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DYNAMIC SCHEDULING OF MULTI-AGENT ELECTROMECHANICAL PRODUCTION LINES BASED ON ITERATIVE ALGORITHMS

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Abstract. In response to the optimization scheduling problem in the dyeing production process, the author proposes a hierarchical scheduling method for dyeing vats based on genetic algorithm and multi-agent. In this method, a hierarchical scheduling algorithm is used to decompose production scheduling into static and dynamic strategies. The static strategy adopts a genetic algorithm that supports batch processing of multiple products, non equality of equipment, order delivery time, switching cost, and other constraints: Dynamic strategy is a coordinated dynamic optimization algorithm that uses multi-agent systems to support the running status of dye tanks based on static strategies. By solving the algorithm with multiple constraints and dynamic factors in the production process, the final result of the dyeing tank operation task is obtained. The simulation compared pure genetic algorithm with manual scheduling, and the results showed that the hierarchical dynamic scheduling strategy based on data-driven achieved the goal of optimizing the production scheduling of dyeing vats. The practical application results also demonstrate the feasibility of this method.

Key words: Multi-agent, Genetic algorithm, hierarchical scheduling, Agent

1. Introduction. The actual workshop production system is a dynamic production environment, and any changes in production plans, processing equipment, scheduling objectives, and other factors will cause changes in production scheduling[1]. In order to achieve coordinated operation of the workshop and achieve global optimization goals, in order to better complete workshop scheduling tasks, achieve reasonable resource allocation, and use ant colony algorithm to construct a dynamic scheduling algorithm for the workshop. The original meaning of Agent is "agent", and A agent is a computing entity with a problem reasoning and solving mechanism that can play its role autonomously. The reason why a multi-agent structure should be applied is because a multi-agent system is a network composed of multiple agents that can coordinate operations. Each agent in the computing system has its own different problem-solving methods and methods[2]. However, agents can dynamically schedule workshops through agreed unified communication protocols and make decisions through bidding, negotiation, and other means.Adopting a multi-agent structure can prevent the dynamic scheduling system structure of the workshop based on multi-agent in System Figure 1 from collapsing due to errors in a certain part of the system, which is beneficial for improving the stability of the system. At the same time, achieving distributed decision-making in the manufacturing system makes the system highly robust and scalable. The basic working principle is as follows: Firstly, the data collection agent plays a role in real-time production monitoring, collecting on-site data during the production process, such as machine tool status, route operation, etc., and providing raw data for the evaluation and decision-making agent in conjunction with the production plan. The integration agent combines various data sent by various data collection agents in an orderly manner and integrates them. Through the preprocessing algorithm in the agent, each data is converted into a unified format that the system can recognize, which is conducive to improving the computational performance of the entire system[3]. The main control agent not only needs to provide various data and evaluation and analysis algorithms available to the decision-making agent, such as correlation algorithms, mean value algorithms, etc., but also is responsible for real-time monitoring of the entire system's operation.If there is an error in the data, instructions can be issued to request the data collection agent to change the frequency of the data provided, thereby achieving global optimization goals based on monitoring. The evaluation and decision-making agent is the core of the entire system and the main executor of scheduling

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tasks. It can request the main control agent to provide real-time data and select appropriate algorithms for specific resource allocation in the workshop. Due to the role of the evaluation and decision-making agent as a workshop scheduling agent, it can make decisions through negotiation, bidding, and other means, and timely send the decision results to the appropriate processing unit agent. When problems occur during scheduling (such as the waiting time for a route to run is too long or rework phenomenon occurs), a processing command can be sent to the general control agent to make the system temporarily stop scheduling and processing, and error information can be timely called out from the shared knowledge base for analysis and resolution by the decision-maker.When the processing task to be processed is too large, the task can be decomposed and distributed by multiple evaluation and decision agents. Finally, the processing information is transformed into a unified decision result through preprocessing algorithms and published to the appropriate processing unit agent. With the continuous increase of decision-making events, the data information in the shared knowledge base will develop towards a direction that is more conducive to dynamic workshop scheduling[4,5]. The processing unit agent can continuously issue instructions to the evaluation and decision-making agent to receive processing tasks. If there is a problem with a certain machine tool during the processing, the equipment monitoring agent will determine that all processing routes passing through the machine tool are unavailable and promptly publish the information to the decision-making agent, so that the decision-making agent can re evaluate and make decisions on the real-time status in the workshop, and select a feasible path from the remaining feasible processing paths to complete the processing task, when the malfunction of the machine tool is eliminated, all processing routes passing through the machine tool will be redefined as available.

The production process of modern dyeing enterprises is mostly carried out in a small batch and multi variety manner. In this production method, achieving reasonable arrangement of production plans and tasks is a complex production scheduling process, which is difficult to solve with a scheduling strategy[6]. It often requires the use of composite scheduling strategies at different stages and conditions. There are currently many literature on this topic, and combining genetic algorithm with multi-agent is a new method that has emerged in recent years to solve complex scheduling problems. The scheduling methods for dyeing production workshops described in existing literature generally only consider delivery time and switching costs when designing models, and rarely design dynamic scheduling under complex and variable production conditions in the workshop. Based on real-time sample data collected by dyeing enterprises, the author studies a genetic algorithm for static scheduling that supports batch processing characteristics of multiple products, non equality of multiple dyeing tanks, pre order backlog, and order delivery time constraints, and research on dynamic optimization algorithms for coordination among multi-agent systems based on the running status of workshop dyeing tanks. By solving multiple constraints and dynamic factors in the production process in a hierarchical manner, a dynamic optimization strategy for dyeing tank operation tasks is obtained, achieving the goal of optimizing dyeing tank operation scheduling.

2. Methods.

2.1. Problem Description. There are M dyeing vats in the workshop, each of which can process any type of product, and the capacity of each dyeing vat varies[7,8]. The minimum and maximum production capacity of each dyeing vat are constrained by the bath ratio. The number of orders that require production and processing is N, and an order may require processing and production of one or more products. The quantity and delivery time required for each product may vary, and the production process may also vary.The time and cost of processing different product types in dyeing vats also vary. Dyeing processing also requires consideration of switching costs. Taking into account the above constraints and minimizing the total production cost under the conditions of meeting the delivery dates of each order as much as possible, the scheduling results are often not optimal due to the lack of consideration of real-time production changes. Therefore, it is necessary to find a dynamic optimization method based on this to achieve the optimization of dyeing tank scheduling.

2.2. Static scheduling model for dyeing vats based on genetic algorithm. In addition to the delivery time, time, and spatial constraints of general production processes, the dyeing production process also has industry characteristics such as the variability of processing equipment, switching costs, and additional resource consumption, which are complex nonlinear, stochastic, and uncertain, this makes it impossible for the dyeing scheduling model to copy the scheduling models in existing literature, and it is necessary to establish a

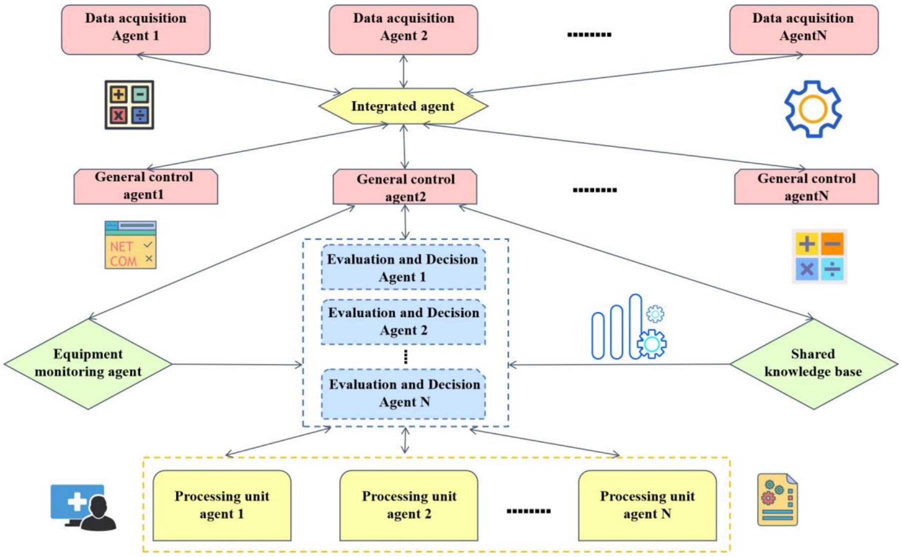

Fig. 1.1: Structure of a Multi Agent Based Workshop Dynamic Scheduling System

scheduling model that is suitable for the actual production status of printing and dyeing enterprises.

(1) Genetic Algorithm. After abstracting the above characteristics of dyeing production, the problem can be described as follows: Assuming that the production workshop will produce n independent products on m dyeing tanks during the planning period [1,T][9,10]. Based on the summary of orders, the contract delivery quantity $d_J(t)(j = 1, 2, ..., T)$ for the jth product on day t can be obtained, and the daily available capacity range of the i-th dyeing tank is $[g_i, G_i](i = 1, 2, ..., m)$, the switching time and cost of the dye tank are linearly related to the capacity of the dye tank. At the initial moment, the storage capacity of product j is $I_j(j = 1, 2, ..., n)$, and the storage capacity I_j represents the delivery quantity of the jth product that was not completed during the previous planning period at the initial planning time[11]. This can be obtained by monitoring the operation process of the dyeing cylinder through the MES manufacturing system in the workshop. After obtaining the quantity of unfinished orders, according to the production schedule requirements, select the total amount of products to be processed in the ERP system order database, and complete the pull dynamic production scheduling within the planned number of days.For enterprises, delayed delivery requires payment of a penalty for breach of contract to customers, assuming that the penalty for delayed delivery per unit of product time is $\alpha_i(j = 1, 2, ..., n)$.

(2) Design of Algorithm. Based on the characteristics of the problem model, in order to effectively reflect the order and quantity of products processed by each dyeing tank on a daily basis, a natural encoding method is adopted[12]. The specific scheme is as follows:

$$p_{11}(t), p_{12}(t), ...; p_{1n}(t), ...; p_{m1}, p_{m2}, ...; p_{mn}(t) \tag{2.1}$$

Among them, $p_{nm}(t)$ represents the output of the nth product on the mth dyeing tank on the th day. When initializing the population, if a random approach is used, it is difficult to guarantee that the resulting solution is feasible. Therefore, the method for initializing the population here is: For the i-th dyeing tank on the t-th day, generate a random number R_i within the interval $[g_i, G_i]$[13,14]. For the quantity of various products produced by this dyeing tank every day, use a random average distribution method and ensure $\sum_{j=1}^{n} p_{ij}(t) = R_i$. Adopting this initialization method not only ensures the diversity of the population, but also ensures that the initial solution is feasible.

The purpose of selection is to select excellent individuals from the current population, so that they have the opportunity to reproduce as parents for the next generation. Based on the fitness values of each individual,

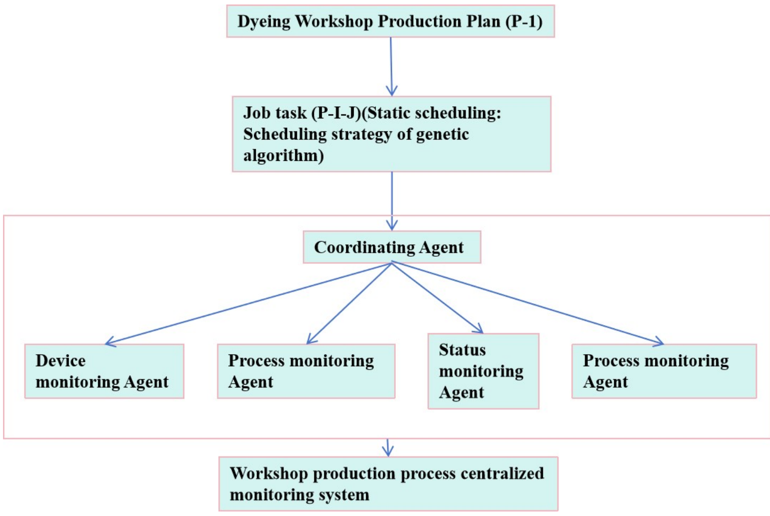

Fig. 2.1: Multi agent based workshop production scheduling model

select some excellent individuals from the previous generation population according to certain rules or methods to inherit into the next generation population. Compared with the simulation experiment results, we chose the operation method of uniform sorting, which sorts all individuals in the population according to their fitness size, and based on this sorting, assigns the probability of each individual being selected.

Cross operation is the most important genetic operation in genetic algorithms[15]. Through crossover operations, a new generation of individuals can be obtained, where each individual within the population is randomly paired and a portion of their chromosomes are exchanged with a certain probability for each individual. In order to meet the constraint requirements of impregnation production during crossover, the two-point crossover method is adopted, which randomly sets two crossover points in the individual coding string, and then conducts partial gene exchange.

Mutation operations are mainly used to adjust some gene values in an individual's coding string, which to some extent overcomes the situation of effective gene deletion and is beneficial for increasing population diversity. In order to ensure that the mutated chromosomes have a good individual coding structure, randomly select the mutated genes and use adjacency search method to insert the gene values that meet the constraint conditions (excluding the gene values that need to be mutated) into the selected mutated genes once, overwrite existing genes to generate new chromosomes, and select the best of them as the offspring of the mutation. And it can also effectively ensure the diversity of the population, the quality of mutated individuals, and the feasibility of producing individuals. Pre set a maximum number of evolution steps N_{max} , and if the maximum number of evolution steps is reached, terminate the algorithm process.

2.3. Multi agent based dynamic scheduling model for dyeing vats. Based on the characteristics of printing and dyeing processes and production processes, a dynamic model for workshop production scheduling based on multi-agent is constructed[16]. This model is based on the real-time operation status of the dyeing tank, combining static scheduling and dynamic adjustment, and achieving the goal of global optimization through the interaction between intelligent agents. The model has a four layer architecture: The first layer is composed of a workshop production planning layer; The second layer is the static scheduling layer; The third layer is the dynamic scheduling layer; The fourth layer is to control friction. As shown in Figure 2.1, it is a multi-agent based workshop production scheduling model.

2.4. Intelligent Agent Collaboration Process. Figure 2.2 shows the internal structure of the intelligent agent. This structure consists of modules such as communication interface, intelligent control, state saving, data collection, data processing, knowledge base, data view, and output, as shown in Figure 2.2 [17].

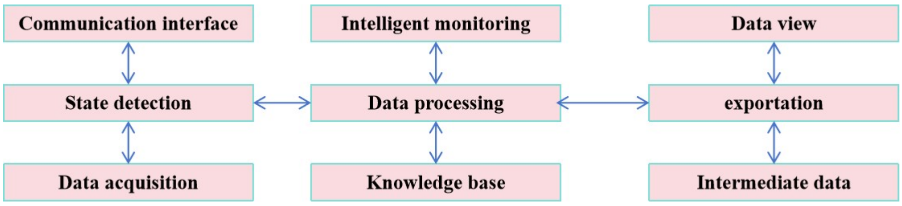

Fig. 2.2: Internal structure diagram of the intelligent agent

The collaborative process of intelligent agents can be divided into two types: Internal and external. Internal coordination is carried out in internal modules, such as communication interface message publishing, external data collection, data processing, intelligent analysis and control, and final data output. The intermediate data recording and working status saving module saves the intermediate results and system status of the data collection and processing process. The planning and control module is the coordinator and commander of various modules within the entire intelligent agent. It calls the corresponding modules for processing according to certain rules and requests from the communication interface module. The rule library stores the internal rules and control algorithms of the monitoring agent, while external coordination involves the interaction and coordination of information such as equipment operation, production process, process status, and operational status for optimizing scheduling. Due to the lack of consideration for the dynamic changes in the production site, the scheduling results obtained by static genetic algorithms are not optimal. Therefore, multi-agent technology needs to be added to reschedule individual scheduling tasks. Firstly, the coordinating agent determines the allocation of tasks on resources and the processing time on production equipment based on production plans and actual resource utilization. Afterwards, the equipment monitoring intelligent agent obtains processing task orders based on its own capabilities, and completes the optimization and scheduling of production tasks based on constraints such as meeting product delivery dates, processes, costs, energy consumption, and quality requirements, combined with the operational status of the production site dyeing vats. Coordination agents are also responsible for coordinating the behavior of various agents, resolving conflicts, synchronization, asynchrony, and other issues between agents, in order to ensure the coordinated operation of the production system.

3. Simulation calculation. Simulation of hierarchical scheduling using typical data samples from a dyeing enterprise to verify the feasibility of the scheme. Select two dyeing vats in a workshop group as the object, and set up four products with a production period of 1-15 days. Assuming that the penalty for one day of delay for each product is 0.1 yuan, the daily available capacity ranges of the two dyeing vats are [35, 45] and [40, 50], respectively[18]. According to the order information, the distribution of order quantities for the four products is shown in Table 3.1. Using the scheduling model and static genetic algorithm designed above, the calculation results were obtained by iterating around 1500-2000 times, with high computational efficiency. The optimal production schedule obtained by solving the algorithm is shown in Table 3.2, with a minimum production cost of 56.1. The planned period is 15 days, and "A/B" indicates that the quantity of products with serial number A processed on this dyeing tank on that day is B. After encapsulating the static genetic algorithm in the inference mechanism of the agent in Table 3.3 and coordinating with multiple agents, the production schedule is formulated, and the production cost calculated by the model is 43.6. Compared with simply using static genetic algorithms, it saves 22.3% in production costs.

Table 3.1: Order Quantity of Four Products per Day

programme	Order quantity of product serial number			
	1	2	3	4
1	61	0	21	0
2	0	81	0	41
3	41	0	0	71
4	0	21	41	0
5	0	0	71	56
6	81	0	41	0
7	0	0	31	61
8	0	0	81	46
9	31	51	0	0
10	0	31	51	21
11	41	0	0	61
12	36	0	51	0
13	0	51	0	41
14	0	41	0	46
15	31	21	0	21

Table 3.2: Scheduling Results Based on Static Genetic Algorithm

fatalism	No.1 dyeing cylinder (capacity: 35 15)		No.2 dyeing cylinder (capacity: 10 50)	
1	2/23	4/21	2/24	4/23
2	2/24	3/20	1/22	2/10 4/17
3	1/24	3/21	2/24	3/24
4	2/24	4/22	2/7 3/24	4/20
5	1/21	2/22	3/23	4/26
6	2/22	4/25	2/24	3/24
7	1/24	3/23	1/29	3/22
8	1/23	3/22	3/24	4/24
9	1/21	4/25	1/4 2/25	3/21
10	2/1 3/22	4/24	1/21	2/26
11	3/21	3/23	1/17 3/9	4/17
12	1/24	4/23	3/21	2/25
13	1/21	2/23	1/24	4/25
14	1/15	2/23 3/4	2/24	3/21
15	2/23	4/21	1/3 2/23	4/25

Table 3.3: Scheduling results based on multi-agent and genetic algorithm

fatalism	No.1 dyeing cylinder (capacity: 35 45)		No.2 dyeing cylinder (capacity: 40 50)	
1	1/23	3/24	1/24	4/26
2	2/24	3/22	1/22	3/10 4/20
3	1/24	4/23	2/24	4/24
4	124	4/22	2/7 3/24	4/20
5	1/21	2/22	1/23	4/26
6	2/22	3/23 4/2	2/24	3/20 4/8
7	2/24	4/21	1/29	3/22
8	1/23	2/2 3/22	3/28	4/24
9	1/21	2/1 3/23	1/4 2/25	3/21
10	2/1 3/22	4/24	1/21	2/26 3/4
11	3/21	4/23	1/16 2/19	3/9 1/17
12	2/24	3/23	1/21	2/25 3/6
13	1/21	2/23 3/3	1/24	3/24 4/4
14	1/15	21/23 4/10	2/24	3/16 4/12
15	2/23	3/24	2/3 3/23	4/26

By comparing the scheduling results of static genetic algorithms, it can be concluded that using the multi agent and genetic algorithm proposed by the author to combine the hierarchical scheduling design of dyeing vats, considering the dynamic changes in the production site, the optimal solution for dyeing vat scheduling can be obtained[19,20]. After actual production workshop operation testing, the algorithm in this article has a good optimization efficiency when dealing with production lines with 60 dyeing tanks producing 8 product types.

4. Conclusion. The author analyzed the characteristics of dyeing production and established a hierarchical scheduling model that meets the actual production constraints. Due to the use of static genetic algorithm as the solution algorithm, it is difficult to consider the impact of actual changes in production site dyeing vats, yarn, and workshop personnel, and the scheduling plan made does not meet the optimal solution of the production site, therefore, the author proposes a hierarchical scheduling strategy for dyeing vats based on genetic algorithm and multi-agent. The comparison of simulation results with static genetic algorithm production scheduling verifies the effectiveness of the hierarchical design method proposed by the author. Through improvement, it can adapt to the formulation of production scheduling plans for large-scale dyeing enterprises. This has certain reference value for effectively solving the job scheduling problem of dyeing production workshops, achieving cost reduction and emission reduction goals.

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