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DYNAMIC SCHEDULING OF MULTI-AGENT ELECTROMECHANICAL PRODUCTION LINE BASED ON BIOLOGICAL ITERATIVE ALGORITHM

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Abstract. In order to solve the dynamic job scheduling problem in current intelligent machining systems, the author proposes a multi-agent electromechanical production line dynamic scheduling based on iterative algorithms. The author designed a collaborative control method for hybrid micro assembly production lines based on multi-agent technology. Firstly, a mathematical model is used to describe the collaborative control objectives of the production line, and a hybrid micro assembly production line information collection and integration framework is constructed to obtain production line information. By combining the dynamic coordination performance of multi-agent technology, a collaborative control model for production lines is constructed, with the goal of minimizing processing costs as the collaborative control objective. The optimal collaborative control scheme is solved to achieve collaborative control of hybrid micro assembly production lines. The experimental results show that compared with traditional methods, the collaborative control task allocation time obtained by applying this method is shorter, with a minimum value of 15.38 seconds, indicating that this method has higher efficiency in collaborative control of production lines. Compared with traditional methods, the collaborative control task allocation time after applying this method is shorter, effectively reducing the production line processing cost, proving the feasibility of this method.

Key words: Multi Agent technology, Production line, Scheduling, Collaborative control, Mixed Microassembly

1. Introduction. With the development of market economy, manufacturing enterprises are facing a series of challenges. Customers have increasingly high requirements for product quality, and product prices have decreased due to competition. It is urgent for enterprises to reduce production costs and enhance their competitiveness [1]. Production scheduling is an important part of manufacturing systems. Properly handling workshop scheduling problems can save a lot of manpower and material resources for enterprises, enable manufacturing equipment and resources to be more fully utilized, improve production efficiency, and enhance competitiveness. Meanwhile, as the workshop production scheduling problem is a typical NP hard problem, its research has high theoretical and practical significance [2]. With the rise of industrial transformation and technological revolution, intelligent manufacturing has emerged and rapidly developed, becoming one of the main development trends in the current manufacturing industry [3]. The core of intelligent manufacturing is the research and application of intelligent sensing and control equipment, high-end CNC machine tools, and major complete sets of equipment. Smart production lines are one of the main achievements of intelligent manufacturing, which effectively combines intelligent factories with digital workshops and has been widely applied in the manufacturing industry, such as automotive manufacturing, electronic manufacturing, etc. [4]. The production line has advantages such as large-scale production, high efficiency, and low cost, and has become one of the key research directions for the development of national manufacturing industry today.

The development of modern manufacturing industry is very rapid, and the complexity of manufacturing products has also increased, which has put forward higher requirements for production lines [5]. The hybrid micro assembly production line has emerged, which mainly uses hybrid micro assembly technology to connect multiple devices with high density, making the production line develop towards lightweight, miniaturization, high reliability, and low cost trends. The application of hybrid micro assembly technology has reduced the scale of production lines, accelerated work efficiency, and improved intelligence level, providing strong assistance for the development of manufacturing industry [6]. At the same time, the internal structure of the production

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line has become more complex, posing significant challenges to the control performance of the production line [7]. The concept of Agent originates from the field of artificial intelligence, and its derived Agent technology is an effective way to solve distributed application problems, which has been widely applied in many fields [8]. Agent is a fundamental component of MAS, and the structure and function of Agent itself, as well as the negotiation mechanism and organization method between Agents, have a direct impact on the performance of MAS. Therefore, building an agent with clear functions, reasonable structure, and efficient communication is the fundamental and key step in studying the dynamic scheduling method of flexible manufacturing based on MAS [9].

2. Literature Review. Under the trend of transforming production organization from a static centralized hierarchical structure to a dynamic distributed network structure, manufacturing systems exhibit new characteristics such as dynamics, complexity, and autonomy. As an application of artificial intelligence, Multi Agent System (MAS) is considered one of the most promising methods for implementing intelligent manufacturing systems and has received widespread attention from scholars both domestically and internationally. In a multi-agent system, agents can autonomously respond to their environment, and each agent is interconnected through distributed and loosely coupled organizational methods, ultimately optimizing the local or global goals of the system through negotiation. The application of multi-agent technology in production scheduling research can enhance the overall scalability and robustness of manufacturing systems, achieve the informatization of production management, and thereby improve production efficiency, safeguarding the transformation and upgrading of the manufacturing industry [10]. Ying, K. C. et al. proposed a mixed integer linear programming (MILP) model and a new metaheuristic algorithm called reinforcement learning iterative greedy (RLIG) algorithm to minimize the completion time of the problem [11]. Duan, W. et al. proposed a constructive greedy heuristic algorithm to efficiently generate and reconstruct solutions to problems. A self-adaptive destruction method has been developed to improve the early development capability of the algorithm and maintain exploration capability in the later stage [12]. Zhou, B. et al. proposed a multi-stage dynamic scheduling algorithm. In the first stage, the static material allocation scheduling problem is decomposed into three sub optimization problems, and dynamic programming algorithms are used to jointly optimize the sub problems to obtain the optimal initial scheduling plan. The superiority of the proposed dynamic scheduling strategy and algorithm was verified through comparative experiments with periodic distribution strategy (PD) and direct insertion method (DI) [13]. Yuan, Z. et al. designed an automatic material scheduling method for industrial production lines based on the FL-NET network. The material scheduling process was divided into two parts: preparation and delivery, and an automatic monitoring platform was established using the FL-NET network structure [14].

The author takes the optimization of Agent electromechanical production line scheduling as the research object. Based on the current difficulties and challenges in the manufacturing industry, an iterative algorithm is used to construct an Agent electromechanical production line scheduling optimization model. The research results aim to provide support for manufacturing enterprises to achieve flexible and intelligent scheduling of production lines, improve production efficiency, adapt to rapidly changing market demands, and promote the manufacturing industry to achieve a more stable position in global competition. The author proposes a dynamic scheduling of multi-agent electromechanical production lines based on iterative algorithms.

3. Method.

3.1. Description of Production Line Scheduling Problems. For hybrid micro assembly production lines, the collaborative control objective refers to the production line scheduling problem. In order to improve the collaborative control effect of the production line, a mathematical model is used to describe the production line scheduling problem, laying a solid foundation for the subsequent implementation of collaborative control. The scheduling of hybrid micro assembly production lines is essentially a combinatorial optimization problem, which involves finding the optimal collaborative control scheme under multiple constraints to minimize the processing time, minimize processing costs, or maximize processing benefits of the production line. The scheduling of production lines is influenced by various factors, such as funds, manpower, energy, etc. Therefore, the scheduling problem is an NP problem and the ultimate goal of collaborative control.

The author takes the minimum processing cost as the objective function for collaborative control of pro-

Table 3.1: Production Line Information Collection Methods

Acquisition method	Types of information collected	collecting device
Collection card collection	Vibration, sound, acceleration, etc	Data acquisition card
PLC acquisition	I/O status	PPI, Modbus, etc
Ethernet collection	Location information, processing information, auxiliary information, etc	WedService, Modbus, etc

duction lines, and the corresponding mathematical model expression is:

$$\begin{cases} C = min(C_1 + C_2) \\ C_1 = \alpha^* p + \beta^* q + \chi^* t \\ C_2 = \sum_i^n \omega_i |P_i = D_i| \end{cases} \tag{3.1}$$

In equation 3.1, C represents the processing cost of the hybrid micro assembly production line; C_1 represents the cost of product processing; C_2 represents the penalty fee for advance or delay; α^* represents the unit processing cost of the i-th product; p represents the quantity of product processing; β^* represents the unit cost required for replacing the device; q represents the number of replacement components; χ^* represents the cost of moving production line components; t represents the number of movements of the production line components; ω_i represents the penalty coefficient for the i-th product being advanced or delayed; P_i represents the completed quantity of the i-th product; D_i represents the planned processing quantity of the i-th product.

$$\begin{cases} C = min(C_1 + C_2 + C_\delta) \\ C_\delta = \sigma \times d \\ d = \begin{cases} 1 & \text{Unique product processing equipment} \\ 0 & \text{Not in the above situation} \end{cases} \end{cases} \tag{3.2}$$

In equation 3.2, C_2 expressing the penalty function expression; σ represents the penalty coefficient; d represents the auxiliary parameter of the penalty function, with a value of 1 or 0.

The above process uses a mathematical model to describe the production line scheduling problem, which determines the objective function of production line collaborative control, providing a basis for the subsequent collection and integration of production line information.

3.2. Production Line Information Collection and Integration. Based on the above constructed production line collaborative control objective function, the information required for collaborative control of hybrid micro assembly production lines is collected and integrated to prepare for the construction of subsequent collaborative control models.

At present, there are three main methods for collecting information on production lines, as shown in Table 3.1. As shown in Table 3.1, there are differences in the types of information collected by different collection devices applied to different information collection methods. The hybrid micro assembly production line contains a lot of equipment, a complex structure, and a variety of information types. Therefore, this study effectively combines the three information collection methods mentioned above, scientifically and reasonably allocates production line information collection tasks, in order to achieve the best production line information collection effect [15]. Applying Microsoft to build a hybrid micro assembly production line information collection framework, connecting heterogeneous devices, breaking the phenomenon of ”digital islands”, achieving information transmission between heterogeneous devices, providing convenience for collaborative control of production lines, and also assisting in information collection and transmission. The information collection framework for hybrid micro assembly production lines is shown in Figure 3.1.

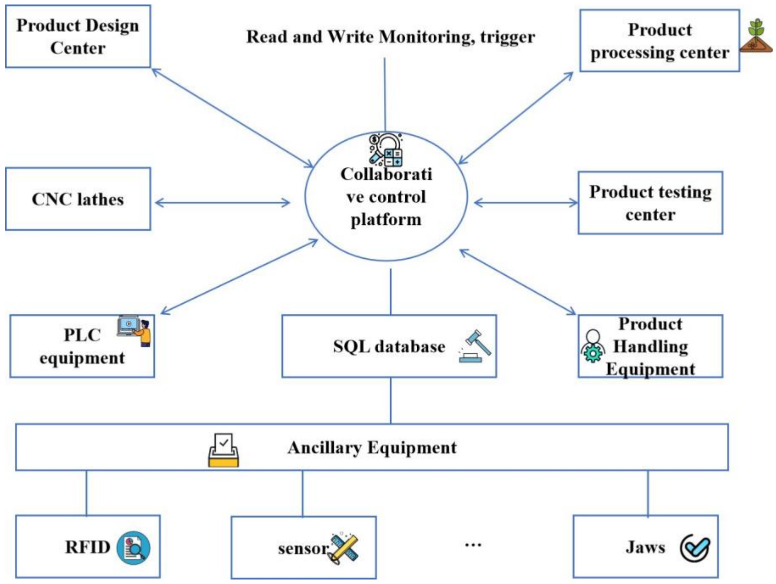

Fig. 3.1: Schematic diagram of production line information collection framework

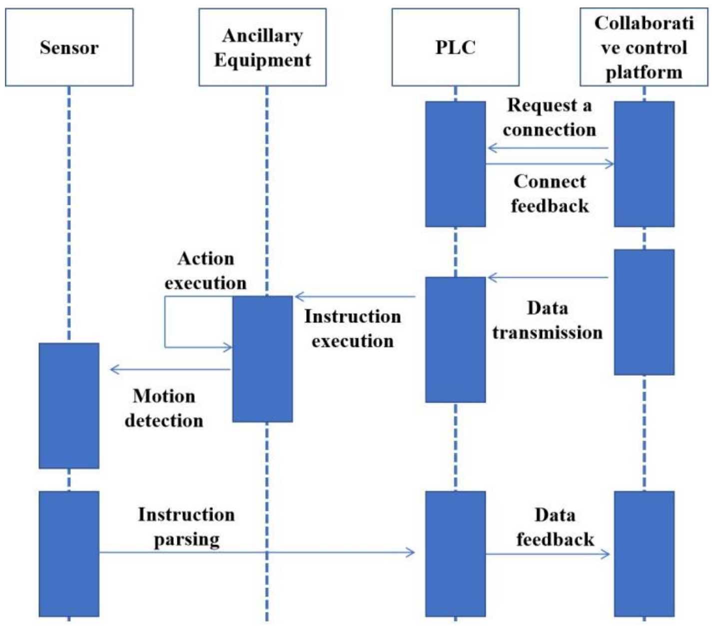

Fig. 3.2: Schematic diagram of information exchange logic for collection devices

As shown in Figure 3.1, in the framework construction, there are many production line information collection devices. In order to ensure the integrity of the collected information, it is necessary to set up the interaction logic of the collection device information, as shown in Figure 3.2.

Interact and integrate the collected information according to the logic shown in Figure 2, and store the integrated production line information in an SQL database, providing convenience for subsequent data applications.

3.3. Collaborative Control Model Construction. Based on the collected and integrated production line information mentioned above, a collaborative control model is constructed using multi-agent technology to provide support for the final implementation of collaborative control.

In multi-agent technology, there are multiple agents with different objectives that can be dynamically coordinated to solve corresponding problems. Multi Agent technology has strong flexibility, adaptability, and reliability, occupying a crucial position in the field of control, and is also one of the main means to solve NP problems today.

The dynamic coordination steps of multi-agent technology are as follows:

Step 1: Release collaborative control task information for the production line. It should be noted that each individual Agent can publish production line collaborative control task information, and a single Agent can publish multiple task information;

Step 2: Agent dynamically coordinates team building. Based on factors such as the collaborative control task information of the production line and the functions of individual agents, select suitable agent individuals to participate in the dynamic coordination team of agents, and construct the team through established rules until the collaborative control task of the production line is completed;

Step 3: Case based reasoning. Based on the published collaborative control task information, search for similar successful cases in the historical records. If there are similar successful cases, carry out dynamic coordination operations according to the cases; If there are no similar successful cases, further accurate selection of coordination attitude is needed;

Step 4: Coordinate attitude selection. This study uses fuzzy number $\xi_\theta(t)$ to describe the coordination attitude of individual agents towards publishing collaborative control task information. The expression for fuzzy number $\xi_\theta(t)$ is:

$$\xi_\theta(t) = \frac{L_0(\theta)}{L_0(\xi)} \tag{3.3}$$

In equation 3.3, $L_0(\theta)$ and $L_0(\xi)$ respectively represent the profit values of Agent individuals θ and ξ in the dynamic coordination process.

According to equation 3.3, select the coordination attitude based on the calculation results, and the specific rules are as follows:

$$\begin{cases} \xi_\theta(t) = 0 \quad \text{Completely selfish} \\ 0 < \xi_\theta(t) < 1 \quad \text{Partial collaboration} \\ \xi_\theta(t) = 1 \quad \text{Complete collaboration} \\ \xi_\theta(t) > 1 \quad \text{Compromise} \end{cases} \tag{3.4}$$

Step 5: Select appropriate coordination strategies based on the coordination attitude determined in Step 4. When $\xi_\theta(t)$=0, the agent's individual coordination attitude is completely selfish, which is called competitive coordination, and the optimal coordination strategy is game theory; When $\xi_\theta(t) \neq 0$, the individual coordination attitude of the agent is collaborative, which is called collaborative coordination. The optimal coordination strategy is partial global planning or FA/C method;

Step 6: Individual Agent Learning. In this step, individual agents should learn coordination strategies, coordination content, and coordination tasks for similar successful cases, in order to complete the corresponding production line collaborative control tasks;

Step 7: Guide the individual agents who have completed the learning to carry out collaborative control tasks on the production line, and disband the dynamic coordination team of the agents when the collaborative control tasks are completed [16].

Through the above process, it can be seen that multi-agent technology has strong dynamic coordination ability, which can provide great support for collaborative control of hybrid micro assembly production lines. Collaborative control of production lines is a complex and cumbersome problem. The author applies the dynamic coordination ability contained in multi-agent technology to construct a collaborative control model for production lines, as shown in Figure 3.3.

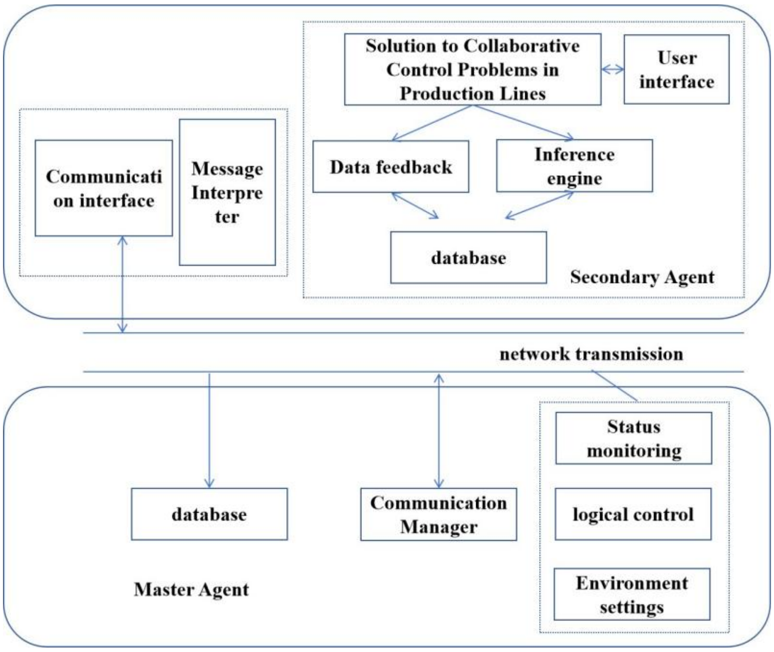

Fig. 3.3: Schematic diagram of collaborative control model for production line

Table 3.2: Collaborative Control Plan Table

Collaborative control steps	Collaborative control conditions	Collaborative control scheme
Step 1	$t_1 > t_2$	$F_1 > F_2$
Step 2	$t_1 < t_2$	$F_1 < F_2$
Step 3	$t_1^* < t_2^*$and $t_1 = t_2$	$F_1 > F_2$
Step 4	$t_1^* > t_2^*$and $t_1 = t_2$	$F_1 < F_2$
Step 5	$t_1^* = t_2^*$and $t_1 = t_2$	$F_1 = F_2$

In addition, a mathematical model is used to represent the internal structure of the Agent:

$$Agent = \{A, MK, D, I, S, R\} \tag{3.5}$$

In equation 3.5, A, M, K, D, I, S, R respectively represent the properties, solutions, relevant regulations, relevant data, reasoning process, information transmission rules, and information reception rules of the Agent.

The above process completed the construction of the collaborative control model for the production line and demonstrated the dynamic coordination performance of multi-agent technology, providing model support for the subsequent implementation of collaborative control.

3.4. Implementation of Collaborative Control on Production Lines. Based on the collaborative control model of the production line constructed above, with the lowest processing cost as the collaborative control objective, the optimal collaborative control scheme is solved to achieve collaborative control of the hybrid micro assembly production line [17].

Applying multi-agent technology to solve the objective function of collaborative control in production lines, the collaborative control scheme is obtained as shown in Table 3.2.

In Table 3.2, t1 and t_2 represent the standard processing costs of the two products; t_1^* and t_2^* represent the processing costs of products with different priority levels; F_1 and F_2 represent the priority of collaborative

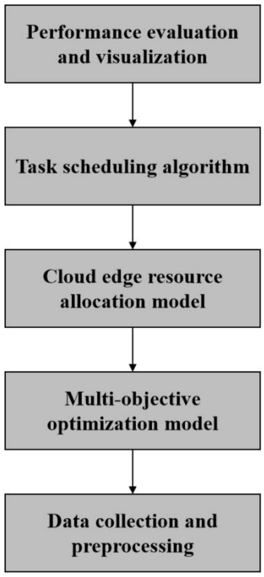

Fig. 3.4: Technical framework diagram of scheduling method

control.

In summary, the author has implemented collaborative control of hybrid micro assembly production lines based on multi-agent technology, minimizing production line processing costs and contributing to the sustainable development of the manufacturing industry [18].

3.5. multi-objective task scheduling for production lines. The author's dynamic scheduling technology framework for multi-agent electromechanical production lines based on iterative algorithms can be divided into several key components. The technical framework diagram of the scheduling method is shown in Figure 3.4.

In the Data Collection and Preprocessing stage, collect data from IoT devices, sensors, and manufacturing resources to provide necessary information for task scheduling. The data may include processing time, machine availability, energy consumption rates, and any other decision related information. Preprocessing may involve cleaning up data, handling missing values, and normalizing or converting data into a format suitable for further processing.

3.6. Collaborative control performance testing of production lines. In order to verify the application performance of the collaborative control method for hybrid micro assembly production lines based on multi-agent technology, the traditional data-driven real-time monitoring and optimization control technology for production lines is used as a comparative method, and the following comparative experiments are designed [19]. The experimental platform is the foundation for testing the collaborative control performance of hybrid micro assembly production lines. According to the performance testing requirements, an experimental platform was built using conveyor belts, loading boxes, sensors, industrial cameras, etc., as shown in Figure 3.5.

As shown in Figure 3.5, the experimental platform includes two conveyor belts and is equipped with industrial cameras and various sensors to obtain production line related information and prepare for collaborative control of the production line. In addition, industrial cameras need to be combined with photoelectric sensors for application. Once the photoelectric sensor senses product information, it transmits the signal in real time to the industrial camera, triggering it to collect information. Experimental equipment is also one of the key influencing factors to ensure the smooth progress of experiments. The main equipment for designing the experiment is a collaborative control server and communication equipment. Among them, the collaborative control server undertakes the tasks of data processing and forwarding, while the communication equipment undertakes the tasks provided by the high-quality communication environment. The experiment uses Ethernet switches

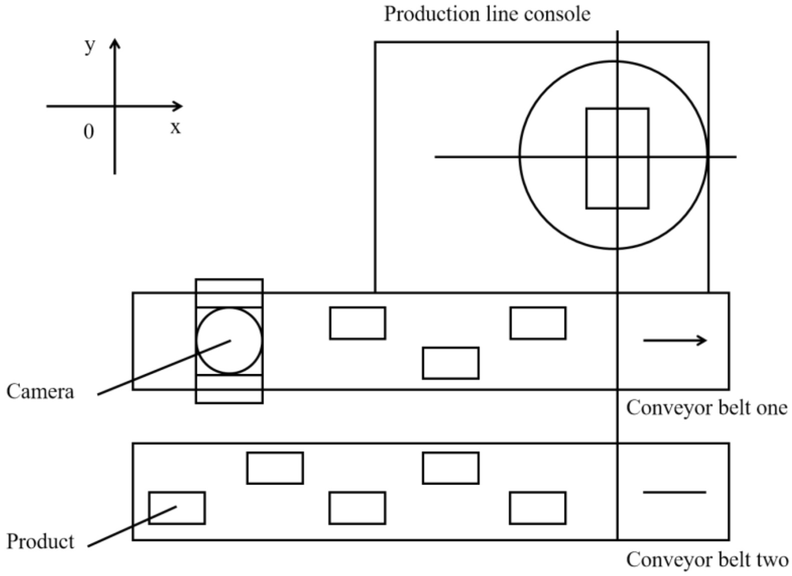

Fig. 3.5: Schematic diagram of experimental platform

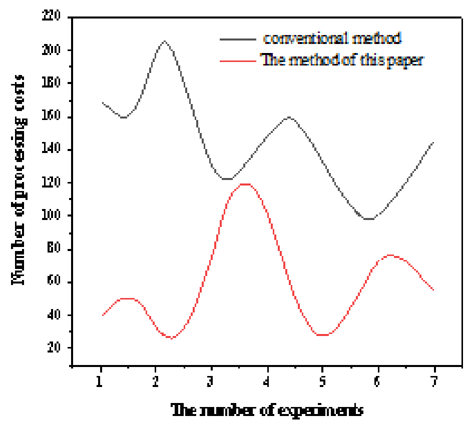

Fig. 4.1: Production Line Processing Cost Data Chart

as communication devices, which can provide a stable and high-quality communication environment within a certain range, providing strong support for performance testing [20].

4. Results and Discussion. Based on the experimental platform built above and the selected experimental equipment, conduct collaborative control performance testing on the hybrid micro assembly production line. In order to quantify the application performance of the proposed method, collaborative control task allocation time and production line processing cost were selected as evaluation indicators. The specific experimental results analysis process is shown in Figure 4.1.

The allocation time of collaborative control tasks indirectly reflects the efficiency of collaborative control in production lines. In general, the shorter the allocation time of collaborative control tasks, the higher the efficiency of collaborative control; On the contrary, the longer the allocation time of collaborative control tasks,

Table 4.1: Collaborative Control Task Allocation Time Data Table

Number of experiments	Author's method	traditional method
1	20.34s	26.53s
2	15.38s	28.41s
3	18.32s	29.23s
4	17.45s	30.16s
5	18.60s	35.05s
6	16.23s	28.53s
7	18.73s	35.27s

the lower the efficiency of collaborative control.

The collaborative control task allocation time data was obtained through experiments, as shown in Table 4.1. As shown in Table 4.1, compared with traditional methods, the collaborative control task allocation time obtained by applying this method is shorter, with a minimum value of 15.38 seconds, indicating that this method has higher efficiency in collaborative control of production lines. The processing cost of the production line directly reflects the effectiveness of collaborative control on the production line. In general, the lower the processing cost of a production line, the better the collaborative control effect; On the contrary, the higher the processing cost of the production line, the poorer the collaborative control effect. The production line processing cost obtained through experiments is shown in Figure 4.1. As shown in Figure 4.1, compared with traditional methods, the production line processing cost obtained by applying this method is smaller, with a minimum value of 240000 yuan, indicating that the collaborative control effect of this method on the production line is better. The above experimental results show that compared to the comparative methods, the collaborative control task allocation time obtained by applying this method is shorter, and the production line processing cost is lower, fully confirming that this method has better collaborative control performance.

5. Conclusion. The author proposes a dynamic scheduling method for multi-agent electromechanical production lines based on iterative algorithms. This study applies multi-agent technology to propose a new collaborative control method for hybrid micro assembly production lines, which greatly shortens the allocation time of collaborative control tasks, reduces production line processing costs, provides more effective method support for collaborative control of production lines, and also provides new ideas and theoretical references for collaborative control research.

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