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Original scientific paper

PRODUCTION MANAGEMENT AND CONTROL BASED ON ANT COLONY OPTIMIZATION AND NEURAL NETWORK

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Abstract
The neural network (NN) has an advantage in handling the massive real-time monitoring data on discrete manufacturing. Therefore, this paper proposes a production management and control method for discrete manufacturing job-shops based on ant colony optimization (ACO). Firstly, the production management and control problem for discrete manufacturing job-shops was described through the functional analysis on the management and control system, followed by establishing the corresponding mathematical model. After that, the ACO was improved to solve the static multi-objective production management and control problem. Then, the authors set up an NN-based production management and control model for dynamic discrete manufacturing job-shop, and detailed the way to select and transform the judgement result on production state and to set up the training set. Finally, the effectiveness of our algorithm was verified through experiments.
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Key Words: Ant Colony Optimization (ACO), Neural Network (NN), Discrete Manufacturing, Job-Shop Production Management and Control

1. INTRODUCTION

The concept of intelligent factory, which features smart resource planning and management, has entered practical application. However, small and medium-sized discrete manufacturing enterprises in China have not developed a mature production management mode, and need to improve the mode towards real-time monitoring, equipment networking, and process transparency [1-4]. At present, discrete manufacturing is shifting from mass production of a single type of products towards the customized production of multiple types of products [5-9]. The job-shop must be supported with robust production management, which is critical to production resource allocation and production plan adjustment. Without production management, it is impossible for enterprises to maximize their operational benefits.

The production in discrete manufacturers involves multiple processing tasks that can be completed with very few resources [10-12]: the parts participate in various operations with different requirements; the products are highly customized; the production technology and machines are more flexible than those in traditional manufacturing. All these make it extremely difficult to manage and control discrete manufacturing job-shops [13-15].

Goto et al. [16] proposed an automatic collection plan for the terminal data based on the wireless sensor network (WSN), and developed a monitoring and management system for discrete job-shop production. Shpilevoy et al. [17] constructed a monitoring system architecture based on the browser/server (B/S) structure, modelled different types of objects using the multi-source information on manufacturing process, and developed the functional modules of the monitoring system under the Spring Framework. Babar and Nonaka [18] identified the material flow relationship between the processing units in the job-shop, and detailed an optimization plan for job-shop layout based on genetic algorithm. Modrak and Soltysova [19] designed the overall architecture and functional framework of the aviation product job-shop, and provided the basic classification and sorting method for relevant data. Iacobici et al. [20] designed a centralized optimization algorithm for job-shop production resources and capacity, and developed the relevant system on Java and Secure Shell (SSH).

Modern manufacturing execution system (MES) takes very different form and application mode from traditional manufacturing, for the discrete manufacturing process and the controlled object are highly complex and independent [21, 22]. Ngandjong et al. [23] compared the scheduling planning, data acquisition, and system integration methods of existing machining and assembly enterprises, put forward a production planning strategy for small-batch personalized products based on the theory of constraints (TOC) and the manufacturing resource planning (MRP), and realized the information release on the planning layer and control layer through electronic Kanban management.

So far, scholars have explored the production management and control of discrete manufacturing job-shops, covering a wide range of topics. However, few have comprehensively managed the operation tasks, materials, and equipment in dynamic job-shops, by virtue of the advantage of the neural network (NN) in handling the massive real-time monitoring data on discrete manufacturing. Thus, this paper presents a production management and control method for discrete manufacturing job-shops based on ant colony optimization (ACO) and neural network (NN), and verifies the effectiveness of our method.

2. PROBLEM DESCRIPTION AND MATHEMATICAL MODELING

Fig. 1 shows the functional framework of production management and control system of discrete manufacturing job-shop.

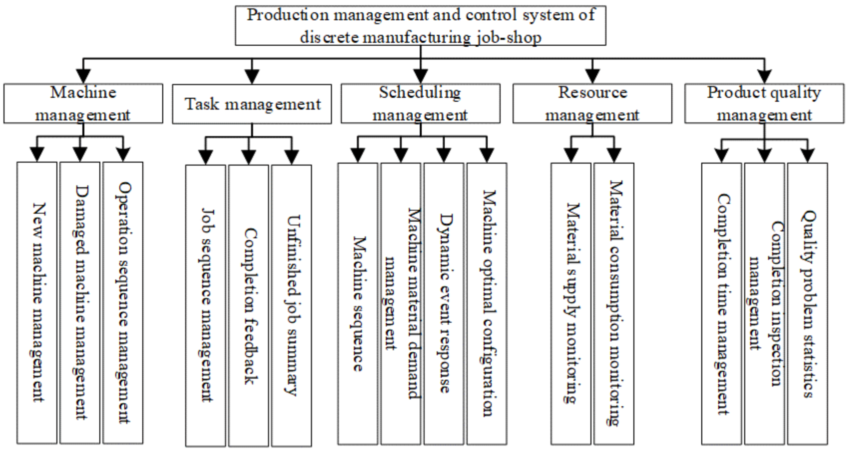

Figure 1: Functional framework of production management and control system of discrete manufacturing job-shop.

Under the framework, the production management and control problem of discrete manufacturing job-shop can be described as follows:

Suppose X jobs, each of which needs to be processed through Y operations, have different processing routes. On each processing route, every machine has its own production material supply, processing priority, and processing time. The goal of production management and control is to reasonably arrange the operation sequence on each machine and supply sufficient materials to optimize the management and control objectives, under the premise of satisfying the requirements on processing technology and product quality monitoring. The production process must meet such constraints as the exclusivity of jobs and machines, and the continuity and equality of operations.

Let $A = \{A_i \mid i = 1, 2, \ldots, X\}$ be the set of jobs, with A_i being the i^{th} job; $B = \{B_j \mid j = 1, 2, \ldots, Z\}$ be the set of machines, with B_j being the j^{th} machine; $C = \{C_j \mid j = 1, 2, \ldots, Z\}$ be the set of materials, with C_j being the material supplied to the j^{th} machine; $D = \{D_{ik} \mid i = 1, 2, \ldots, X; k = 1, 2, \ldots, Y\}$ be the set of operations, with D_{ik} being the k^{th} operation of the i^{th} job. Then, the operations can be written in the form of a matrix:

$$D = \begin{pmatrix} D_{11} & D_{12} & \cdots & D_{1Y} \\ D_{21} & D_{22} & \cdots & D_{2Y} \\ \cdots & \cdots & \cdots & \cdots \\ D_{X1} & D_{X2} & \cdots & D_{XY} \end{pmatrix} \tag{1}$$

The matrix of processing time corresponding to the matrix of operations can be expressed as:

$$T = \begin{pmatrix} T_{11} & T_{12} & \cdots & T_{1Y} \\ T_{21} & T_{22} & \cdots & T_{2Y} \\ \cdots & \cdots & \cdots & \cdots \\ T_{X1} & T_{X2} & \cdots & T_{XY} \end{pmatrix} \tag{2}$$

Let S_{ikj}, F_{ikj}, and TL_{ikj} be the start time, completion time, and makespan of D_{ik} on B_j, respectively; C_{ikj} be the total material consumption of D_{ik} on B_j. Then, the minimization of maximum makespan can be defined as:

$$F_1 : \min F_{ikj}^{max} \tag{3}$$

The minimization of total delay can be defined as:

$$F_2 : \min T^{\max} = \min(\sum_{i=1}^{X}\sum_{k=1}^{Y} T_{ik}) \ = \min(\sum_{i=1}^{X}\sum_{k=1}^{Y} \max\{0, F_{ikj} - TL_{ikj}\}) \tag{4}$$

For any job, the start time of any operation being executed on any machine must satisfy:

$$S_{ikj} \geq 0 \tag{5}$$

Let ΔT_{ikj} be the longest preparation time of D_{ik} on B_j. Then, the start time of the adjacent operations for any job must satisfy:

$$S_{ikj} - S_{ik(j\text{-}1)} \geq \Delta T_{ik(j\text{-}1)} \tag{6}$$

Suppose there exists a sufficiently large positive number ε_1. Then, the exclusivity of jobs can be expressed as:

$$F_{ijk} - F_{ljk} + \varepsilon_1(1 - \delta_{ilj}) \geq \Delta T_{ikj} \tag{7}$$

where, φ_{ilj} is the decision function for the priority of jobs:

$$\delta_{ilj} = \begin{cases} 1, \text{the } i^{\text{th}} \text{ job will be processed on the } j^{\text{th}} \text{ machine earlier than the } l^{\text{th}} \text{ job} \\ 0, \text{otherwise} \end{cases} \tag{8}$$

At any time, the material supply and demand in the job-shop must satisfy:

$$C_{Supply} \geq \sum_{j=1}^{Z} C_j \tag{9}$$

Suppose there exists a sufficiently large positive number ε_2. Then, the exclusivity of the machine selected for any job at any time can be expressed as:

$$F_{ikj} - \Delta T_{ikj} + \varepsilon_2(1 - \beta_{ijh}) \geq F_{ihk} \tag{10}$$

where, β_{ijh} is the decision function for the priority of machines:

$$\beta_{ijh} = \begin{cases} 1, \text{the } j^{\text{th}} \text{ machine will process the } i^{\text{th}} \text{ job earlier than the } h^{\text{th}} \text{ machine} \\ 0, \text{otherwise} \end{cases} \tag{11}$$

3. PROBLEM SOLVING

Through coding and decoding, the production management and control problem of discrete manufacturing job-shop can be transformed into the optimal path problem of the ACO. Fig. 2 explains the foraging process of individual ants in the improved ACO. Leaving from the start point, each ant needs to pass through multiple path nodes representing jobs, and repeatedly traverse the nodes and update the pheromone between nodes, before finding the shortest path that represents the optimal solutions to the objective functions of production management and control.

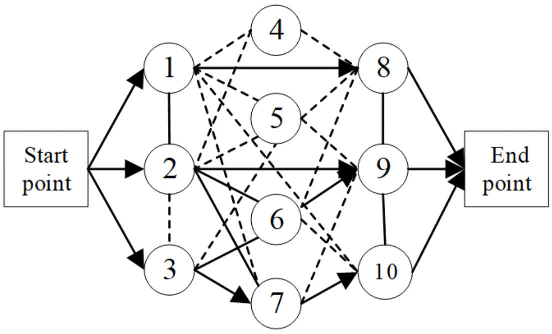

Figure 2: Foraging process of individual ants in the improved ACO.

First, three sets of the same size as the solution set were established: the set of candidate solutions *AN* representing the set of next job nodes that could be selected by all ant individuals; the set of results *R* representing the traversal optimization results of all ant individuals; the tabu list *Taboo*, i.e., the set of job nodes that cannot or have been selected by all ant individuals.

The next is to determine the coding and decoding methods. There are two common coding methods: the direct coding that optimizes the evolution of production state to realize the optimization objectives; the indirect coding that generates the management and control plan through the assignment of job priority. This paper combines the two coding methods, and codes the production management and control problem of discrete manufacturing job-shop based on the operation sequence. Let E_{ikj} be execution of the k^{th} operation of the i^{th} job on the j^{th} machine. The total number of times the same serial number appears is the total number of operations of the job, and the first occurrence of the serial number indicates the current operation the job is in.

Table I: Operation implementation.

Job number	Time (serial number of machines)			
A_1	2 (B_2)	5 (B_1)	3 (B_3)	4 (B_1)
A_2	4 (B_2)	2 (B_1)	—	—
A_3	2 (B_1)	3 (B_3)	4 (B_2)	—

Based on an example of production management and control, the jobs A_1, A_2, and A_3 in the job-shop are subject to the production management and control sequence of [1 3 3 1 2 2 1 1 3]. From the sequence, it can be seen that A_1, A_2, and A_3 have 4, 2, and 3 operations. According to the operation implementation in Table I, the four operations of A_1 are executed for 2, 5, 3, and 4 min on machines B_2, B_1, B_3 and B_1, respectively; the two operations of A_2 are executed for 4, and 2 min on machines B_2, and B_1, respectively; the three operations of A_3 are executed for 2, 3, and 4 min on machines B_1, B_3, and B_2, respectively. The operation sequence corresponding to the above results on production management and control is [$E_{112}, E_{311}, E_{323}, E_{121}, E_{212}, E_{221}, E_{133}, E_{141}, E_{332}$]. Table II presents the coding results on the items of production management and control.

Then, the ant colony should be initialized, and the algorithm parameters be adjusted dynamically. The basic idea of initialization is to assign a high priority to the job with a long total makespan on all machines, and a low priority to that with a short total makespan on all machines. Meanwhile, the dynamic adjustment of algorithm parameters aims to adaptively change parameters α and β, which respectively represent the importance of pheromone and heuristic factor. These two parameters have a great impact on the convergence and range of the algorithm optimization. In the early phase of iterations, α was kept small and β was kept large to speed up convergence; in the late phase of iterations, when the pheromone of each path had been updated to a certain extent, α was kept large and β was kept small to improve the pheromone-based global optimization ability.

Table II: Coding results.

Items of production management and control	1	3	3	1	2	2	1	1	3
Jobs	A_1	A_3	A_3	A_1	A_2	A_2	A_1	A_1	A_3
Operations	D_{11}	D_{31}	D_{32}	D_{12}	D_{21}	D_{22}	D_{13}	D_{14}	D_{33}
Machines	B_2	B_1	B_3	B_1	B_2	B_1	B_3	B_1	B_2
Operation executions	E_{112}	E_{311}	E_{323}	E_{121}	E_{212}	E_{221}	E_{133}	E_{141}	E_{332}

The u^{th} ant at the i^{th} job node selects the next job node l based on the state transition probability. In our algorithm, the state transition probability depends on the prior knowledge selection probability and random probability in Eq. (12), which strikes a balance between full utilization of historical information and randomness of new path exploration:

$$p=\begin{cases} p_1=\operatorname{argmax}_{l\notin Taboo_u}\left\{\left[\mu_{il}(\mathrm{t})\right]^{\alpha}\cdot\left[\lambda_{il}(\mathrm{t})\right]^{\beta}\right\} & \sigma\le\sigma' \\ p_2=p_{il}^{u}(\mathrm{t})=\begin{cases}\dfrac{\mu_{il}^{\alpha}(\mathrm{t})\cdot\lambda_{il}^{\beta}(\mathrm{t})}{\sum_{r\notin Taboo_u}\mu_{ir}^{\alpha}(\mathrm{t})\cdot\lambda_{ir}^{\beta}(\mathrm{t})}, l\notin Taboo_u \\ 0,\ \text{Otherwise}\end{cases} & \sigma>\sigma' \end{cases} \tag{12}$$

where, σ' and σ, both of which fall in (0, 1), are the degree of prior knowledge utilization and a random number uniformly distributed in the range, respectively. To speed up convergence and improve the quality of feasible solutions, both local and global updates were selected to update the path pheromone, laying an important basis for optimization. Let P_{il}^{*} be the result of the current optimal path in this cycle. Then, the pheromone on each path can be updated by:

$$\begin{aligned}\mu_{il}(t+1)&=(1-\tau)\mu_{il}(t)+\Delta\mu_{il}^{*}(t)\\ &=\begin{cases}(1-\tau)\mu_{il}(t)+\dfrac{M}{P_{il}^{*}}, \text{The optimal path contains edge } (\mathrm{i},\mathrm{l})\\ (1-\tau)\mu_{il}(t),\quad \text{Otherwise}\end{cases}\end{aligned} \tag{13}$$

where, τ is the pheromone volatilization coefficient.

4. NN-BASED PRODUCTION MANAGEMENT AND CONTROL MODEL

For static discrete manufacturing job-shop, the elements of production management and control are fixed. By contrast, the dynamic discrete manufacturing job-shop faces abrupt events like sudden increase or cancelation of orders, and shutdown induced by machine damages, making it difficult to mine the change law of the elements of production management and control, or acquire the relevant information. Fig. 3 describes the mode for the administrator of discrete manufacturing job-shop to respond to and handle dynamic events. Fig. 4 provides the block diagram of the production management and control model. Firstly, the improved ACO was introduced to solve the static multi-objective production management and control problem. Next, the optimal production management and control plan was described according to the judgement result on production state, and the description was converted into the training set for the NN. Based on the training set, the constructed NN was trained, and used to re-sort the operation sequence of the conflicting jobs on the same machine under the dynamic scenario, forming the final production management and control plan.

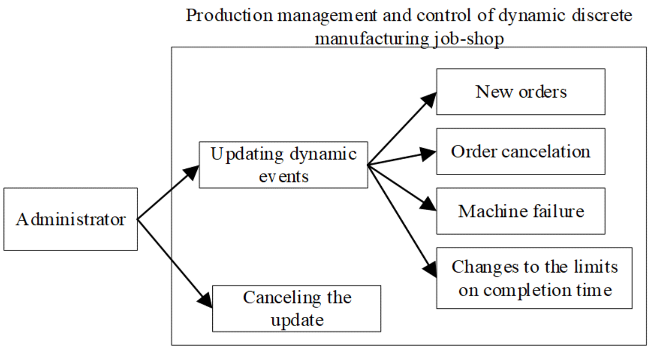

Figure 3: Dynamic event response and handling mode.

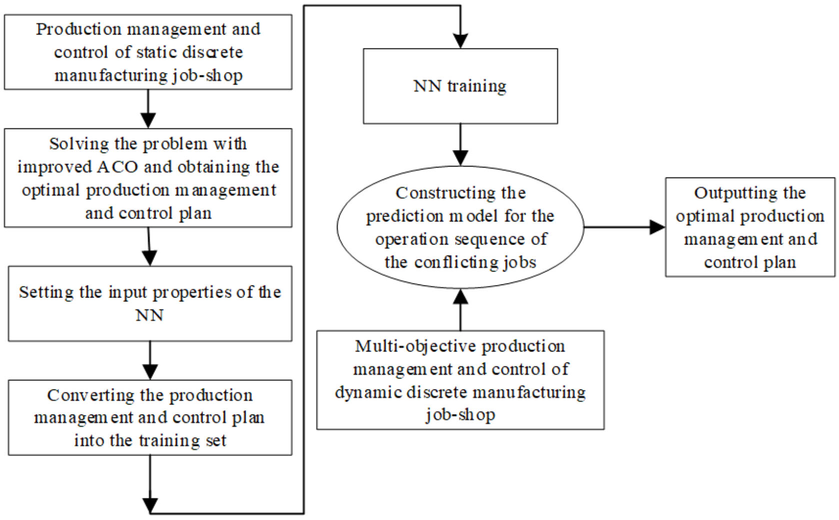

Figure 4: ACO and NN-based production management and control model.

4.1 NN outputs of production management and control objectives

During the production management and control of dynamic discrete manufacturing job-shop, if different operations of different jobs wait on the same machine after a dynamic event, then these jobs and the machine are considered conflicting jobs and machine. The NN production management and control aims to determine the priority of any jobs whose operations need to be implemented on the same machine. Analysis shows that the NN outputs of the objectives are not associated with the operation sequence of non-conflicting jobs or machines. The outputs merely determine the sequential order between the operations of two jobs, which have nothing to do with the number of operation sequences in the entire job-shop. With the help of the priority between the operations of conflicting jobs on the same machine, the NN can determine the operation sequence under any dynamic event.

4.2 Selection and transformation of judgement results on production state

The judgement results on the basic production state must be determined before predicting the sequence of the different operations in any two jobs on the same machine, with the aid of the NN. The dynamicity of the production management and control of dynamic discrete manufacturing job-shop only depends on the operation sequence of the jobs at the moment of the dynamic event, and the machine that executes the operation sequence. In this paper, the comparison results are summarized into five categories: yes, no, greater than, equal to, and smaller than. The five corresponding judgement items were defined as: the occurrence or absence of a dynamic event *JI*1; comparison of the processing time between all operations being executed *JI*2; comparison of residual processing time *JI*3; comparison of waited time between all operations in waiting state *JI*4; comparison of the number of the operations in waiting state on the same machine *JI*5. Fig. 5 presents the re-sorting and prediction model for conflicting operations based on the NN.

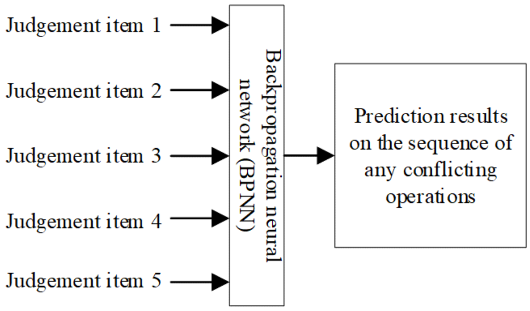

Figure 5: NN-based re-sorting and prediction model for conflicting operations.

4.3 NN construction

The multilayer feedforward BPNN was chosen to construct a production management and control model for dynamic discrete manufacturing job-shop. In our BPNN, the input layer contains the five judgement items for production state. Except the occurrence or absence of a dynamic event, any other judgement item could output three kinds of results. Thus, the number of input layer nodes N_I equals $2 + 12 = 14$. The output of the NN is either the priority of 0 or the priority of 1. Hence, the number of output layer nodes N_O is two. The number of hidden layer nodes N_H needs to be calibrated repeatedly or calculated by:

$$\begin{cases} N_H = \sqrt{N_I + 1} + \phi \\ N_H = ln2^{N_I} \\ N_H = \sqrt{N_I N_O} \end{cases} \tag{14}$$

where, ϕ is a constant in the interval of [1, 10]. Fig. 6 shows the structure of the NN.

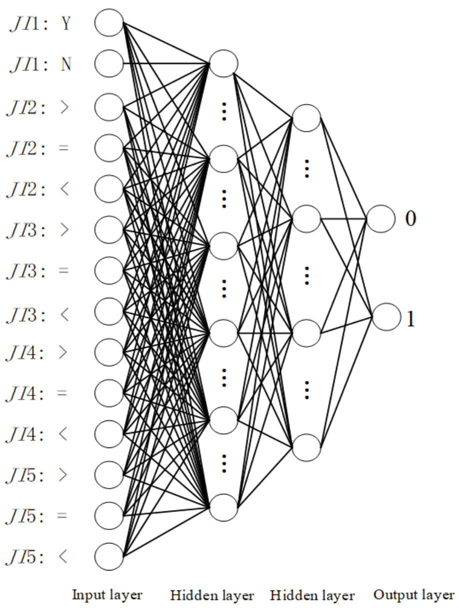

Figure 6: Structure of the NN.

4.4 Construction of training set

From the optimal production management and control plan obtained by solving the static multi-objective production management and control problem with the improved ACO, the conflicting jobs on the same machine were selected for comparison. The comparison results of the five judgement items were taken as a group and transformed into an NN training sample expressed with a 14-digit binary array. If the judgement items of the i^{th} operation are all smaller than those of the j^{th} operation, then the training sample imported to the NN can be expressed as: 10001001001001. If the i^{th} operation has a lower priority than the j^{th} operation, then the NN will output 01. Fig. 7 explains the construction of training samples.

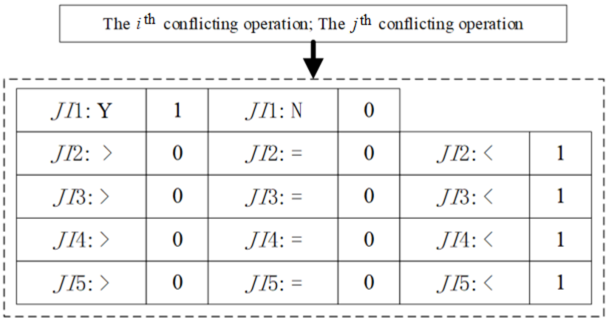

Figure 7: Construction of training samples.

5. EXPERIMENTS AND RESULTS ANALYSIS

Comparative experiments were designed to verify whether our improved ACO is effective in solving the static multi-objective production management and control problem. The original and improved ACOs were ran independently for 30 times. The feasible solutions of each algorithm were merged, removed of repeating items, and subject to the sorting of Pareto optimal solutions. As shown in Fig. 8, the original ACO obtained relatively few Pareto optimal solutions, while the improved ACO acquired many such solutions. Under the same conditions, the improved algorithm has an advantage in solution uniformity.

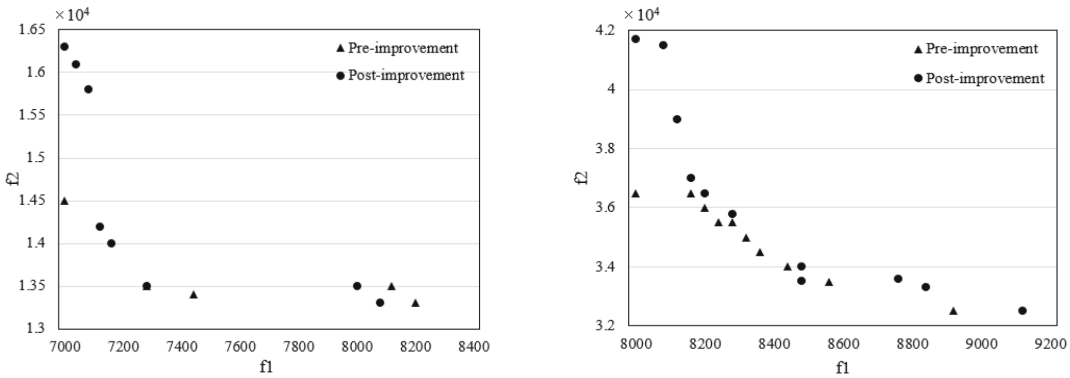

Figure 8: Pareto solution sets for static production management and control.

To further verify the superiority of the improved ACO, Fig. 9 compares the solution sets of the original and improved ACOs after a dynamic event, which were obtained through the sorting of Pareto optimal solutions. The dynamic event did not affect the operation of the improved ACO; the improved ACO achieved better results than the original ACO. Thus, our algorithm has relatively large search space and strong search ability.

To verify the effectiveness of our NN model in handling the production management and control of dynamic discrete manufacturing job-shop, the results of our model were compared with five traditional production management and control rules designed based on an actual production case. As shown in Table III, the job-shop has five jobs, and six machines. Table IV presents the relevant processing information of the new jobs added to the operation list after the dynamic event occurs.

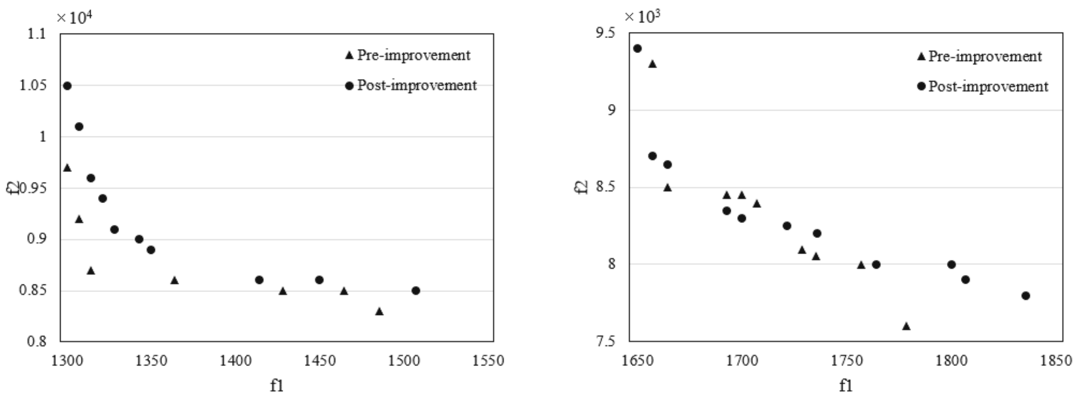

Figure 9: Pareto solution sets for production management and control after a dynamic event.

Table III: Information on jobs and operations.

Jobs	Machines					
	1	2	3	4	5	6
1	2-1	4-3	5-6	4-6	2-3	5-4
2	2-3	3-5	5-1	6-4	1-5	4-3
3	3-2	4-1	6-3	1-2	2-5	5-4
4	2-4	1-2	3-6	4-3	5-6	6-1
5	2-4	4-1	6-5	1-4	5-2	3-2

Table IV: Information on jobs added after the dynamic event.

Jobs	Machines						Event duration
	1	2	3	4	5	6	
5	2-4	4-2	1-6	5-6	3-4	2-4	15
6	2-6	3-2	5-4	6-2	1-5	4-6	17
7	3-1	4-5	6-4	1-3	2-4	5-6	13
8	2-3	1-5	5-6	5-3	1-6	4-1	20
9	3-4	4-5	6-2	1-5	5-3	3-6	35

Fig. 10 shows the optimal production management and control plan obtained by solving the static multi-objective production management and control problem with the improved ACO, with F_1 and F_2 as the optimization objectives. It can be seen that 73.25 h is needed to execute the plan. The mean complete cycle of the plan was obtained as 55.21 h. All the resulting plans were organized into a set of production management and control plans.

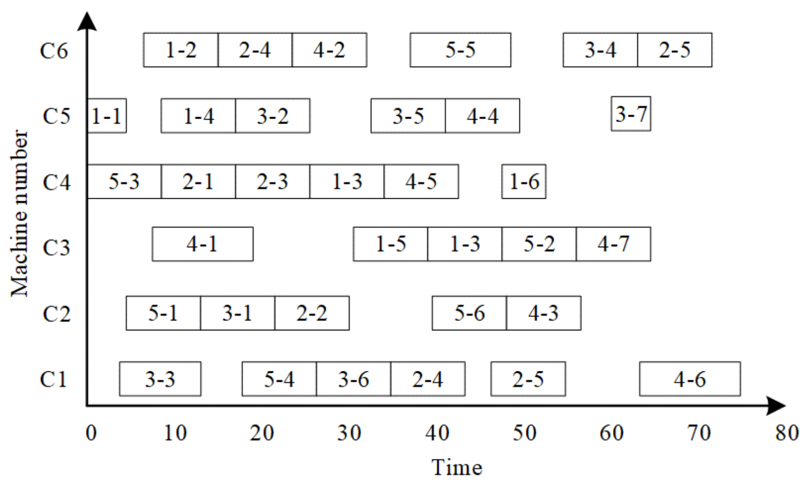

Figure 10: Gantt chart of static production management and control.

Next, a training set was established for the NN based on the set of production management and control plans. On this basis, our BPNN was trained, which includes 14 input layer nodes, 10 first hidden layer nodes, 8 second hidden layer nodes, and 2 output layer nodes. The trained BPNN was applied to solve the production management and control of dynamic discrete job-shop. As shown in Fig. 11, 76.47 h is needed to execute the plan.

Our model was compared with five traditional production management and control rules, namely, shortest processing time, first come, first served, delivery priority, maximum workload, and critical ratio. As shown in Table V, compared with the five traditional rules, our NN prediction model has a clear advantage in solving results, and an acceptable runtime.

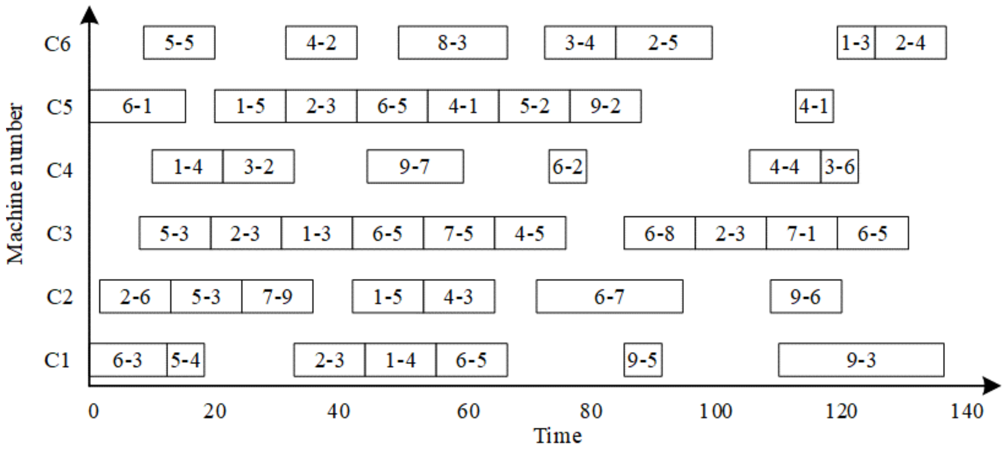

Figure 11: Gantt chart of dynamic production management and control.

Table V: Calculation results.

Rules	Results	Runtime (s)
Shortest processing time	121	0.075
First come, first served	94.72	0.069
Delivery priority	107.37	0.079
Maximum workload	114.75	0.083
Critical ratio	129	0.069
Our model	81.4	1.23

Table VI compares the results of different rules on 10 random actual production examples. The results show that our model outputted better results than the traditional rules. This further confirms the advantages of our algorithm and model in solving the production management and control of discrete manufacturing job-shop.

Table VI: Calculation results.

Examples	Shortest processing time	First come, first served	Delivery priority	Maximum workload	Critical ratio	Our model
1	101.47	121.10	111.7	126.3	101.79	83.85
2	115.41	105.76	99.05	122.14	141.08	83.21
3	101.46	101.86	113.59	114.85	120.68	86.35
4	127.56	120.45	103.56	113.42	108.54	79.11
5	127.85	129.70	98.64	107.15	99.60	79.57
6	119.80	121.46	106.83	117.72	103.97	87.25
7	121.85	104.97	97.85	114.96	103.97	88.94
8	111.66	105.65	127.34	129.64	121.86	83.17
9	109.63	101.85	99.54	101.05	102.75	89.50
10	116.72	99.45	118.34	102.35	121.82	90.31

6. CONCLUSIONS

This paper proposes a production management and control method for discrete manufacturing job-shops based on ACO and NN. The improved ACO was compared with the original ACO, which shows that, under the same conditions, the improved algorithm has an advantage in solution uniformity. In addition, experimental results prove that our NN model can effectively handle the production management and control problem of discrete manufacturing job-shop.

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