

Multi-dimensional Manufacturing Resources of Workstations and Workers are Collaboratively Optimized for Dynamic Scheduling Technology

Ning Shang

Tianjin University of Technology and Education, Tianjin, China

ABSTRACT

Multi-dimensional manufacturing resources of workstations and workers are collaboratively optimized scheduling technology. A dynamic scheduling model is constructed for the common dynamic disturbances such as equipment failure, worker absenteeism and emergency order insertion in the actual production process. By analyzing the influence range of disturbance events on the production plan, a local rescheduling mechanism based on the affected process set is proposed, and the strategy of combining event-driven and periodic rescheduling is adopted, and the improved APSO algorithm is used to quickly repair and re-optimize the production plan after disturbance. The deviation of the new scheme from the original production plan is reduced, and the robust operation of the production system in a dynamic environment is realized.

KEYWORDS

Adaptive Particle Swarm Algorithm; Dynamic Scheduling; Multi-resource Collaboration and Optimization.

1. INTRODUCTION

In the actual production environment, the scheduling system often faces various uncertainties, such as equipment failures, worker absences, urgent order insertion, process changes, etc. These disturbances can disrupt the original static scheduling plan, leading to reduced production efficiency and delays in delivery times. Therefore, it is of great significance to study dynamic scheduling technology with real-time response ability to improve the robustness and adaptability of complex equipment manufacturing systems. Based on Chapters 3 and 4, this chapter further introduces dynamic disturbance events, constructs a dynamic scheduling model for the collaborative optimization of multi-dimensional manufacturing resources between stations and workers, and proposes a dynamic scheduling strategy based on the improved APSO algorithm. Sudden disturbances such as temporary order insertion and machine tool equipment failure often occur in the workshop. Once such unpredictable events occur, they often disrupt the original production plan and schedule, which in turn affects the achievement of production goals and has a significant impact on the production efficiency of the workshop and the stability of system operation. It may even lead to a rapid decline in the performance indicators of the existing scheduling scheme, making the overall scheme unfeasible. Therefore, when formulating and optimizing scheduling strategies, various uncertain disturbances must be fully considered in order to more effectively respond to the scheduling needs in the real production environment. The dynamic scheduling of flexible workshops under disturbance conditions has received widespread attention in recent years, and related research has been deepened, and many scholars at home and abroad have carried out a lot of research in this field.

For different types of dynamic perturbation events and optimization goals, scholars at home and abroad have proposed diversified modeling and solution methods. Considering multiple types of disturbances and comprehensive factors: Baykasoğlu et al[1] established a comprehensive scheduling model for production and maintenance under the event-driven rescheduling strategy, which considered various dynamic events such as new order arrival, machine failure, urgent order, order cancellation, and delivery date change, and used a greedy stochastic adaptive search algorithm to solve the problem. Li et al.[2] designed a rescheduling method based on Moncaroso's algorithm for four disturbance events: new job arrival, machine failure, job cancellation, and job processing time change. Li et al[3] studied the dynamic scheduling of insufficient transportation resources, established a multi-objective optimization model with the goal of minimizing completion time and total energy consumption, and developed a hybrid deep Q-network solution. Zhang et al[4] deep reinforcement learning method to learn adaptive trigger strategies in a multi-robot multi-station system, and used an improved artificial bee colony algorithm to redistribute robots. Focusing on specific perturbation events and the application of advanced algorithms, such as insertion orders/new orders: Zhang et al.[5] established a dynamic scheduling model for insertion orders and designed a two-stage genetic programming hyperheuristic algorithm with feature selection. Luo[6] aims to minimize total delay and uses Deep Q-network to solve the dynamic scheduling problem under new order insertion. Wang et al[7] established an energy-saving model that minimizes the impact of completion time and total machine load on total energy consumption, and proposed an improved NSGA-II algorithm for emergency order insertion and machine failure. Machine/equipment failure: Zhang et al[9] established a dynamic scheduling model with fuzzy delivery time based on machine failure as a disturbance, and proposed an improved immunogenetic algorithm. Zhang et al.[9] used event-driven execution rescheduling and optimized the perturbation model considering machine failure using the improved Drosophila algorithm. Jiang Fei et al[10] Under the ambiguity of the delivery time, the machine failure is used as the interference to form a multi-objective problem to maximize customer satisfaction, and the gray wolf optimization algorithm is used to solve it. Processing time change: Based[10] proposed a heuristic model that considers worker efficiency, machine settings, and other factors to minimize the completion time.

2. PROBLEM DESCRIPTION AND MATHEMATICAL MODELING

2.1. Dynamic Perturbation Event Analysis

Machining equipment failure: In the process of workshop production and processing, machining equipment failure is a common dynamic disturbance event, which is manifested as the situation that one or more machining equipment cannot work normally when idle or in use. The start time of the fault is usually a known parameter, which can be obtained through monitoring systems or manual records, and the end time of the fault can be predicted based on maintenance experience or equipment status. If the fault occurs during the idle period of the equipment, all planned machining operations after the disturbance node will be affected, and the scheduling plan needs to be readjusted according to the recovery time of the equipment. If the fault occurs during the use of the equipment, the process being processed on the machine will be forced to be interrupted, resulting in the workpiece being not completed. At this time, the interrupted process should be rearranged as a new process, the related processes before and after the interrupted workpiece should be deleted, and the affected process should be defined as the sum of all processes after the disturbance time and the new rework process.

Worker absenteeism: Worker absenteeism is a dynamic disturbance event caused by human factors, manifested as the operator's inability to arrive at the post within the planned time or leave the post midway, resulting in a temporary decrease in production capacity. The start time of absence is usually known and can be determined by the attendance system, while the time to return to work can be predicted or estimated based on actual conditions. If a worker is absent during idle hours, all operations under the responsibility of that worker after the disturbance node need to be reassigned to

other workers, or the production sequence must be adjusted to ensure production continuity, so the affected process is all related operations after the disturbance time. If a worker is absent during a job, the current process will be interrupted, the process will need to be rescheduled, and the subsequent process for which the worker is responsible will also be rescheduled. Therefore, the affected processes include all processes after disturbing the node and those that need to be reworked due to interruptions. Overall, worker absenteeism can lead to unstable production rhythms and unbalanced resource allocation, which can cause production delays and increased scheduling complexity, adversely affecting overall production efficiency.

New workpiece insertion: New workpiece insertion is another common type of dynamic disturbance in the production floor, usually due to the emergence of urgent customer needs or temporary orders, requiring the insertion of new workpieces into the original production plan. The basic parameters of the new workpiece, such as the insertion time, quantity and route, are known. The perturbation node of such a perturbation event represents the moment when a new artifact is inserted. Its scope of influence is mainly all operations after this moment, as well as all processes of new workpieces. Since the insertion of new workpieces takes up machining resources and station time, the machining sequence, batch and completion time of the original workpiece may change. To mitigate the impact of disturbances, dynamic scheduling algorithms are often used to replan the sequence of process execution, balancing equipment load and machining priorities to ensure that new workpiece delivery deadlines are met while minimizing disruption to the original plan.

2.2. Mathematical Modeling

Another difficulty is to establish a mathematical model and its handling mechanism to deal with a variety of production disturbance events. At the same time, in order to solve the problem better and more rigorously, the question puts forward the following assumptions:

- (1) All machining equipment is available at the time of disturbance;
- (2) All processing personnel are available at the time of disturbance;
- (3) All affected processes can be processed at the moment of disturbance;
- (4) The processing time required for the same process on different equipment is the same;
- (5) There is no sequence constraint between processes belonging to different workpieces;
- (6) One machine can only process one process at the same time;
- (7) A processing person can only operate one equipment at the same time;
- (8) Any machining sequence cannot be interrupted during processing until the process is completed;
- (9) Regardless of the time required for process turnover;
- (10) The proficiency coefficient of the processing personnel is known;
- (11) The assembly relationship between a single small order is known, and the assembly time is also determined;
- (12) The lead time due to product model changes is known.

(1) Order-related parameters

Order Collection: $J_i = \{J_1, J_2, \dots, J_n\}$ where n is the order quantity;

d_i : is the delivery J_i date of the order;

Sub-order collection: $S_{J_i} = \{S_{J_{i1}}, S_{J_{i2}}, \dots, S_{J_{ih}}\}$ where h is J_i the number of sub-orders of the order;

Sub-order manufacturing unit assignment: S_{jik} Represents J_i k the manufacturing unit assigned to the first sub-order of the order, where $S_{jik} \in U$.

(2) Resource-related parameters

Collection of processing equipment: $M = \{M_1, M_2, \dots, M_m\}$ where m represents the number of processing equipment or stations;

Manufacturing Unit Set: $U = \{1, 2, 3\}$, where 1 represents the antenna manufacturing unit; 2 indicates the seeker manufacturing unit; 3 represents the full ammunition (final assembly) manufacturing unit;

Worker set: $W = \{W_1, W_2, \dots, W_l\}$, l which is the total number of workers;

Worker proficiency coefficient: $Sk_w \in [0.8, 1.4]$ The smaller the coefficient, the higher the skill level of the worker;

Available Worker Collection: $W_{ij} \subseteq W$, indicates J_i j the worker set that can be assigned to the order process;

MS: The collection of available equipment for the operation in the S phase.

(3) Process-related parameters

Actual processing time: $Q_{ijw} = Q_{ij} \cdot Sk_w$ which Q_{ij} is the J_i j theoretical processing time of the first process of the order, Q_{ijw} which is the actual processing time after considering the proficiency of the worker;

O_{ij} : J_i The first process of the j order $j=1, 2, 3 \dots G_i$, which G_i is the J_i number of processes included in the order;

Process Stage Collection: $S = \{1, 2, \dots, s\}$ s , represents the total number of stages;

P_{ijs} : J_i The s processing or assembly time of the process in the stage of the order;

R_{ij} : The J_i preparation time for orders in the manufacturing unit due to model changes;

Model construction

Based on the above assumptions and symbols, a mathematical model can be established as follows:

$$\text{Min} : C_{\max} \quad (1)$$

$$\text{Min} : D \quad (2)$$

The two scheduling objectives that represent the problem are to minimize the maximum completion time for all orders and minimize the total delay of all orders, respectively.

$$C_i = \max_{j=1, \dots, r_i} (T_{ij} + P_{ij}) \quad (3)$$

$$C_{\max} = \max_{i=1, \dots, n} (C_i) \quad (4)$$

The formula(3) and sum (4) give the specific calculation method for the maximum completion time for all orders.

$$T_i = \max \{0, C_i - d_i\} \quad (5)$$

$$T_i = \max \{0, C_i - d_i\} \quad (6)$$

$$D = \sum_{i=1}^n T_i \quad (7)$$

The formula(6) and sum (7)give the specific calculation method for the total extension of all orders.

$$Z = \alpha \cdot C_{\max} + (1 - \alpha) \cdot D \quad (8)$$

The expression (8)represents the weighted sum of the maximum completion time and total delay, where the α is the weight factor used to balance the maximum completion time and the total delay.

(4) Set constraints

The constraints considered in this section are: resource constraints, process constraints, unit selection constraints, assembly manufacturing unit constraints, single-piece unitized flow constraints, assembly cascade constraints, and preparation time constraints based on product model. Here is the specific constraint build.

$$t_{i(j+1)} \geq t_{ij} + p_{ij} \quad \forall i, j \quad (9)$$

$$\sum_{u \in U} z_{ik}^u = 1 \quad \forall i, k \quad (10)$$

$$\sum_{m \in M} x_{ijm} = 1 \quad \forall i, j \quad (11)$$

$$\sum_{i \in J} \sum_{k \in S_{ji}} x_{ijq} \leq 1 \quad \forall q, t \quad (12)$$

$$TS_{Jik} \geq PS_{Ji'k'} \quad \forall i, k, i', k' \quad (13)$$

$$TS_{Jik} \geq PS_{J(i+1)k} + R_{ij} \quad \forall i, k \quad (14)$$

$$\sum_{w=1}^l y_{ijw} = 1, \quad \forall i, j \quad (15)$$

$$S_{ij} + Q_{ijw} \leq S_{ij'} + M(1 - z_{ijj'}), \quad \forall i, j, i', j', w \quad (16)$$

$$0.8 \leq SK_w \leq 1.4 \quad (17)$$

The expression (9)represents the process sequence constraint: for any two adjacent processes of the order, the start time of the latter process must be strictly greater than or equal to the completion time of the previous process; The expression(10) represents the unit selection constraint, and the sub-order of each order can only be assigned to one manufacturing unit; The expression (11)represents the single-piece unitized circulation constraint, and the sub-order of each order must complete the processing in the single-piece circulation mode. The formula (12)represents the constraints of the mixed flow manufacturing unit, which contains several stages, and the resources of each stage cannot be allocated to multiple tasks at the same time. The expression (13)represents the assembly cascade constraints: there is a cascading assembly constraint relationship between products, and the sub-order is the key material order of another sub-order, that is, the start of another sub-order needs to be conditional on the completion of the sub-order; Expression(14) Preparation Time Constraint: If the product model of the order changes, the preparation time needs to be added. The formula (15)represents the assignment constraints of machining personnel and equipment: each operation must be assigned to a worker for machining. The formula(16) represents the process constraint for each worker: each worker can only process one process at a time. The expression(17) limits the constraints of workers' proficiency.

This chapter adds the corresponding dynamic disturbance constraints of machining equipment on the basis of Chapter 4, and the dynamic disturbance constraint model is as follows:

$$T_{ij} = OT_{ij}, \forall K_{ij} = 0 \quad (18)$$

$$X_{ijm} = OX_{ijm}, \forall K_{ij} = 0, \forall m \quad (19)$$

$$Y_{ijw} = OY_{ijw}, \forall K_{ij} = 0, \forall w \quad (20)$$

The formula(18) indicates (20)that all machining sequences that start before the disturbance node, the processing time, processing equipment and processing workers in the new scheme are consistent with the original scheme.

$$(T_{ij} - RT) \cdot (T_{ij} - AS_m) \cdot X_{ijm} \geq 0, \forall i, j, m \quad (21)$$

$$(P_{ij} - RT) \cdot (P_{ij} - AS_m) \cdot X_{ijm} \geq 0, \forall i, j, m \quad (22)$$

$$(T_{ij} - RT) \cdot (T_{ij} - AS_l) \cdot Y_{ijl} \geq 0, \forall i, j, l \quad (23)$$

$$(P_{ij} - RT) \cdot (P_{ij} - AS_l) \cdot Y_{ijl} \geq 0, \forall i, j, l \quad (24)$$

The formula(21) means (22)that if the process O_{ij} is processed on the equipment M_m , the start time of processing and the time of the processing conclusion cannot be within the equipment failure time period (if there is no fault, the inequality is still true), the formula(23) means(24) that if O_{ij} the processing equipment of the process is operated by the worker W_l , then the processing start time and the end time of the process cannot be in the time period of personnel absence (if there is no personnel absence, the inequality is still valid).

$$T_{ij} + P_{ijs} = P_{ij}, \forall i, j, s \quad (25)$$

$$T_{ij} + P_{ijs} = P_{ij}, \forall i, j, s \quad (26)$$

$$OT_{ij} + P_{ijs} = OP_{ijs}, \forall i, j, s \quad (27)$$

$$P_{ijs} = [Q_{ij} \cdot SK_w \cdot X_{ijm} \cdot Y_{ijl}], \forall i, j, m, l, s \quad (28)$$

The equation(25) sum (26)describes the numerical relationship between the machining start time, machining end time and machining time of the machining sequence in the old and new schemes. The actual(28) processing time of the process is the product of O_{ij} the processing hours and the experience coefficient of its single piece SK_w . If the O_{ij} processing equipment fails before the process is completed, the processing time of the current process in the new scheme will no longer be [32] calculated as shown in the formula, depending on the equipment and processing personnel arranged in the unfinished part.

2.3. Dynamic Scheduling Technology based on Improved APSO Algorithm

There are significant differences between the single-piece circulation-multi-dimensional resource-dynamic scheduling problem studied in this chapter and the single-piece circulation-multi-dimensional resource scheduling problem discussed in Chapter 5. Chapter 5 takes all processes of all orders as the scheduling object, which belongs to global static scheduling; However, this chapter only partially adjusts the affected processes that change under dynamic disturbances, so it belongs to the dynamic scheduling optimization problem of some processes. In order to adapt to this dynamic

environment, this chapter proposes a coding strategy for affected processes. As shown in Figure 1. Under the premise of maintaining the original coding structure, the strategy only labels the genes corresponding to the affected processes to indicate that they need to reallocate processing resources in the decoding stage. Unlabeled genes are considered to remain unchanged in the original processing plan and do not need to be decoded. Compared with the traditional full-process coding, the proposed method improves the local search efficiency in dynamic scheduling without destroying the overall sequence structure. In the process of decoding, this chapter adopts the resource allocation method based on the proficiency coefficient of processing personnel, and selects equipment, allocates processing personnel and calculates the machining sequence time for the affected processes to be marked gene by gene, so as to ensure the feasibility and rationality of the local adjustment process. Then, combined with the POX cross-operator and adaptive probabilistic inheritance strategy proposed in Chapter 4, the APSO algorithm is introduced to carry out global optimization to obtain the optimal scheduling scheme in the dynamic environment.

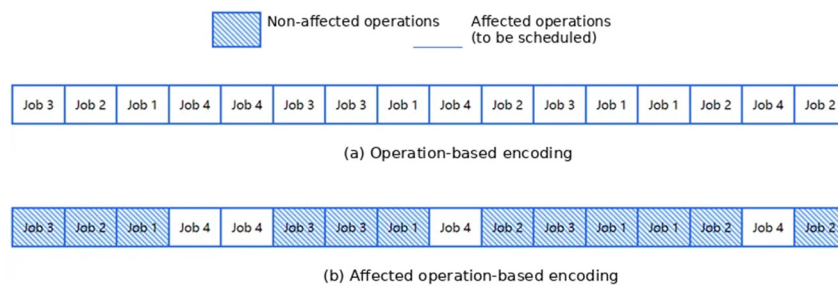


Figure 1. Process-based coding vs. affected process-based coding

2.4. Instance Verification and Result Analysis

2.4.1. Experimental Data Preparation

Table 1. Detailed data of test examples

Case	n	nmac	nman	nop	meq	proc	ptm	del	pmac	pman
HFS1	5	18	16	12	[2,3]	[12,45]	10	[400,420]	[2,3]	[0.8,1.5]
HFS3	10	24	26	15	[2,3]	[12,45]	20	[805,860]	[3,4]	[0.8,1.5]
HFS5	20	24	26	15	[3,6]	[12,50]	20	[1405,1460]	[3,6]	[0.8,1.5]

In order to verify the rationality of the dynamic scheduling problem model of the collaborative optimization of multi-dimensional manufacturing resources of the constructed workstation and workers, and to improve the feasibility and effectiveness of the APSO optimization algorithm to solve the problem, this chapter uses the pycharm software running on Windows 11 system as the simulation environment and Python as the code language, and takes the comprehensive scheduling goal of dynamically measuring the maximum machining time and the maximum completion time of all scheduling as the objective function. At the same time, different sudden disturbance events are brought into the model to verify their feasibility. The initial population size is set to 150, and the maximum number of iterations is set to 200, considering that the relative difference of weights is smaller, the stronger the comprehensive ability of individuals, this section will schedule the weight of the target^a Set to 0.5. Therefore, this paper uses the improved HFS1-HFS6 cases designed in Chapters 3 and 4 as the source of example data for relevant verification. where "njob" indicates the number of orders; "nmac" indicates the number of processing equipment; "nman" indicates the number of handlers; "nop" indicates the number of jobs in the order; "meq" indicates the range of optional processing equipment for each process; "proc" indicates the processing time frame for each process; "PTM" indicates the lead time due to the change in the order model; "del" indicates the range

of time when the order will be delivered; "PMAC" is the range of the number of machining personnel that can be selected for each machine; "pman" indicates the range of proficiency levels of each machining person. Take one each of HFS1, HFS3 and HFS5 as the original operation plan. The data information is shown in Table 1.

2.4.2. Experimental Results and Analysis

In this section, different disturbance events are brought into the scheduling model to test their feasibility and rationality, and three sudden disturbance events are introduced on the basis of the improved HFS1, including equipment failure, worker absenteeism and emergency insertion of new workpieces. The specific sudden disturbance information is shown in Table 2 below:

Table 2. Specific sudden disturbance information

Sudden disturbances	Details
Equipment failure	A random selection of failures occurs from all machining equipment, divided into idle and machining
Worker absenteeism	Absences occur at random from all processing personnel
New order insertion	In the old scheme, a random order is selected and a new workpiece is inserted at the moment of 100

After bringing in various sudden perturbations, the APSO algorithm is used to solve them 10 times, and the best verification results are selected for comparison with the old scheme. The experimental results mentioned above confirm the accuracy and feasibility of the model constructed in this chapter in dealing with a variety of perturbation events. In order to further test the ability of the improved adaptive particle swarm algorithm to cope with dynamic disturbances in the model constructed above, this section takes worker absenteeism as an example, and uses the standard PSO algorithm, standard GA algorithm and the improved APSO algorithm to solve the cases of HFS1, HFS3 and HFS5 used in this chapter 10 times, and compares the best comprehensive target scheduling value iteration curves. The population size is set to 150 and the number of iterations is set to 200. The iteration curve of the comprehensive scheduling target value is shown in the following figure 2, figure 4, figure 5.

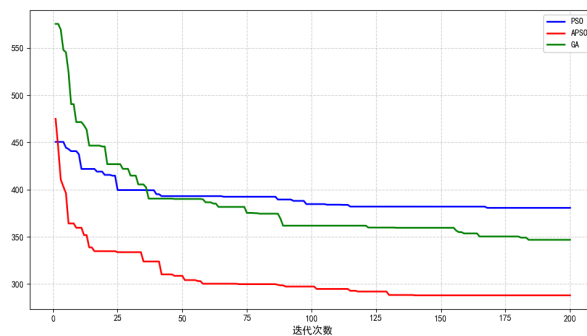


Figure 2. Solve the HFS1 iteration curve of dynamic scheduling case

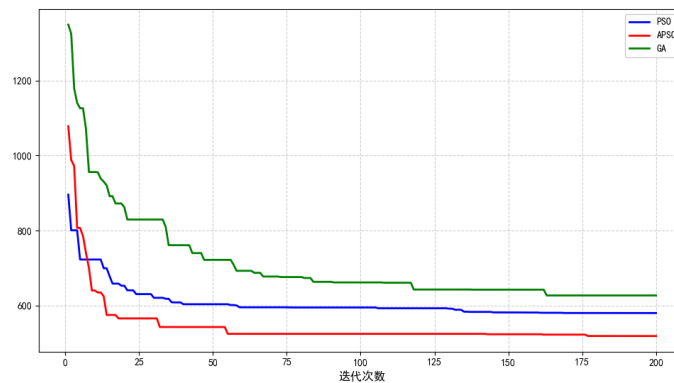


Figure 3. Solving the HFS3 iteration curve of the dynamic scheduling case

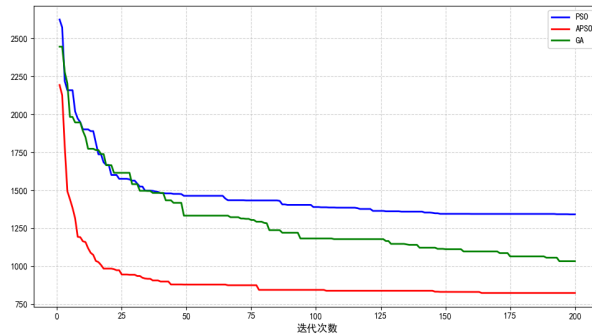


Figure 4. Solving the iteration curve of HFS5 in the dynamic scheduling case

From Figure. 2, 3 and 4 above, it can be seen that in the introduction of dynamic perturbations on a small, medium and large scale, the quality of the solution of the improved adaptive particle swarm algorithm fluctuates in the early stage of iteration, but with the increase of the number of iterations, the optimal scheduling target value that can converge is better than the standard PSO algorithm and the standard GA algorithm. With the increase of case scale, the optimal scheduling objective function value obtained by the improved adaptive particle swarm algorithm is significantly better than that of the standard PSO algorithm and GA algorithm.

3. SUMMARY

This chapter studies the dynamic scheduling technology of multi-dimensional optimization of manufacturing resources between stations and workers, and focuses on how to effectively adjust production scheduling under dynamic disturbance events. In view of the common disturbances such as machining equipment failure, worker absenteeism and new workpiece insertion, a dynamic scheduling model for multi-dimensional resource collaborative optimization is constructed, and a scheduling strategy based on the improved APSO algorithm is proposed. The model can achieve local adjustment in a dynamic environment, and by optimizing only the disturbed processes, it ensures the effective use of resources in the scheduling process and reduces the impact on the original scheduling plan. In order to verify the effectiveness of the model, a number of experimental cases are designed to optimize the scheduling by introducing different dynamic disturbance events and using the improved APSO algorithm. Experimental results show that the improved APSO algorithm can effectively adjust the scheduling scheme, minimize the maximum completion time and total delay, and ensure the balance between production schedule and delivery time when dealing with disturbances such as equipment failure, worker absenteeism and new workpiece insertion. At the same time, the improved scheduling scheme is less different from the original plan, which effectively avoids the waste of resources caused by dynamic adjustment.

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