_0	Start time of rescheduling.
H_a	Overtime.	t_p	Time of next material deployment.
H_r	Rest time.	$SUM_{l,\varphi}$	The number of φ-type components from t_0 to t_p in new scheme.
T	Point of time when the process is completed.	$SUM^0{}_{l,\varphi}$	The number of φ-type components from t_0 to t_p in initial scheme.
D	The number of consumed working days.	ξ	Income from production using unit idle time.
ω	Priority of component among all components of same type.	γ	Labor cost of mold handling in unit time.
B_k	Buffer space between kth and $(k+1)th$ workstations.	Δt	Time to complete a mold handling.
$J_{l,j-1-Bk}$	Components in the buffer space before the jth component.	$f^1{}_{MR}$	Complexity measuring: the number of assembly lines involved.
$WT_{l,j-1,k}$	Waiting time for the $(j-1)th$ component to be sent to the buffer zone between the kth and $(k+1)th$ workstations.	$f^2{}_{MR}$	Workload measuring: difference in the number of various component types on different assembly lines.
ω_α	Priority of component among all components using mold α.	$f^3{}_{MR}$	Mold conversion cost measuring: labor cost for handling.
X_α	Total number of mold α.	$f^{1*}{}_{MR}$	Maximum values of $f^1{}_{MR}$.
g	Set of time occupied from $(\omega_\alpha - X_\alpha)th$ to $(\omega_\alpha - 1)th$ mold α released.	$f^{2*}{}_{MR}$	Maximum values of $f^2{}_{MR}$.
f_{WI}	Minimum working idle time of workstations.	$f^{2*}{}_{MR}$	Maximum values of $f^3{}_{MR}$.
f_{CS}	Minimum cost of delay and storage.	Z^*	Ideal point.
$d_{l,j}$	Delivery time of component j.	f_{min}	Minimum point.
$\tau_{l,j}$	Delay rate of component j.	f_{max}	Maximum point.
$\varepsilon_{l,j}$	Storage rate caused by early completion of component j.	$f^*{}_{1WI}$	Highest values of sub objective function f_{WI} in the first generation.
f_{MS}	Minimum total production time.	$f^*{}_{1MS}$	Highest values of sub objective function f_{MS} in the first generation.
$Max_{\forall l \in N^+ \mid l \le L}$	Maximum of completion time in all assembly lines.	$f^*{}_{1CS}$	Highest values of sub objective function f_{CS} in the first generation.
ET_f	Consistency of component types.	$f^*{}_{1TQ}$	Highest values of sub objective function f_{TQ} in the first generation.
EQ_f	Consistency of change times.	f_{new}	New fitness evaluation function according to the TCH.
f_{TQ}	Minimum of ET_f and EQ_f.	W_{WI}	Calculation weight of optimization goal f_{WI}.
$T_{l,f}$	The number of component types on assembly line l.	W_{MS}	Calculation weight of optimization goal f_{MS}.
$Q_{l,f}$	The number of component change times on assembly line l.	W_{CS}	Calculation weight of optimization goal f_{CS}.
T_θ	Total production time occupied by inserted orders.	W_{TQ}	Calculation weight of optimization goal f_{TQ}.
$f^l{}_{WI}$	Idle time of all processes in assembly line l.	$C^0{}_j$	The latest completion time of all components on assembly line l.
		$C'(J_{1,j}, N_{1,7})$	The latest delivery time of all components on assembly line l.

Figure 1. The special notations appearing in this study.

2. Related works

2.1. Production process and scheduling of PC components

In the traditional operation mode of PC factory, different production regions of the components are fixed and independent, where the reinforcement skeleton and poured concrete are transported among them. The production mode of assembly line is applied gradually, but each link of component production is discrete. Gradually, some researchers proposed to form a more functional and structured factory by computer-integrated manufacturing (CIM) in the factory [10], where the factory is divided into different production levels, where the upper level organization has management authority over the lower level organization. For example, Abdalla and Knight [11] proposed a new approach for concurrent product and process design of mechanical parts based on CIM. It consists of an integrated expert and computer-aided design system that meets the requirements for achieving the concept of design for manufacturability or concurrent engineering. In addition, the distributed structure and matrix organization of factory production have been researched more, which means that every functional production unit in the factory could have certain computing and decision-making capabilities, and different production modules have more interactions and feedback, so the entire production system is flexible and can make more optimized decisions and cope with more complex changes. For instance, Gu *et al.* [12] proposed a distributed physical architecture of smart factory based on intelligent agents. Experimental results in a small discrete factory validated that this approach has generality and superiority in solving real-time scheduling problems. Additionally, the Matrix Fusion Factory proposed by Siegert *et al.* [13] allows the production system to scale internal complexity and make it adaptable to external complexity. Experimental results show that this approach can reduce waste and improve efficiency, thereby unlocking the free potentials and capacities of the workforce.

In repetitive tasks based on specific rules, human efficiency is lower compared to automated programs [14], especially when dealing with unexpected events. The orders of PC components have relatively large uncertainty because they are submitted according to the progress of the construction site where many changes and emergencies occur frequently. In addition, the overall production scheme may be affected when the assembly line falls into downtime due to that some abnormal conditions happen in a certain process. To achieve more efficient and objective decision-making, researchers pay more and more attention to the change of production demand and the handling of abnormal conditions to improve the robustness and anti-interference ability of the scheduling system. For example, Gong *et al.* [15] modeled an optimal setup of human-machine collaboration in a flexible smart factory to address frequently changing order demands. Hingst *et al.* [16] related the characteristics of learning curves to changeability of factories to develop a framework for assessing the impact of change. This framework provides a basis for factory planning to consider the constant improvement of factories regarding key figures to determine time frames which are more suitable for initiating planned change. Various anomaly handling mechanisms include the time-driven mechanism for troubleshooting at fixed intervals and the event-driven mechanism for response strategies triggered by abnormal events. However, the former has a certain hysteresis, and the latter maybe cause insufficient stability. Therefore, the hybrid-driven mode combining the advantages of the former two was proposed, which added a real-time interference trigger mechanism to the periodic anomaly check, improving the efficiency of the troubleshooting and the stability of the system.

2.2. Swarm-intelligence (SI) collaboration and scheduling mechanism

In the research of production scheduling model construction, some researchers abstracted entity units and production processes into multi-agent system (MAS) to make production scheduling management more systematic [17,18], which has been proved to improve the global optimization capability of scheduling system [19,20]. The agents are more integrated and systematic through the design of the system framework and optimization of the cooperation mechanism, resulting in higher cooperation efficiency and anti-interference capability. Swarm-intelligence (SI) collaboration is originally inspired by collective behaviors of natural biological swarm, such as ants and bees, which is a popular multi-agent framework for obtaining global patterns and behaviors now. SI algorithm can be divided into two main clusters, animal swarm and insect swarm, wherein GWO and WOA are the former, and yet ABC, ACO, and FA are the latter [21]. SI is a relatively new branch direction of evolutionary computation comparing with other approaches with single solutions, and SI algorithms adopted approximate and non-deterministic patterns to efficiently explore the search space for near-optimal solutions.

The concept of SI collaboration enables the discrete production elements in factory to have organization and structure [22], which is the basis of a series of optimization problems. A sophisticated SI system shall include distributed and parallel mechanism, dynamic adaptation to environment, resilience to fault, and scalability of attribute, and the collective behavior will emerge which can handle complex tasks through interactions with each agent and the environment if the mechanism is well-designed [23]. In many industrial production case studies, compared with the traditional scheduling methods, the swarm-intelligence collaboration method has been verified to achieve better performance. For example, Mahmud *et al.* [24] proposed an integrated framework of multi-objective supplier selection and production scheduling in a multi-purpose machine environment. This model integrated the supply portfolio into production scheduling with a customer-imposed delivery time window to increases the flexibility for a decision-maker in providing a higher number of Pareto solutions and more diverse and regular frontiers within reasonable computational time. Additionally, Aminzadegan *et al.* [25] applied the Adaptive Genetic Algorithm (AGA) and the Ant Lion Optimization (ALO) based on multi-agent scheduling, aiming to minimize the sum of resource allocation, transportation costs, tardiness penalty costs, and lost sale costs. The results show that the proposed method performs better than the other algorithms in terms of optimum solutions and average performance time.

The combination of negotiation mechanism and intelligent algorithm with SI collaboration model in the PC factory can improve the interaction and collaboration between agents and achieve better operation efficiency. Some researchers introduced the bidding mechanism of contract net protocol (CNP) theory into the SI, which could allocate tasks among agents by signing contracts [26]. Wherein, the initiator agents release the tendering and the participant agents bid according to their own state and confirm the winning bidder according to the evaluation rules and then sign a contract with the winner. However, the production scheduling tasks of PC components are mutually constrained in terms of the resources or space, and it is a dynamic process with the continuous input of new orders. The traditional CNP mechanism has the shortcomings of vicious competition and local optimization, which cannot completely solve the production scheduling problems in large PC factories. Therefore, more and more concepts are integrated with the optimization of CNP mechanism, such as timing characteristics [27], constraint satisfaction [28] and some optimization algorithms [29,30].

2.3. Multi-objective optimization

The optimization of the collaboration mechanism is to promote the interaction and cooperation between multi-agents to achieve production goals. Some researchers initially proposed single objective optimization algorithms, such as punctual delivery [31] and minimum penalty [32]. As the optimization objectives pursued by factories become more and more diversified, and there is often competition and mutual exclusion between multiple targets, many multi-objective optimization methods are realized in actual production. For example, Wang *et al.* [33] proposed a dynamic multi-objective optimization evolutionary algorithm based on a particle swarm prediction strategy and a prediction adjustment strategy. The results indicate that this prediction adjustment strategy demonstrates competitive performance on most of the test problems. Furthermore, Li *et al.* [34] proposed a novel multi-level population hybrid search evolution algorithm for constrained multi-objective optimization problems. Experimental results show that the proposed method outperforms other multi-objective optimization algorithms.

Three main types of multi-objective optimization methods are usually used, namely Pareto dominance, performance evaluation index and decomposition strategy. Pareto method and GA were combined to solve multi-objective problems, and then many related algorithms were proposed to find more optimal solutions, such as PAES [35], SPEA [36], and NSGA-II. The multi-objective optimization evolutionary algorithm (MOEA) with fast convergence speed and local search ability is usually adopted to realize balance between the convergence and diversity in the objective space and the diversity in the decision space [37]. Zhang and Li [38] proposed the multi objective evolutionary algorithm based on decomposition (MOEA/D) which had lower computational complexity at each generation than MOGLS and nondominated sorting genetic algorithm II (NSGA-II). The information generated by the progeny of the solution of each subproblem only needs the information from their respective neighbors. Based on this, many researchers have proposed more optimization algorithms, such as local search hybridization [39], selection mechanism with stable matching [40], MOEA/D-DE algorithm [41] and MOEA/D-M2M algorithm [42]. Wherein Tchebycheff approach (TCH) [43] can decompose multi-objective problems into subproblems [44,45], which is easier for fitness allocation and diversity control to well solve the multi-objective optimization problem of convex Pareto front.

The PC production scheduling is a nondeterministic polynomial problem, which needs to comprehensively consider the objectives, characteristics and constraints at each stage based on the classic scheduling problem due to its complex technology and long processing cycle. With the increase of the number of objectives in production scheduling, the contradiction between the diversity and convergence of the solution set intensifies. Therefore, the optimization methods that only apply to two or three objectives are no longer appropriate. In addition, because most individuals in the solution set are non-dominated, the solution set cannot converge to the Pareto front, the evolution process is slowed down, and the decision of the optimal solution is difficult to implement. Therefore, it is appropriate to adopt improved CNP method to drive effective collaboration of SI and introduce TCH for multi-objective decision making of regular production scheduling and rescheduling in PC factory.

3. Methodology

This study takes the production process of PC components as the research object and maps the entity objects and scheduling processes of the production to a SI collaboration network with adaptive and communication cooperation capabilities, and the mutual cooperation mode between each module is designed. The dynamic-interval synergy auction (DISA) strategy is proposed to improve CNP by setting up a dynamic time window to avoid local optimization and the emergence of suboptimal solutions caused by the limitations of individual TA's data information and environment. The length of next time window to be opened is adjusted in real time according to the current status of assembly lines. Instead of being processed immediately, the tasks entering the same window will be packaged into a whole for optimization calculation at the end of the window to form the global optimal scheme. The optimization goals and resource constraints are quantified aiming at the complex processes and various environment changes in the PC production. This study introduces the Tchebycheff decomposition strategy into the genetic algorithm to improve convergence speed and reduce computational complexity, with the aim of aggregating different objective evaluation functions into a new fitness evaluation function. The genetic algorithm based on TCH decomposition strategy is used to solve the optimal production scheduling scheme under different conditions such as interference-free, order change, and equipment fault respectively. The proposed architecture for negotiation and scheduling strategy in PC factory is shown in Figure 2. In addition, this model designs a coding mechanism for PC components based on Omniclass classification standard in order to ensure the information circulation among components, and the attributes of components are extended based on Industry Foundation Classes (IFC) extension mechanism to achieve information collaboration and traceability in the prefabricated building supply chain. This model was verified in a PC factory. Based on market research conducted across China, the scale and production capacity of this factory are considered mid-range. The order information and disturbance factors used in this case simulation reflect typical scenarios that often occur in real-world production processes. The case simulation was calculated using Matlab 2021b to obtain feasible scheduling schemes and rescheduling schemes of the dynamic production process, providing reference and suggestions for scheduling optimization of other PC factories.

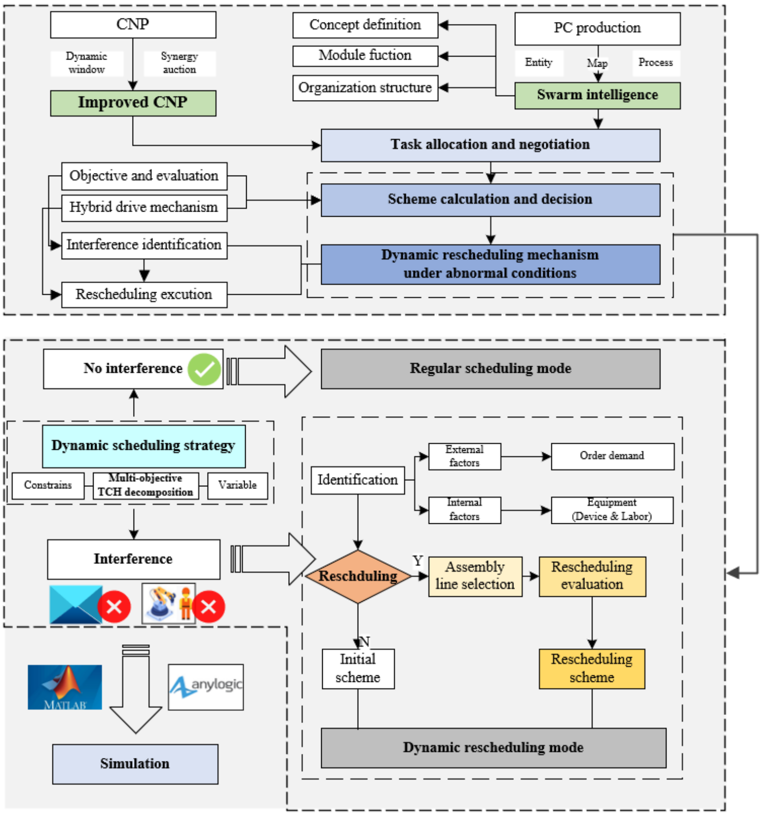


Figure 2. The architecture for negotiation and scheduling strategy in PC factory.

3.1. Multi-agent and two-stage scheduling conceptual model

This model maps production scheduling process into eight agents according to the allocation of machines, labors, materials and other resources in production process, which are respectively Order Agent (OA), Equipment Agent (EA), Assembly Line Agent (ALA), Task Agent (TA), Task Management Agent (TMA), Scheduling Agent (SA), Process Agent (PA), and Real-time Monitoring Agent (RMA).

SI collaboration system is divided into cognitive agent, reactive agent, and hybrid agent. The cognitive agent weighs the information collected and makes some basic decisions. The structure of reactive agent is relatively simple which can respond quickly to environmental changes and command from others. The hybrid agent combines the characteristics of the former two layers. The categories and module functions of eight agents in this model are shown in Table 1.

OA is responsible for sorting and recording external orders, classifying and summarizing by assembly line, and coding each PC component. EA is the mapping of entity resources with production functions, such as production machinery and labor on each workstation. ALA is the mapping of assembly line, which can create, manage and destroy EAs. TMA is a major decision maker in the selection of optimal scheme and rescheduling scheme. After receiving the orders from OA, TMA will generate TAs and apply to SA for feasible schemes to select the optimal scheme. TA is the mapping of each production task. PA is the mapping of production process, which is generated with the creation of TA. SA is a knowledge base that stores intelligent scheduling algorithms to calculate feasible scheduling schemes with real-time resources and task data. RMA is responsible for monitoring the status changes of various resources and agents in the production system.

Table 1. The categories and module functions of agents.

Category	Agent	Execution	Database	Reasoning	Decision	Evaluation	Supervision
Cognitive agent	OA		●	●	●	●	
	SA		●	●	●	●	
	RMA			●	●	●	
Hybrid agent	TMA			●	●	●	●
Reactive agent	TA	●		●			●
	ALA	●		●	●	●	●
	PA	●					
	EA	●					

PC component production scheduling in the factory mainly includes two key parts: resource integration and component production scheduling, therefore, this study builds a two-stage scheduling conceptual model of PC production, as shown in Figure 3. Production scheduling in PC factory is order oriented, which aims to maximize benefits by consuming the least time and resources, so the order information obtained must be preprocessed before production. Generally, the PC factory will receive orders from different projects within a certain transportation radius, and each order may contain different types of components, such as exterior wall panels, interior wall panels, composite slabs, and other special components. The orders from different projects are split and merged according to the type of components by order management department. The building components in the design drawings are divided into production units according to the demand and industry standards, and then the production units with the same category are merged into a new order for improving the utilization of personnel and equipment and realizing continuous production. After the orders are integrated to form a virtual task and sent to the scheduling department, the department will make optimal arrangements for component production according to the order information and the status of each assembly line, following the principle of punctual delivery and maximization of benefits.

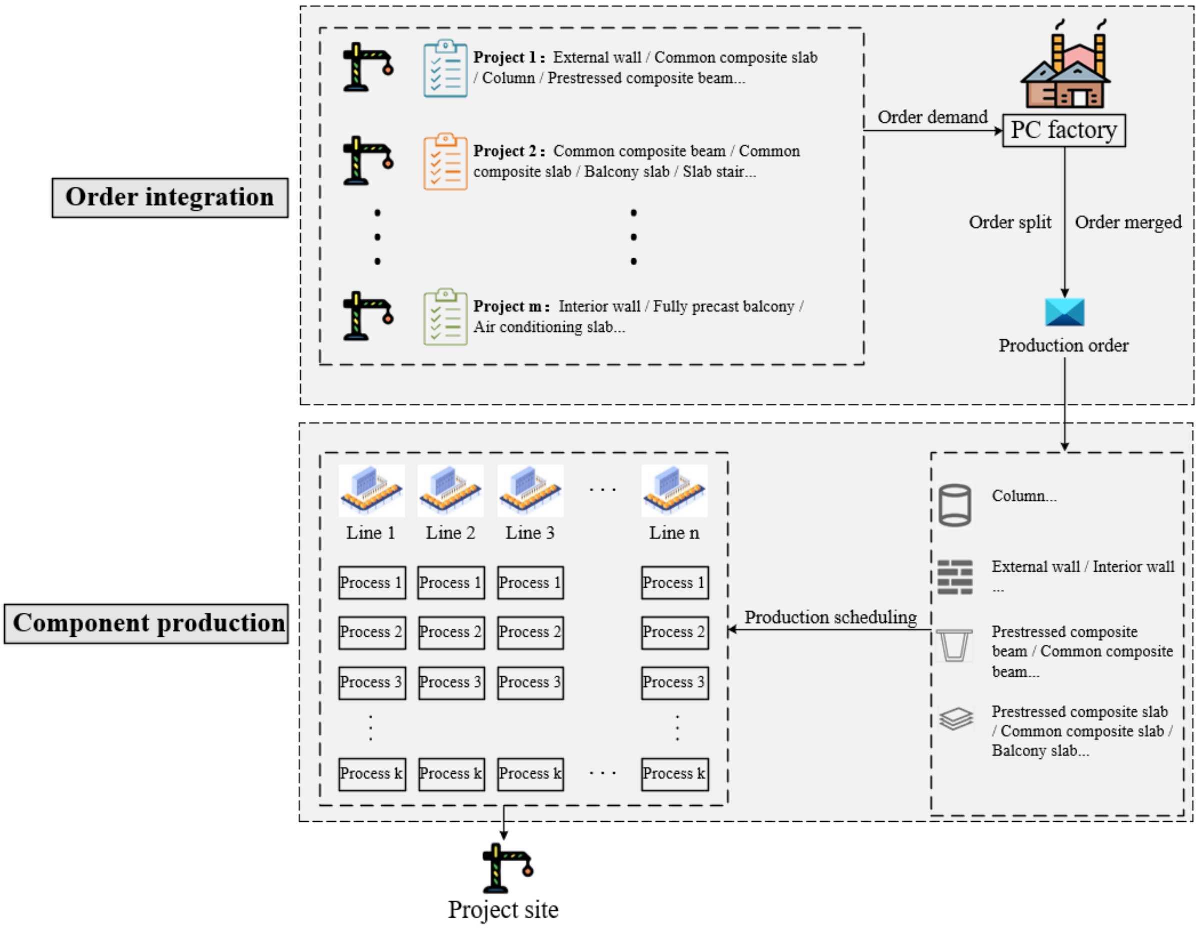


Figure 3. The two-stage scheduling conceptual model of PC production.

3.2. Improved-CNP based collaborative scheduling mechanism of PC production

The dynamic-interval synergy auction (DISA) scheduling strategy based on the CNP in this model is applied to the selection of the optimal scheme. As shown in Figure 4, firstly, whin a time interval, TMA decomposes the tasks and analyzes the demand after component tasks arrive, and then TMA sends TAs recording code, mold type, program duration and cost information to the dynamic time window. Then TAs enter the scheduling request set and wait for scheduling calculation until the end of the time window. The start time of a dynamic time window is the time when the TMA sends the first computing task TA to SA, and the window ends after corresponding window length, where the window length d_n is affected by ALAs and resource status.

According to task information and production status, SA calculates feasible scheduling schemes under constraint conditions and feeds them back to TMA Then the TA will be updated by TMA to new TA whose attribute set will be extended including alternative ALAs and time information. TMA initiates the tendering-bidding process between new TAs and ALAs, and then makes the final scheme decision according to the objective function and evaluation function. Finally, the winning ALA signs a contract with new TAs and organizes production. In this process, TMA, TA, ALA and SA work together to solve the optimal global multi-objective scheduling scheme in a certain period of time through mutual information interaction and negotiation. The directional arrows in the Figure 4 indicate the communication direction and negotiation process between intelligent agents.

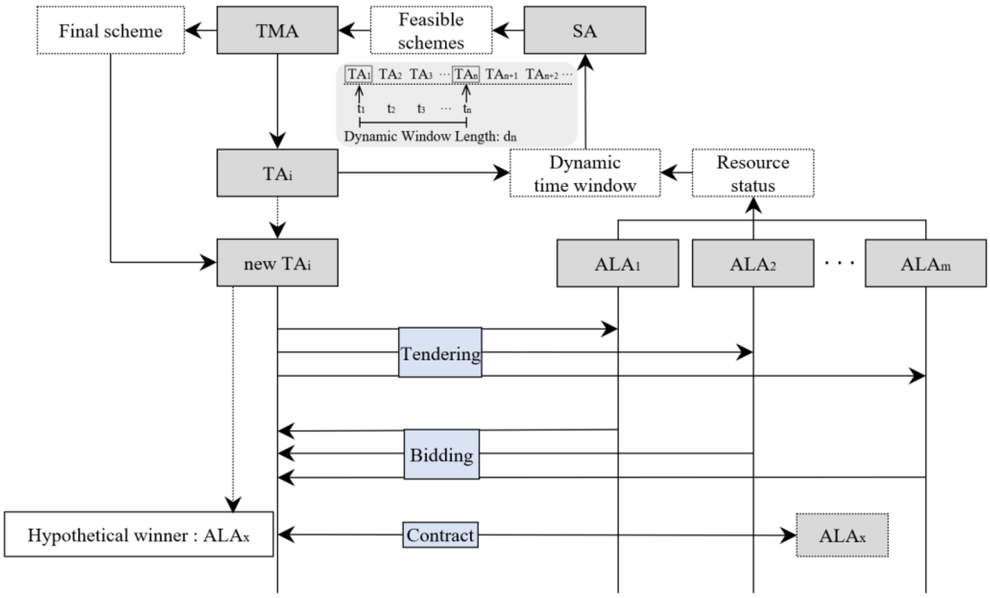


Figure 4. The DISA strategy based on CNP.

3.3. Information coding

In this model, each PC component is encoded based on the Omniclass coding method, and a complete component code includes the following units in turn: Order number, Component type, Component subtype, Component number, Building number, Floor number, and Delivery time. As shown in Table 2, the code 02-SL-02-03-05-02-480 means the third common composite slab in the precast slab in the second order, which is located on the second floor of Building 5, and the delivery time is 480 h.

Table 2. Component type code.

Component type	Type code	Component subtype	Subtype code
Precast column	C	Column	01
Precast beam	BE	Prestressed composite beam	01
		Common composite beam	02
Precast slab	SL	Prestressed composite slab	01
		Common composite slab	02
		Steel-truss composite slab	03

Table 2. *Cont.*

Component type	Type code	Component subtype	Subtype code
Precast wall	W	External wall	01
		Non-bearing exterior wall	02
		Interior wall	03
		Door & window integrated wall	04
		Parapet	05
Precast stair	ST	Slab stair	01
		Beam stair	02
Precast balcony	BA	Fully precast balcony	01
		Balcony slab	02
Precast air conditioning slab	A	Air conditioning slab	01

3.4. Swarm-intelligent based scheduling model in undisturbed state

As shown in Section 3.1, agents have certain distributed decision-making capabilities to reduce the burden of the system. TA and EA communicate with TMA and ALA respectively to complete the tasks of their own processes. In this study, a dynamic organizational structure is designed to obtain the global optimal solution and improve the robustness of the SI collaboration system. The operation process of the whole production scheduling is as follows, and the structural forms and interaction relationships of eight agents are shown in Figure 5.

Step 1: OA integrates all orders and extracts effective information for production scheduling, and then codes components to send order information to TMA.

Step 2: TMA generates TAs according to order information and applies to SA for calculation, then selects the optimal scheme and updates the TA information to form new TAs. Then TAs and associated ALAs sign the contract and then ALAs will arrange TAs for production in turn by corresponding EAs.

Step 3: The EA accesses its own task list, and it will start production of this component immediately if there is no component being or to be produced, otherwise, this component will be listed in the waiting queue. EA updates its own status information after completing the processing task, and then notifies ALA to release this component to the next EA.

This organizational structure has matrix characteristics, combining the advantages of distributed structure and ladder structure, so information among agents can interact vertically and horizontally simultaneously. If the impact of abnormal interference is small, associated modules can directly negotiate to make local adjustments based on the distributed structure without triggering global rescheduling. In addition, different agents in the system have different levels of decision-making authority, which ensures the robustness and fault tolerance.

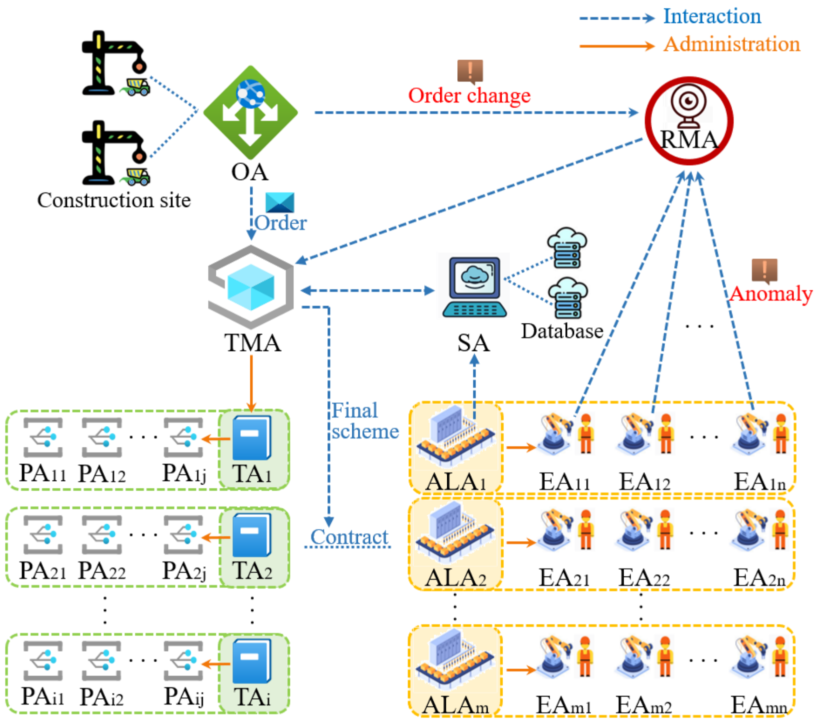


Figure 5. The SI collaboration structure in PC factory.

3.4.1 Production constraints

Assumptions:

(1) There are only 7 workstations on each assembly line. Each workstation on each assembly line can only produce one component, and each component can only be produced on one workstation.

(2) Each processing time is the average according to experience statistics.

(3) Each component must complete all processes in the sequence N1 to N7.

(4) The buffer space between workstations is limited, but the storage space of completed components is infinite.

In this study, there are l assembly lines and n components to be produced in the factory. There are y machines in each assembly line for production. The n_j components need to be produced on the l assembly line, the number of the j_{th} component entering the l assembly line is J_{lj}, and the component entering the k_{th} workstation is $N_{l,k}$. The $S\left(J_{l,k}, N_{l,k}\right)$, $P_{l,j,k}$ and $C(J_{l,j}, N_{l,k})$ represent the start time, production time, and completion time of the j_{th} component in the k_{th} workstation of l_{th} assembly line respectively. The daily working hours are divided into normal ones H_w (8 h in this model) and abnormal ones H_n including overtime H_a and rest time H_r.

In the production process, N_1 is mold assembly, N_2 is reinforcement installation, N_3 is concrete pouring and vibration, N_4 is concrete curing, N_5 is mold removal, N_6 is inspection and repair, N_7 is component storage. The constraints of production in this study can be summarized into four types: productivity, labor, assembly line and mold quantity.

(1) Productivity constraints

In the same period, a PC component can only be produced on one workstation, and a workstation can only produce one component, too. Therefore, except for the concrete curing (N_4) and component storage (N_7) which both can be processed in parallel, the k_{th} process of the j_{th} component cannot be undertaken before the completion of the $N_{l,k-1}$ process or the $J_{l,j-1}$ component, which is expressed as Equation (1) and (2).

$$S(J_{l,j},N_{l,k}) \geq \begin{cases} Max[C(J_{l,j-1},N_{l,k}),C(J_{l,j},N_{l,k-1})] & ,k \neq 4,7 \\ C(J_{l,j},N_{l,k-1}) & ,k=4,7 \end{cases} \tag{1}$$

$$C(J_{l,j},N_{l,k}) \geq S(J_{l,j},N_{l,k})+P_{j,k} \tag{2}$$

(2) Labor constraints

N_3 and N_4 are two special processes. The N_3 must be continuous, otherwise the concrete quality problems will be caused, so N_3 must be completed in one day during normal working hours or overtime, and it will be put aside until the next day if the remaining working time is insufficient. In this model, it is considered that the curing and storage sites are infinite, so N_4 does not cause additional resource consumption including labor or material. Therefore, the completion time of N_3, N_4, and other processes are as Equation (3)–(5) respectively.

$$C(J_{l,j},N_{l,k}) \geq \begin{cases} T & if\ T \leq 24D+H_w+H_a \\ 24(D+1)+P_{j,k} & if\ T > 24D+H_w+H_a \end{cases}, k=3 \tag{3}$$

$$C(J_{l,j},N_{l,k}) \geq \begin{cases} T & if\ T \leq 24D+H_w\ \ or\ \ T \geq 24(D+1) \\ 24(D+1) & if\ 24+H_w < T < 24(D+1) \end{cases}, k=4 \tag{4}$$

$$C(J_{l,j},N_{l,k}) \geq \begin{cases} T & if\ T \leq 24D+H_w \\ T+H_n & if\ T > 24D+H_w \end{cases}, k=1,2,5,6,7 \tag{5}$$

where T is the point of time when the process is completed, and D is the number of consumed working days.

(3) Assembly line constraints

In many factories, due to the large size of prefabricated components, the buffer space between different workstations is limited, which serves as a necessary constraint. When the buffer space is insufficient (*i.e.*, when the buffer is fully occupied), the completion time $C(J_{l,j},N_{l,k})$ is expressed as Equation (6)–(8).

$$WT_{l,j-1,k} = \begin{cases} C(J_{l,j-1-B_k},N_{l,k+1})-P_{l,j-1-B_k,k+1}-C(J_{l,j-1},N_{l,k}) & ,C(J_{l,j-1},N_{l,k}) < C(J_{l,j-1-B_k},N_{l,k+1})-P_{l,j-1-B_k,k+1} \\ 0 & ,C(J_{l,j-1},N_{l,k}) \geq C(J_{l,j-1-B_k},N_{l,k+1})-P_{l,j-1-B_k,k+1} \end{cases} \tag{6}$$

$$k=1,2,3,5,6$$

$$WT_{l,j-1,k}=0 \qquad ,k=4,7 \tag{7}$$

$$C(J_{l,j},N_{l,k}) \geq Max\{C(J_{l,j-1},N_{l,k})+WT_{l,j-1,k},C(J_{l,k},N_{l,k-1})\}+P_{j,k} \tag{8}$$

where $WT_{l,j-1,k}$ is the waiting time for the $(j-1)_{th}$ component to be sent to the buffer zone between the k_{th} and $(k+1)_{th}$ workstations. B_k is the buffer space between k_{th} and $(k+1)_{th}$ workstations, which is determined by the layout of assembly line, and $j_{l,j-1-BK}$ means the components in the buffer space before the j_{th} component. The buffer space is occupied when the completion time of k_{th}

process is less than the start time of the $(k+1)_{th}$ process. In addition, there is no waiting time before N_4 and N_7 because they can be processed in parallel.

(4) Mold constraints

The number of molds available in the factory is limited, so the next component can only wait for the previous mold to be released when the existing molds of the same type are occupied. The constraint of the waiting mold α of the component J is expressed in Equation (9).

$$S(J_{l,j}^{\alpha,\omega,\omega_\alpha}, N_{j,k}) \geq Min\{g(\alpha,\omega,\omega_\alpha,X_\alpha)\} \tag{9}$$

where ω represents the priority of the component among all components of the same type, and ω_α represents the priority of the component among all components using mold α. The total number of mold α is X_α, and g represents the set of time occupied from $(\omega_\alpha - X_\alpha)_{th}$ to $(\omega_\alpha - 1)_{th}$ mold α released. When ω_α is greater than X_α, it indicates a shortage of mold α, requiring the component to wait for processing. When $\omega_{\alpha w}$ is less than or equal to X_α, it indicates that the component can be processed directly without waiting.

3.4.2 Objective function

The reasonable allocation of resources is the essence of production scheduling, and the way to maximize benefits is to match resources and requirement. Therefore, in this model, the production mode of PC, relationship between operations, delivery time, machine utilization, storage cost and other factors are considered in the scheduling optimization problem to establish multiple optimization objectives as Equation (10) to (15).

(1) Minimum working idle time f_{WI} of workstations:

$$f_{WI} = \sum_{L=1}^{l}\sum_{K=1}^{7}[C(J_{l,n_l}, N_{l,k}) - S(J_{l,1}, N_{l,k}) - \sum_{J=1}^{nl} P_{l,j,k}] \tag{10}$$

(2) Minimum cost of delay and storage f_{CS}:

$$f_{CS} = \sum_{l=1}^{L}\{\sum_{j=1}^{nl}\tau_{l,j} * Max[0, C(J_{l,j}, N_{l,7}) - d_{l,j}] + \sum_{j=1}^{nl}\varepsilon_{l,j} * Max[0, d_{l,j} - C(J_{l,j}, N_{l,7})]\} \tag{11}$$

where $D_{l,j}$ is the delivery time of component j, $\tau_{l,j}$ is the delay rate of j, and $\varepsilon_{l,j}$ is the storage rate caused by early completion of j.

(3) Minimum total production time f_{MS}:

$$f_{MS} = Max_{\forall l \in N^+ | l \leq L} C(J_{l,n_l}, N_{l,7}) \tag{12}$$

where $Max_{\forall l \in N^+ | l \leq L}$ represents the maximum of completion time in all assembly lines.

(4) Minimum change of component f_{TQ}:

$$ET_f = \sqrt{\frac{\sum_{l=1}^{L}(T_{l,f})^2}{L}} \tag{13}$$

$$EQ_f = \sqrt{\frac{\sum_{l=1}^{L}(Q_{l,f})^2}{L}} \tag{14}$$

$$f_{TQ} = Min(ET_f, EQ_f) \tag{15}$$

Equation (13) and (14) indicate that the consistency of components can be obtained by the mean value of consistency of single assembly line, where ET_f and EQ_f respectively represent the consistency of component types and change times respectively, and the smaller their values are, the smaller the change degree of components are, which is conducive to productivity improvement. Wherein $T_{l,f}$ and $Q_{l,f}$ respectively represent the number of types and change times of components on the assembly line l. The replacement of components is caused by a mismatch between the components and the molds. The removal and installation of different molds consume significant time and labor, leading to a decline in production efficiency. Therefore, the production process should aim to minimize the replacement of components and molds as much as possible.

3.5. Dynamic rescheduling

The production status is not always stable due to random events, such as machine breakdowns, order changes, or human factors. The events are defined as external disturbances and internal disturbances based on the event sources.

External disturbances mainly refer to changes in order demands, which are caused by the designer, construction status, or material suppliers. Most order changes come from customers and directly affect production planning. These changes can lead to variations in component parameters, quantities, and delivery deadlines, which are the most significant factors influencing scheduling costs [46,47]. Additionally, the force majeure factors such as weather conditions, policy changes, accidents, or material shortages can also lead to changes in assembly deadlines. The plan changes in the construction sites are common, such as earlier or delayed deadlines, which can also change plans for the deliveries of components. If the scheduling plan cannot be adjusted promptly, it may delay the on-site construction and increase the costs. Conversely, if construction progress is delayed and components are produced according to the original schedule, it could lead to increased storage and maintenance costs for the prematurely finished components.

During the component production process, there are also internal risks, which are defined as internal disturbances, including machine failures, worker absenteeism or leave, delays in material allocation, or operational errors. These random risk events can affect the timely delivery of components and increase production costs.

This model establishes a dynamic cooperative rescheduling mechanism for PC components based on the hybrid drive mechanism in the knowledge base in advance. After the parameter changes of OA or EA are monitored by RMA, it will select the corresponding scheduling strategy according to the influence and then feedback to TMA and SA for calculation and decision.

3.5.1 External disturbance

Firstly, according to the change of the order, the assembly lines with lower mold conversion are selected to participate in rescheduling to realize local rescheduling, which is expressed as Equation (16)–(18). Secondly, all components are rescheduled as the method in Section 3.4.

$$T_{\theta} = \sum_{j=1}^{\theta} \sum_{k=1}^{7} P_{j,k} \tag{16}$$

$$f_{WI}^{l} = \sum_{k=1}^{7} [C(J_{j,nl}, N_{l,k}) - S(J_{l,1}, N_{l,k}) - \sum_{j=1}^{nl} P_{l,j,k}] \tag{17}$$

$$f_{WI}^{*} = \{f_{WI}^{l}(i) \mid f_{WI}^{l}(1) > f_{WI}^{l}(2) > \ldots > f_{WI}^{l}(L) \quad , l = 1,2,\ldots,L\} \tag{18}$$

where T_θ is the total production time occupied by inserted orders. The idle time f^{l}_{WI} is the difference between the total production time of all components and the duration of all processes in the assembly line, and then the set of idle time f^{*}_{WI} on the assembly line can be obtained in descending order as Equation (18). The number of selected assembly lines, Q, depends on T_θ and f^{l}_{WI}. If T_θ is equal to or greater than f^{l}_{WI}, all assembly lines will be selected, which is global rescheduling, otherwise Q assembly lines involved in rescheduling are selected and rescheduled.

3.5.2 Internal disturbance

When random interference occurs, firstly calculate the maintenance time T (including labor recovery), then judge whether the production according to the original plan after repair will result in delayed delivery. If the delivery can still be made on time, the initial scheme will continue to be adopted to avoid increasing rescheduling costs, and the production process will be postponed according to the maintenance time. If the component is being produced when the equipment fails, the completion time C of the process is expressed in Equation (19), if the workstation is idle when the equipment fails, the C is expressed in Equation (20).

$$C(J_{l,j},N_{l,k})\geq S(J_{l,j},N_{l,k})+P_{l,j,k}+t_e-t_s \quad ,t_s\geq S(J_{l,j},N_{l,k}) \tag{19}$$

$$C(J_{l,j},N_{l,k})\geq S(J_{l,j},N_{l,k})+P_{l,j,k}+t_e \quad ,t_s< S(J_{l,j},N_{l,k}) \tag{20}$$

where t_s and t_e represent start time and end time of the equipment fault respectively, and (t_e-t_s) means the repairment time.

3.5.3 Evaluation of rescheduling

This model uses the number of assembly lines involved in rescheduling to measure the complexity, expressed in f^{1}_{MR}. And the workload can be measured by the difference in the number of various component types on different assembly lines between the rescheduling and the initial scheme, expressed in f^{2}_{MR}. They are calculated in Equation (21) and (22) as follows:

$$f^{1}_{MR}=L_r \tag{21}$$

$$f^{2}_{MR}=\sum_{l=1}^{L}\sum_{\phi=\phi_1}^{\phi_v}\left|Sum_{l,\phi}(t_0,t_0+T_p)-Sum^{0}_{l,\phi}(t_0,t_0+T_p)\right| \tag{22}$$

where L_r represents the number of assembly lines changed after rescheduling, the φ represents the component type, t_0 represents the rescheduling start time, t_p represents the time of next material deployment, $Sum_{l,\phi}$ and $Sum^{0}_{l,\phi}$ represent the number of type-φ components produced from t_0 to (t_0+t_p) in the new scheme and in the initial scheme respectively.

In addition, when the components are adjusted from the original assembly line to another one, the labor cost for handling is used to measure the mold conversion cost in this model, based on the above idle time decisions, which is expressed as Equation (23).

$$f^{3}_{MR}=Max^{Q}(\xi * f^{l}_{WI}+\gamma * \Delta t * \theta_{l',l}) \tag{23}$$

where ξ represents the income from production using unit idle time f^{l}_{WI}, the γ represents the labor cost of mold handling in unit time, the Δt represents the time to complete a mold handling.

After the above objectives are normalized, the cost of rescheduling is obtained by adding them, which is expressed as Equation (24).

$$f_{MR} = \frac{f^{1}_{MR}}{f^{1*}_{MR}} + \frac{f^{2}_{MR}}{f^{2*}_{MR}} + \frac{f^{3}_{MR}}{f^{3*}_{MR}} \tag{24}$$

where f^{1*}_{MR}, f^{2*}_{MR}, and f^{3*}_{MR} are the maximum values of f^{1}_{MR}, f^{2}_{MR}, and f^{3}_{MR} in the same indicator set respectively.

3.6. IFC-based production information delivery

Expanding IFC attributes in the production management of prefabricated component factories can significantly improve operational efficiency, resource optimization, and decision-making processes. By incorporating more detailed attributes such as materials, dimensions, quality requirements, and logistics information, IFC enables better data exchange between different software applications used in design, construction, and manufacturing. This integration allows for a seamless connection between design and production phases, leading to more accurate production planning, reduced errors, and faster adjustments to design specifications. It also enhances resource management by providing detailed data on molds, machine capabilities, and worker skills, thereby optimizing production schedules and minimizing lead times. Furthermore, real-time tracking and monitoring become more feasible, allowing managers to respond promptly to delays or defects. Additionally, the incorporation of expanded IFC attributes facilitates better quality control by enabling traceability of each component's material properties and inspection results. Finally, logistics and inventory management are optimized by providing detailed information about storage requirements, transportation needs, and delivery schedules, ensuring timely delivery and reducing material waste. By leveraging these expanded IFC attributes, prefabricated component factories can streamline their production processes, improve efficiency, and ultimately achieve better project outcomes.

In order to ensure information collaboration and traceability in the supply chain of prefabricated buildings, based on the extension mechanism of IFC, this study expands the information of production scheduling of PC components in attribute set, so that the time parameter information of each process in component production can be saved in BIM, and the production time attribute belongs to the self-defined IFC extension.

The exterior wall panel 1 in order 1 is taken as an example, as shown in Figure 6, first the IFC file exported from Revit is extended, and then BIM Vision is used to view the attributes of the component. As shown in Figure 7, the production time attribute value of each process of the component is displayed, which shows that the method based on attribute set extension described is effective, and the IFC semantics generated after extension are correct.

```
#8270054=IFCPROPERTYSINGLEVALUE('Time Of Template Cleaning And Installation',$,IFCREAL(1.5),$);
#8270055=IFCPROPERTYSINGLEVALUE('Time Of Assembling Reinforcement And PlacingEmbedded Parts',$,IFCREAL(1.5),$);
#8270056=IFCPROPERTYSINGLEVALUE('Time Of Pouring And Vibrating Concrete',$,IFCREAL(0.4),$);
#8270057=IFCPROPERTYSINGLEVALUE('Time Of Curing Concrete',$,IFCREAL(12.),$);
#8270058=IFCPROPERTYSINGLEVALUE('Time Of Demoulding',$,IFCREAL(1.),$);
#8270059=IFCPROPERTYSINGLEVALUE('Time Of Checking And Repairing',$,IFCREAL(0.4),$);
#8270060=IFCPROPERTYSINGLEVALUE('Time Of Component Storage',$,IFCREAL(12.),$);
#8270061=IFCPROPERTYSET('0k3VWfn6iHx8E_bE8yNskd',#41,'Pset_WallCommon',$,(#8270054,#8270055,#8270056,#8270057,#8270058,#8270059,#8270060));
#8270062=IFCRELDEFINESBYPROPERTIES('0k3VWgn6iHxBs4bE8yNskd',#41,$,$,(#24840),#8270061);
ENDSEC;
END-ISO-10303-21;
```

Figure 6. IFC document expansion.

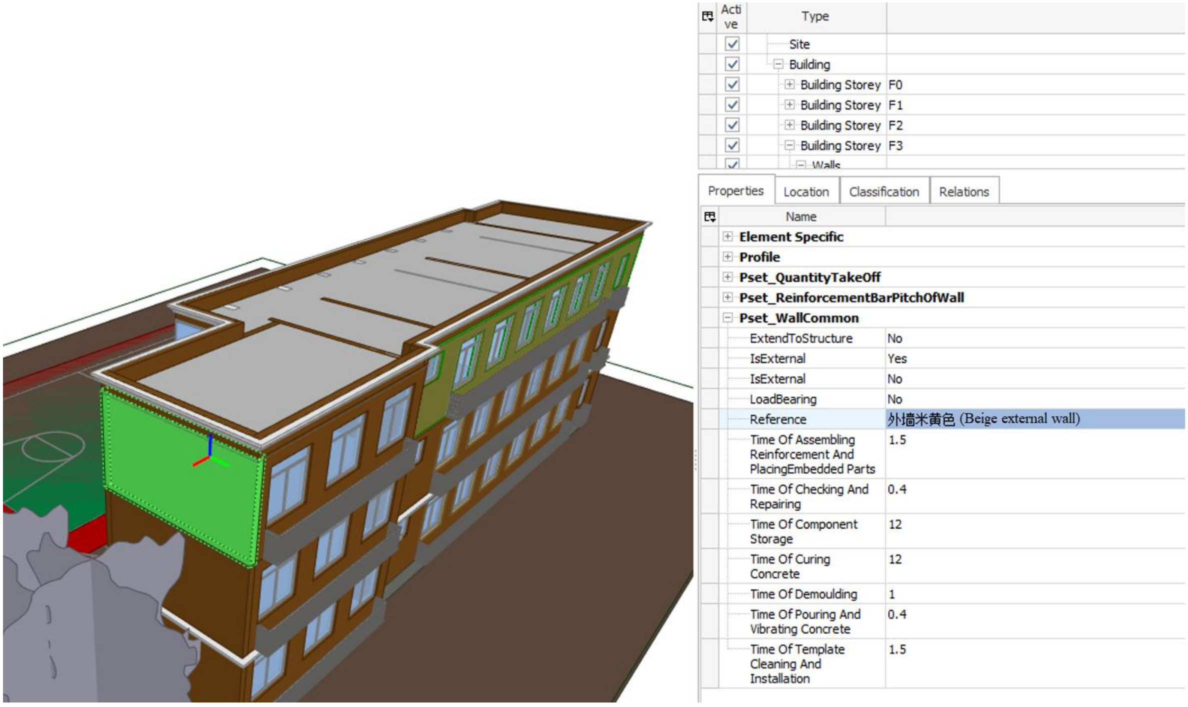


Figure 7. Extended attributes displayed in the attribute bar of PC component (in BIM Vision).

4. Case study and results

To enhance cooperation among agents and improve scheduling efficiency, this study uses an improved-CNP mechanism and the TCH decomposition algorithm. The advantages of this method, compared to traditional approaches, are verified through a case study in a PC factory in China, as shown in Figure 8. The factory covers an area of 45,000 square meters, with a storage area of 25,000 square meters. Its annual production capacity can supply 3 million square meters of building materials. The main products supplied by the factory include building components (such as precast columns, exterior wall panels, shear walls, composite slabs, composite beams, balconies, stairs, *etc.*), municipal components (such as subway tunnel segments, precast caissons, *etc.*), and decorative components (such as corridor panels and cultured stone).

It was assumed that the factory received 4 orders as shown in Table 3. And four integrated assembly lines were selected for simulation, and the number of mold resource was: three Type A, two Type B, two Type C, one Type D and one Type E, where A to E represented the mold type of exterior wall panel, interior wall panel, balcony slab, air conditioning slab, and precast stairs respectively. In this case, storage space is unlimited, and different components can be stored together. The buffers between workstations are limited, and the components that arrive first are processed first. Except for concrete curing and storage, subsequent processes must wait for the completion of the previous process. Each assembly line has one workstation for each process, arranged sequentially. Each workstation can produce different types of components. The storage cost is $2/hour, and the delay costs for different component types are shown in Table 3.

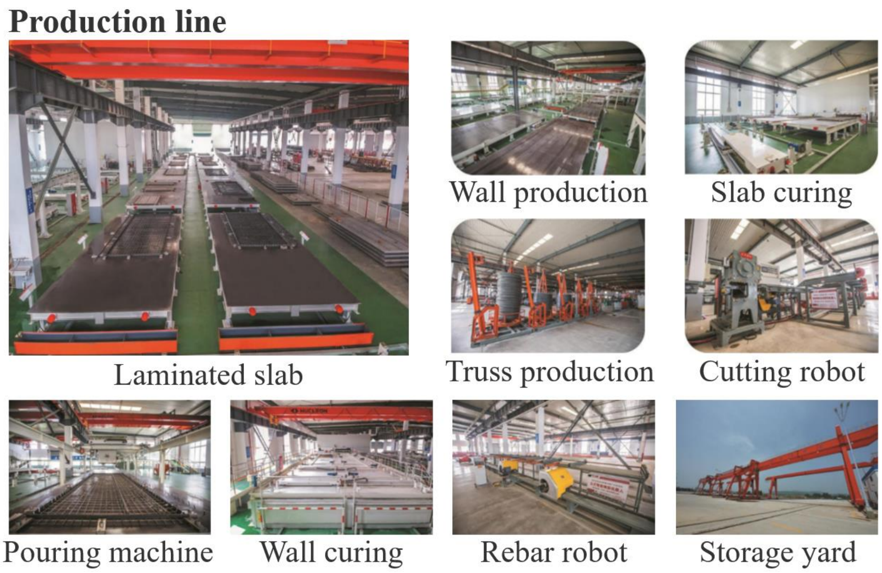


Figure 8. The PC factory in China.

Table 3. Simulation order information.

Component	Order number	Component type	Mold type	Delivery time (h)	Delay rate ($/h)	Storage rate ($/h)	Component code
1	1	Exterior wall 1	A1	96	20	2	01-W-01-02-01-01-96
2	1	Exterior wall 2	A2	144	10	2	01-W-01-02-02-02-144
3	1	Balcony slab	C1	168	10	2	01-BA-02-02-01-01-168
4	2	Interior wall 1	B1	96	20	2	02-W-03-01-01-01-96
5	2	Interior wall 2	B2	120	15	2	02-W-03-01-02-02-120
6	2	Interior wall 3	B3	144	10	2	02-W-03-01-03-03-144
7	2	Balcony slab	C2	144	10	2	02-BA-02-01-02-01-144
8	3	Exterior wall 1	A3	72	20	2	03-W-01-01-03-03-72
9	3	Exterior wall 2	A4	120	15	2	03-W-01-02-04-04-120
10	3	Precast stairs	E1	144	10	2	03-ST-01-01-03-01-144
11	4	Exterior wall	A5	96	20	2	04-W-01-01-05-05-96
12	4	Air conditioning slab	D1	120	15	2	04-A-01-01-05-01-120
13	4	Interior wall	B4	144	10	2	04-W-03-01-04-02-144

Note: The delivery time, delay rate, and storage rate are specific production parameters. The parameters in this study are based on assumptions from a real-world case

4.1. Regular scheduling

Two-layer decimal integer coding was selected to encode the component information into chromosomes, and the first layer was the component number, and the second layer was the assembly line number, as shown in Table 4.

Table 4. Two-layer chromosome code.

Component sequence	12	1	3	6	11	8	2	5	4	7	10	9	13
Assembly number	1	3	2	4	3	2	4	1	1	3	2	4	3

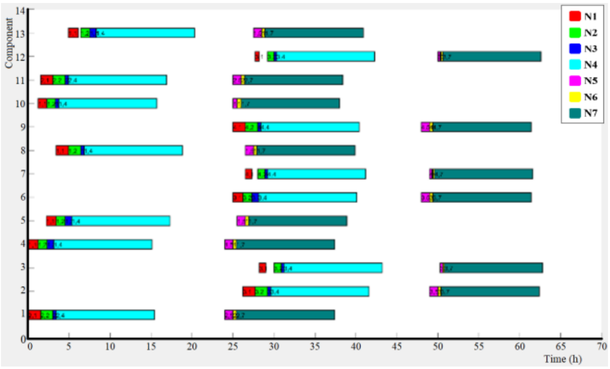
The initial population of 200 was randomly generated, and the ideal point Z^* and extreme point $f_{\min}$ and $f_{\max}$ of the initial population were calculated. The production objective is normalized according to Equation (25).

$$f_{new} = w_{WI}(\frac{f_{WI}}{f^*_{1WI}} - Z^*_{WI}) + w_{MS}(\frac{f_{MS}}{f^*_{1MS}} - Z^*_{MS}) + w_{CS}(\frac{f_{CS}}{f^*_{1CS}} - Z^*_{CS}) + w_{TQ}(\frac{f_{TQ}}{f^*_{1TQ}} - Z^*_{TQ}) \tag{25}$$

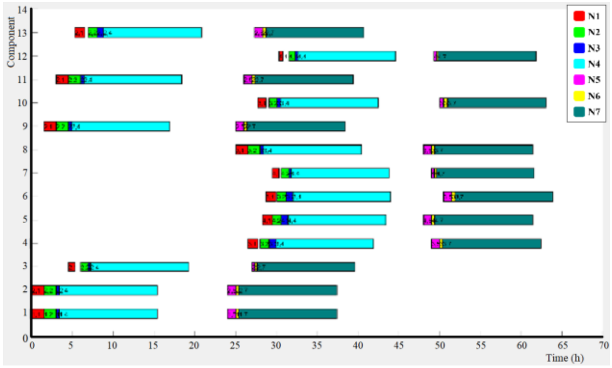
where f^*_{1WI}, f^*_{1MS}, f^*_{1CS}, and f^*_{1TQ} are the highest values of each sub objective function in the first generation. and W_{WI}, W_{MS}, W_{CS} and W_{TQ} are the weights of different optimization goals, and f_{new} is a new fitness evaluation function according to the TCH decomposition strategy, where the evolutionary population fitness value is constantly approaching the ideal value Z^* until convergence.

In most factories, minimum total production time is the most critical because it directly impacts factory throughput, enabling timely delivery of components to construction sites and improving the factory's capacity to handle multiple projects. Reducing production time influences increasing overall efficiency and revenue. Minimum change of component reduces disruptions caused by mismatches in molds or design adjustments. Minimum cost of delay and storage aims to minimize financial losses from delays and excessive inventory costs. However, their direct impacts on the production process are smaller compared to total production time. Therefore, the fact that optimizing production time has the largest impact on factory performance, while the other objectives serve as secondary considerations that help improve operational efficiency.

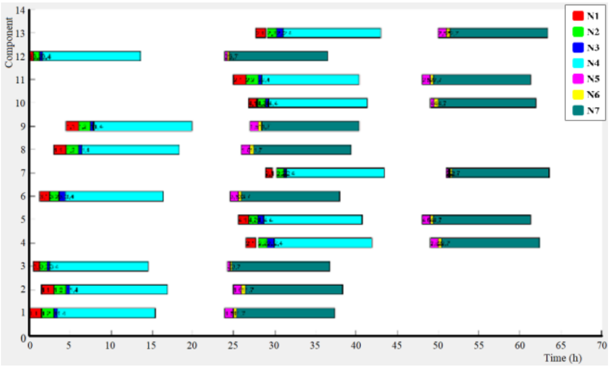
These weights vary depending on the specific production conditions. In the assumptions of this simulation, the above steps were implemented in Matlab 2021b with the weights of the optimization goals were 10%, 70%, 10%, and 10%, according to the production experience. Four feasible schemes were obtained, and the average maximum completion time is 63.58 h. as shown in Figure 9. In addition, to verify the advantages of this study, four scheduling schemes under the traditional algorithm without TCH are shown in Figure 10, and the average maximum completion time is 84.88 hours, which shows that the schemes adopting DISA and TCH strategy can save more than 20% completion time in this case. Scheme 1 was selected as the optimal scheduling scheme according to the total production time as the evaluation index. In this scheme, the total production time was 62.8 h, and the idle time of workstations was 10.4 h. The fitness curve is shown in Figure 11. The completion time of each process in scheme 1 is shown in Table 5.



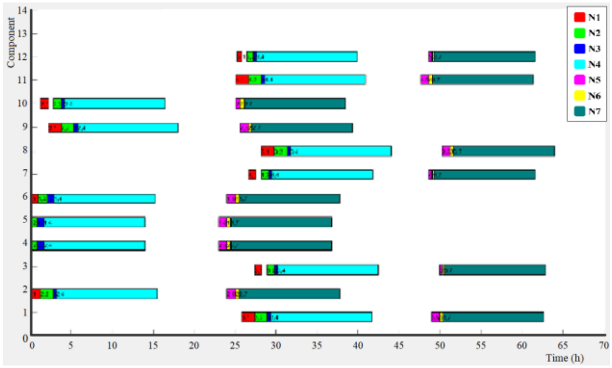
(a) Scheme 1.



(b) Scheme 2.

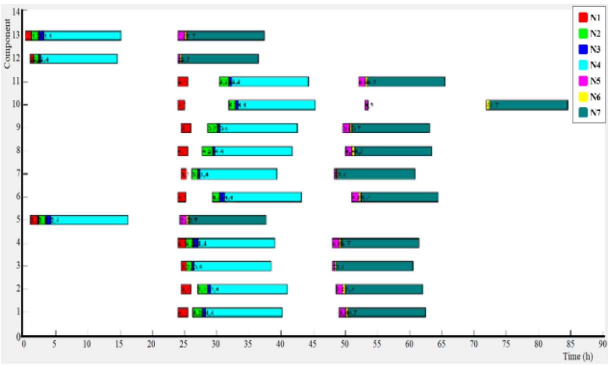


(c) Scheme 3.

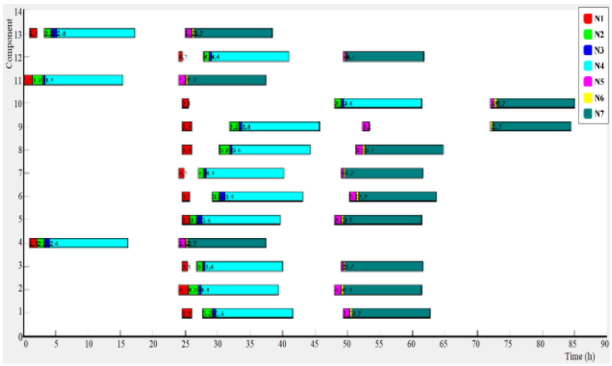


(d) Scheme 4.

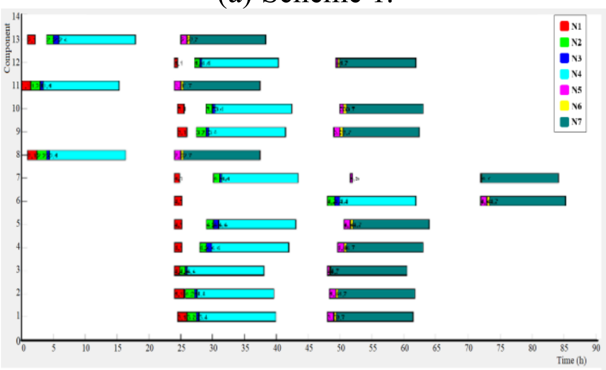
Figure 9. Feasible schemes without interference (in Matlab 2021b).



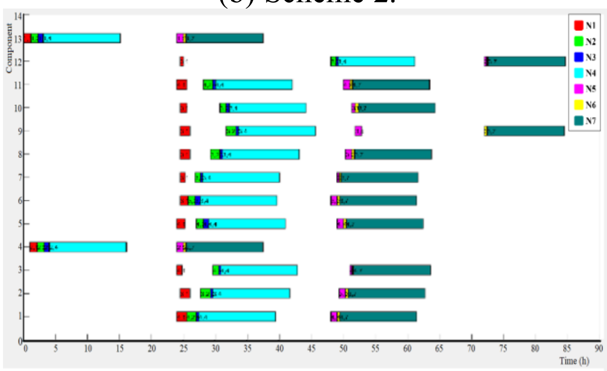
(a) Scheme 1.



(b) Scheme 2.



(c) Scheme 3.



(d) Scheme 4.

Figure 10. Scheduling schemes under traditional algorithm without TCH (in Matlab 2021b).

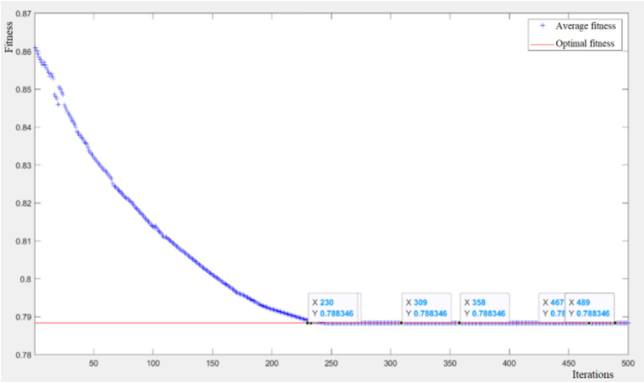


Figure 11. Fitness curve of scheme 1.

Table 5. The completion time of each process in scheme 1.

Component sequence	Completion time of each process (h) N1	N2	N3	N4	N5	N6	N7
4	1.2	2.3	3.1	15.1	25.0	25.4	37.4
10	2.2	3.3	3.7	15.7	25.5	26.0	38.0
5	3.4	4.5	5.3	17.3	26.5	26.9	38.9
8	4.9	6.4	6.8	18.8	27.5	27.9	39.9
13	6.1	7.5	8.3	20.3	28.5	28.9	40.9
1	2.5	4.0	4.4	16.4	25.0	25.4	37.4
11	4.0	5.5	5.9	17.9	26.0	26.4	38.4
6	26.2	27.3	28.1	40.1	49.0	49.4	61.4
2	27.7	29.2	29.6	41.6	50.0	50.4	62.4
12	28.2	30.0	30.3	42.3	50.3	50.6	62.6
3	29.0	30.9	31.2	43.2	50.6	50.8	62.8
9	26.5	28.0	28.4	40.4	49.0	49.4	61.4
7	27.3	28.9	29.2	41.2	49.3	49.6	61.6

4.2. Dynamic anomaly rescheduling

4.2.1. Order change

It was assumed that the initial scheme 1 had been begun, and the material allocation had been completed, and the first process of component 1 had just been completed. The order 1 changed at t = 2.5 h requiring the delivery time of component 12 to be 60 h ahead.

In this case, OA changed the code of component 12 to 04-A-01-01-05-57.5. At this point, the event is identified by the RMA as an anomaly type related to the early delivery date and is reported to the TMA for rescheduling decisions, including selection of the assembly line, rescheduling calculations for the SA, and evaluation of the rescheduling plan. Once SA and TMA collaborate to make decisions and generate the optimal rescheduling plan, they negotiate with ALA for allocation and proceed with component production. The total idle time was ranked as $f^4{}_{WI} > f^3{}_{WI} > f^1{}_{WI} > f^2{}_{WI}$. Because the delivery time of component 12 was 60 h ahead, and T_j was calculated to be 2.6 h which was less than f^{4}_{WI}, so assembly line 4 was selected for rescheduling according to Section 3.5.

The result of running algorithm code in Matlab2021b with these constraint parameters modified and the weights of optimization objectives unchanged is shown in Table 6 and Figure 12. The scheduling scheme on assembly line 4 was 12-2-6-3, and the maximum completion time was 62.9 h, with 0.1 h more than the maximum completion time of the initial scheme, which met the delivery time of component 12.

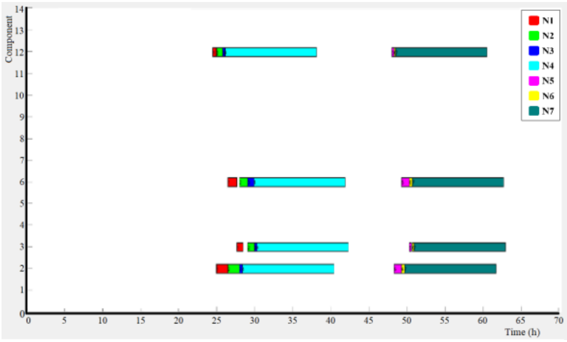


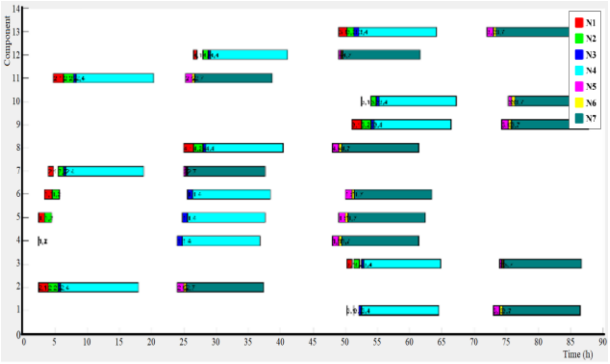
Figure 12. Rescheduling scheme of assembly line 4 (in Matlab 2021b).

Table 6. The rescheduling scheme on assembly line 4.

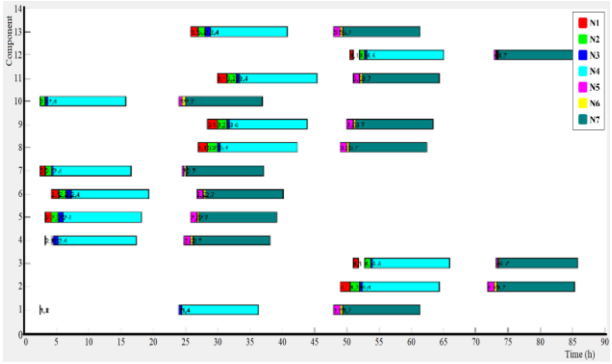
Component	Completion time of each process (h)						
sequence	N1	N2	N3	N4	N5	N6	N7
2	26.5	28.0	28.4	40.4	49.3	49.7	61.7
3	28.5	30.0	30.3	42.3	50.6	50.9	62.9
6	27.7	29.1	29.9	41.9	50.3	50.7	62.7
12	25.0	25.8	26.1	38.1	48.3	48.5	60.5

4.2.2. Equipment fault

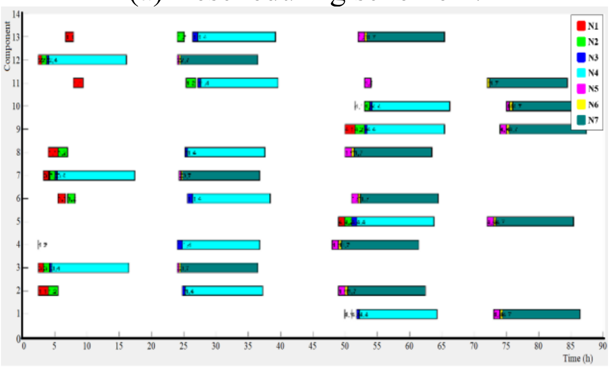
It was assumed that at the time t_1 = 2 h in initial scheme 1, the concrete mixer on assembly line 1 failed unpredictably, and the concrete pouring had not started at that time. After 0.5 h maintenance, the device was expected to be completely repaired after 5.5 h. The rescheduling time t_0 was 2.5 h, and the equipment recovery time t_2 was 8 h, $S(J_{l,j}, N_{1,3}) \geq 24$ h. When a machine failure occurs, the concrete pouring process cannot be executed. The corresponding parameters of the EAs change, and their operational status switches to a “fault” state. This event is identified by the RMA as a machine failure anomaly type. The RMA notifies the relevant ALA1 of the failure of EA13 and reports it to the TMA for rescheduling decisions. The feasible rescheduling schemes of running algorithm code in Matlab 2021b is shown in Table 7 and Figure 13. Rescheduling evaluation was calculated according to Equation (24), and TMA finally determined Scheme 4 considering the maximum completion time and rescheduling cost.



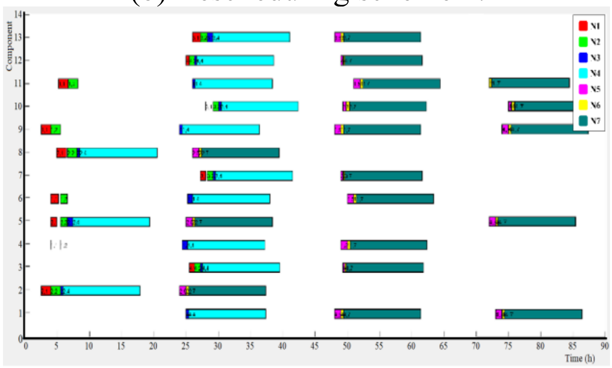
(a) Rescheduling scheme 1.



(b) Rescheduling scheme 2.



(c) Rescheduling scheme 3.



(d) Rescheduling scheme 4.

Figure 13. Feasible rescheduling schemes under equipment fault (in Matlab 2021b).

Table 7. The feasible rescheduling schemes under equipment fault.

Scheme	Assembly number	Component sequence	Completion time (h)	Maximum completion time (h)
1	1	4-5-6	63.4	88.3
	2	2-7-11	38.7	
	3	13-1-3-9-10	88.3	
	4	8-12	61.6	
2	1	1	61.4	85.8
	2	10-7-4-5-6	40.2	
	3	13-8-9-11	64.4	
	4	2-12-3	85.8	
3	1	4-2-8-6-13-11	84.4	88.0
	2	12	36.5	
	3	3-7	36.8	
	4	5-1-9-10	88.0	
4	1	9-4-6-11	64.4	64.4
	2	2-5-8	39.4	
	3	13-7-10	62.3	
	4	1-12-3	61.8	

5. Conclusion

The production of prefabricated components (PC) presents unique challenges compared to traditional manufacturing processes, primarily due to their increased complexity, highly customized designs, variable production scales, and strict quality requirements. Conventional factory management methods, which rely on standardized processes and predictable workflows, are insufficient to address these demands. In PC production, scheduling must adapt to dynamic conditions such as order changes and equipment faults, while decision-making requires real-time data and adaptive strategies to manage frequent disruptions like mold shortages and equipment failures. To tackle these issues, this study integrates a hybrid-driven dynamic scheduling and rescheduling model based on swarm-intelligence collaboration, enhancing flexibility and reducing downtime through real-time monitoring and decentralized negotiation mechanisms. The introduction of the Dynamic-Interval Cooperative Strategy (DISA) further addresses limitations of conventional Contract Net Protocol (CNP), such as excessive traffic and local optimization, by shifting from centralized to decentralized negotiation. Comparative simulations using MATLAB demonstrate that the improved model significantly reduces total production time and improves cost efficiency in rescheduling compared to traditional mathematical models and manual decision-making. By applying this framework to a real-world factory in China, the study highlights its practical value in improving production efficiency and addressing challenges unique to modern PC manufacturing, providing both theoretical insights and actionable solutions for the industry.

(1) Based on the SI collaboration, a dynamic scheduling and rescheduling model for the PC production is established. The entities and logic of PC production are mapped into eight agents Order Agent (OA), Equipment Agent (EA), Assembly Line Agent (ALA), Task Agent (TA), Task Management Agent (TMA), Scheduling Agent (SA), Process Agent (PA), and Real-time Monitoring Agent (RMA). The module functions and interaction relations of each agent are defined, and the uncertain interference events in the production process are analyzed and classified, and the rescheduling mechanism based on hybrid drive is designed.

(2) This model defines the coding principles of different PC components, and then introduces the concept of DISA, which changes the centralized negotiation to decentralized negotiation mode. The dynamic time window mechanism is introduced to the calculation queue to avoid the local optimization of the feasible schemes, aiming at the disadvantages of the traditional CNP mechanism such as excessive traffic, vicious competition and local optimization.

(3) Based on the TCH decomposition strategy, a multi objective and multi constraint optimization model without interference is constructed. Besides, under the hybrid drive mechanism, different rescheduling evaluation functions and corresponding strategies are constructed for different types of interference events.

(4) The scheduling schemes and the rescheduling schemes were obtained by taking the actual production of a factory as an example under three conditions: no interference, order change, and equipment fault, in Matlab 2021b. Compared to manual decision-making, the solutions obtained from the SI collaboration model based on improved CNP and TCH decomposition strategies are automatic and can save over 20% of total production time.

6. Limitation

This study only provides feasibility and confirmatory experiments for the application of swarm intelligence management concept in prefabricated component factories. The calculation results are generated under the assumptions, however, there are some assumptions which can make the model more applicable are not considered. For example, more constraints and objectives. Additionally, this study conducted experiments within the scope of its limitations and cannot represent results in larger or more diverse factory settings. Some calculation parameters are determined according to the actual production experience in the survey results, which may vary in different regions or production conditions. Therefore, the model maybe needs to be adjusted for other products or different production environment conditions.

For future research, it is a good idea to expand the research on the processing of PC components under completely different production modes, and more excellent algorithms should be tried to solve similar problems, which is also another direction. In addition, quantifying more production factors, such as the time and losses associated with mold replacement, worker efficiency, and differences in costs for various components in the storage area, can facilitate more precise calculations and optimization. Integrating the model and algorithm with existing factory management systems, such as ERP and MES, is another direction to provide a more comprehensive and advanced management system.

Acknowledgements

The authors gratefully acknowledge the financial support provided by the “National Key Research and Development Program of China (2022YFC3803600)”, and the “National Natural Science Foundation of China (72071043)”.

Conflicts of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors’ contribution

Conceptualization, S.L.; Methodology, S.L.; Formal analysis, S.L.; Writing - original draft, S.L. and G.C.; Data curation, C.P.; Visualization, C.P., G.C. and Z.X.; Writing - review & editing, C.P., Y.L. and Z.X.; Investigation, Y.L.; Supervision, Z.X. All authors have read and approved the final manuscript and agree with the order of authorship.

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