

Dynamic scheduling for manufacturing workshops using Digital Twins, Competitive Particle Swarm Optimization, and Siamese Neural Networks

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ABSTRACT

Flexible manufacturing workshops often encounter scheduling challenges due to complex processes and cumbersome procedures. To address these issues, a dynamic scheduling method is proposed. Initially, a discrete manufacturing workshop scheduling problem model is developed, considering the unique characteristics of the workshop. Digital Twin technology and a Competitive Particle Swarm Optimization algorithm are then integrated to create the scheduling model. Finally, Siamese Neural Networks are incorporated to form a dynamic scheduling mechanism that optimizes disturbance scheduling. The research model demonstrated a quick convergence, efficiently searching for the optimal fitness value using both the Sphere and Griewank functions. In the scheduling objective function test, the model achieved a maximum completion time of 244.8 minutes, the shortest time compared to similar technologies. In Siamese Neural Network experiments, the model successfully suppressed the influence of disturbances, maintaining optimal scheduling performance. Without adjustments for disturbances, the maximum completion time was 58.5 minutes. After optimization, it decreased to 54.2 minutes. These results demonstrate the effective application of the proposed technology in workshop scheduling. The findings provide valuable technical insights for the application of intelligent technologies in workshop scheduling optimization.

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1. Introduction

With the rapid development of digital technology, the global manufacturing industry has entered the era of Industry 4.0. The emerged digital twin technology has solved the shortcomings of traditional manufacturing in workshop control and decision-making [1]. It utilizes the mapping relationship between virtual space and physical entity space to achieve data fusion, and uses digital twin technology to achieve high-precision management, control, and decision-making in industrial manufacturing [2]. In industrial manufacturing, many manufacturing workshops commonly face workshop scheduling. Workshop scheduling arranges scheduling plans based on process conditions, material quantities, and machine usage to effectively reduce manufacturing cost and improve production efficiency. However, in actual manufacturing, a product will go through multiple processes, multiple machines, and other processing steps during production [3]. Due to the multiple influencing conditions and the susceptibility to external disturbances in the manufacturing process, many scheduling decisions in manufacturing workshops are not ide-

al. Therefore, to solve the scheduling problem in manufacturing workshops, a dynamic scheduling mechanism based on Siamese Network (SN) is proposed. There are two innovations in the research. One is the introduced digital twin technology and competitive particle swarm optimization to construct a data fusion scheduling model, achieving efficient scheduling in the workshop. Secondly, SN is introduced to optimize workshop disturbances, and the production efficiency of workshop manufacturing is improved by readjusting scheduling after disturbance. The research content will provide technical support for the improvement of workshop scheduling and the effective application of digital twin technology. The research has two contributions. Firstly, by combining digital twin technology and machine learning technology, a data fusion scheduling model was constructed, effectively improving the scheduling efficiency of manufacturing workshops and promoting the development of workshop intelligence. The second is to study the introduction of twin neural networks to optimize workshop disturbances, significantly improving the production efficiency of the workshop in the face of disturbances, and enhancing the safety and stability of the manufacturing workshop.

2. Literature review

Effective workshop scheduling is beneficial for resource integration and improving the overall operational efficiency of the production line. Relevant scholars have conducted extensive research on this. Luo *et al.* found that multi-resource constrained workshop scheduling faced many difficulties. To improve workshop efficiency and scheduling effectiveness, a problem decision model based on Markov was designed to represent the numerical state characteristics and related constraint relationships of the workshop through mathematical models. The results showed that this technology could significantly improve the work efficiency of the workshop. The technology was superior to similar models [4]. Li *et al.* found that automatic guided vehicles have become an indispensable tool in workshop production. In practical work, their scheduling system is unable to handle specific working conditions. A dynamic scheduling technique was proposed in this study, which utilized its characteristics and task requirements to establish a scheduling model. The proposed technology was reliable and solved the scheduling problem of automatic guided vehicles in complex environments [5]. Liu *et al.* found that the automatic tractor in current intelligent manufacturing plays a critical role in automated production lines, but it cannot be effectively integrated into the workshop scheduling system, which affects the efficiency of workshop operations. In response to this, a flexible automatic traction vehicle scheduling technology was proposed. Then, an optimization model was established using an optimized genetic algorithm, which was then used to complete scheduling optimization through learning. The results indicated that the improved technology could effectively improve the scheduling effect of the workshop, and its performance was superior to similar scheduling technologies [6]. Zhang *et al.* found that due to various factors such as environment and time constraints, it is difficult for carrier-based aircraft to complete maintenance work within an effective time. In response to this, an analysis was conducted on its maintenance scheduling. A carrier-based aircraft maintenance scheduling technology considering comprehensive factors was proposed. The improved genetic algorithm was used to establish a scheduling model, and the scheduling performance was improved through parameter optimization. Experimental tests showed that the proposed technology could significantly improve the maintenance effectiveness of carrier-based aircraft. The scheduling process was flexible and reliable [7].

With the development of deep learning technology, workshop scheduling technology based on twin technology has ushered in important development and plays an important role in workshop scheduling. Tliba *et al.* found that production lines faced problems such as low efficiency and unreasonable resource utilization in actual management due to factors such as resource and workshop allocation. To overcome the above problems, considering the constraints of workshop conditions and resource status, a twin driven dynamic scheduling technique based on twin technology was proposed. In specific scenarios, the proposed technology had good adaptability while meeting the constraints, improving the efficiency of workshop scheduling [8]. Huo *et al.* proposed a dynamic scheduling model based on digital twins and bacterial foraging algorithm to

improve the efficiency of production line scheduling. The model allocated and sorted schedules based on two sub problems in the scheduling process. Corresponding models were established. In the study, a certain mechanical grinding tool production line was selected as an experimental case. The technology was applied to the working environment. The results showed that the research technology could optimize the production line scheduling well, with higher efficiency and avoiding previous production line interruptions [9]. Peng *et al.* conducted research on automated industrial production lines and found that the contradiction between workshop system control management and execution layer affected industrial manufacturing efficiency. To improve the production efficiency of the production line, an intelligent scheduling architecture based on digital twin technology was proposed, which combined fuzzy control and deep learning, and reflected the impact relationship between different process scheduling through digital modeling. Finally, applying it to railway manufacturing workshops could significantly improve the workshop resource utilization and enhance the production efficiency of the production line [10]. In addition, Khadiri *et al.* found that solving the dynamic scheduling problem of production lines was necessary in intelligent manufacturing to effectively enhance the allocation efficiency and manufacturing efficiency of production lines. In this regard, a dynamic workshop scheduling system based on distributed holographic architecture and digital twin technology was proposed in the research. This technology solved the resource scheduling problem of manufacturing systems through bidirectional model design, and improved the controllability and control effect of the entire workshop [11].

According to the above research findings, twin technology can effectively optimize workshop scheduling and play a key role in intelligent control of the workshop. Therefore, to improve the production efficiency of manufacturing workshops, a smart workshop scheduling technology based on digital twin technology is proposed. Through workshop modelling and constraint analysis, workshop scheduling is improved to enhance the development effect of intelligent manufacturing in enterprises.

3. Research methodology

3.1 Modelling of discrete manufacturing workshop scheduling problem

To improve the workshop scheduling efficiency in manufacturing workshops, a SN-based manufacturing workshop scheduling model is built to promote the rapid development of the manufacturing industry [12]. The framework of workshop scheduling optimization technology based on SN is shown in Fig. 1.

In workshop scheduling based on twin networks, the first step is to clarify the workshop scheduling problem, followed by data fusion to determine the flow information mode. Finally, the scheduling model is established to solve the manufacturing workshop scheduling problem [13]. In specific discrete manufacturing workshops, Job-shop Scheduling Problem (JSP) is actually a production process priority decision-making process, in which multiple single projects are decomposed and scheduled [14]. The shortest allocation time is sought to complete production tasks in a limited resource environment [15]. Therefore, based on the scheduling characteristics of the manufacturing workshop, O_{ip} is the p -th process of workpiece i . The objective function is set to f , which will be represented as Eq. 1.

$$f = \min \left(\max(C_{ip}) \right) \quad (1)$$

In Eq. 1, C_{ip} represents the completion time of the p -th process of workpiece i in the production workshop. In the specific production scheduling process, there may be differences in the selection of optimization indicators based on enterprise plans, actual inventory materials, and process characteristics, but the priority goal is basically to complete tasks in the shortest possible time. At the same time, in manufacturing tasks, it is necessary to carry out according to the relevant requirements of the task, so corresponding workshop scheduling constraints need to be met [16]. One is that a certain process in manufacturing matches a unique production machine, and the machine can only operate on specific processes. Therefore, its constraint is shown in Eq. 2 [17].

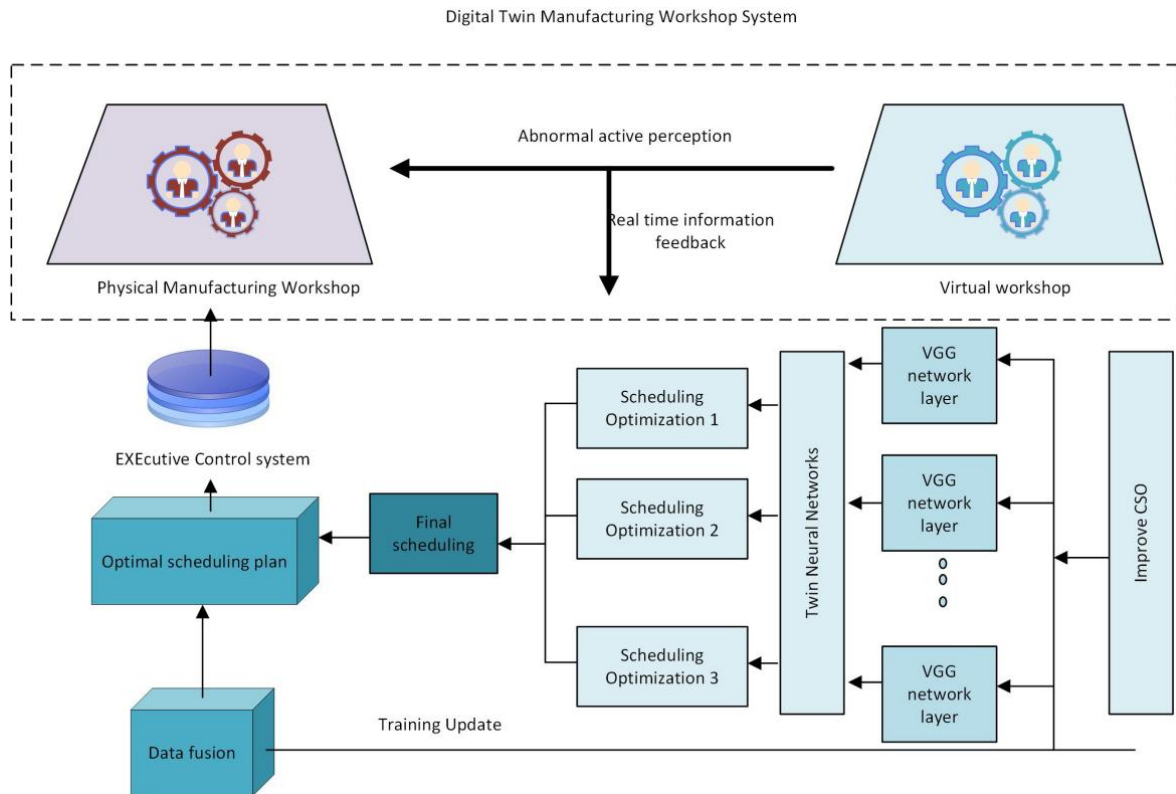


Fig. 1 Framework of workshop scheduling optimization technology based on SN

$$\sum_{k=1}^J X_{ipk} = 1, i = 1, 2, \dots, N, p = 1, 2, \dots, J \quad (2)$$

In Eq. 2, X_{ipk} represents the operational status of process O_{ip} on production machine k . N represents the number of workpieces. J represents the number of workpieces. In addition, in actual production, each machine needs to complete the previous task process before proceeding to the next task. The second constraint expression is shown in Eq. 3.

$$C_{ipk} \leq Q_{(i+1)pk}, i = 1, 2, \dots, N, p = 1, 2, \dots, J, k = 1, 2, \dots, m_p \quad (3)$$

In Eq. 3, $Q_{(i+1)pk}$ represents the next starting time of process O_{ip} on production machine k . C_{ipk} represents the completion time of process O_{ip} on production machine k , m_p represents the number of production machines. In addition, each workpiece in the manufacturing workshop also needs to complete the previous process before proceeding to the next task. The third constraint expression is shown in Eq. 4.

$$C_{ipk} \leq Q_{i(p+1)k}, i = 1, 2, \dots, N, p = 1, 2, \dots, J, k = 1, 2, \dots, m_p \quad (4)$$

In Eq. 4, $Q_{i(p+1)k}$ represents the start time of the next process in the production machine. The entire manufacturing workshop scheduling optimization process is shown in Fig. 2.

According to the workshop scheduling process in Fig. 2, the workshop scheduling problem needs to start from the manufacturing process path. Under the constraints of manufacturing, the manufacturing process is optimized to achieve the minimum task time.

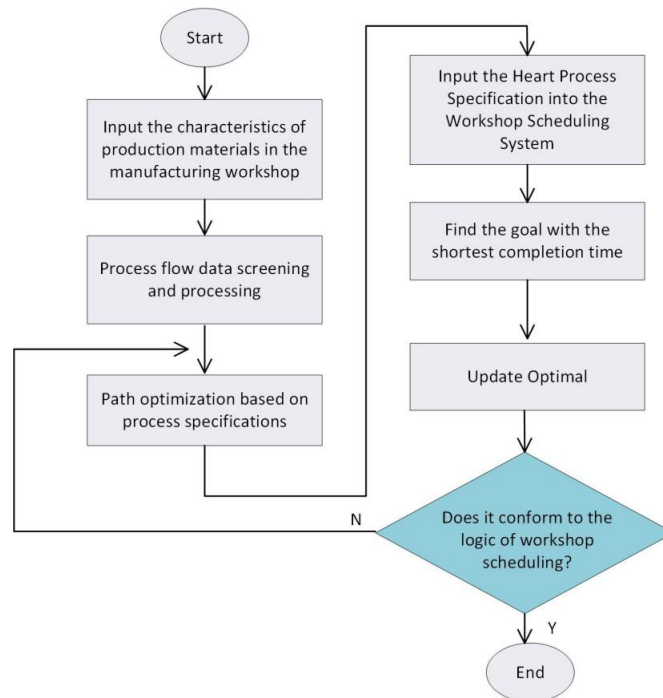


Fig. 2 Manufacturing workshop scheduling optimization process

3.2 Construction of data fusion scheduling model based on digital twins

The previous section analyses the scheduling problem in discrete workshops. In actual production in discrete workshops, due to the characteristics of product attributes, multiple process information needs to be analysed in manufacturing, resulting in heterogeneous data and difficulty in scheduling solution [18]. To address this issue, the research needs to describe complex production problems as similar feature problems. This study introduces digital twin technology for data fusion and uses an improved Competitive Swarm Optimizer (CSO) to solve it. The digital model of the workshop based on digital twin technology is shown in Fig. 3.

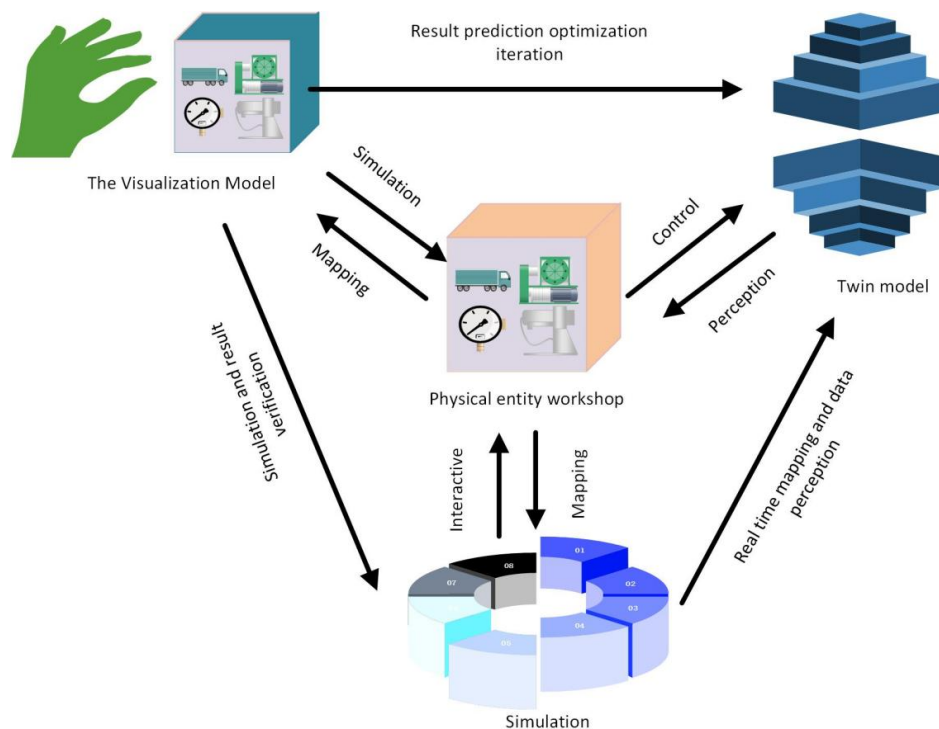


Fig. 3 Digital twin workshop digital model

From Fig. 3, digital twin technology has established a connection between virtual workshops and physical manufacturing workshops and achieved control and management of workshop production and manufacturing through interaction and mapping [19]. Therefore, it is used in the study to integrate multi-source information from manufacturing workshops, providing a foundation for subsequent scheduling solutions. In the digital twin manufacturing workshop, in order to describe the virtual real control relationship of the workshop, the initial three-dimensional coordinates and the adjusted three-dimensional coordinates are defined as P and p' respectively, as expressed in Eq. 5.

$$\begin{cases} P = (x, y, z) \\ P' = (x', y', z') \end{cases} \quad (5)$$

In Eq. 5, x , y and z are the initial coordinate parameters. x' , y' and z' represent the coordinate parameters after movement. According to the coordinate parameters. Multiplying P' with the four-dimensional coordinate $(x, y, z, 1)$ can calculate a three-dimensional model action change matrix, as shown in Eq. 6.

$$P' = PM = (x, y, z_1) \begin{bmatrix} b_{11} & b_{12} & b_{13} & p_x \\ b_{21} & b_{22} & b_{23} & p_y \\ b_{31} & b_{32} & b_{33} & p_z \\ t_x & t_y & t_z & s \end{bmatrix} \quad (6)$$

In Eq. 6, t_x , t_y and t_z represent the three-dimensional coordinate translation parameters. p_x , p_y and p_z represent the perspective projection transformation matrix in three-dimensional space, with three parameters serving as projection midpoints. The 9 parameters, including b_{11} and b_{12} , are coordinate transformation matrix parameters responsible for model scaling and rotation. s represents the integer scaling coefficient in the three-dimensional model which mainly controls the scaling size of the model in three-dimensional space. The twin manufacturing workshop information model is shown in Fig. 4.

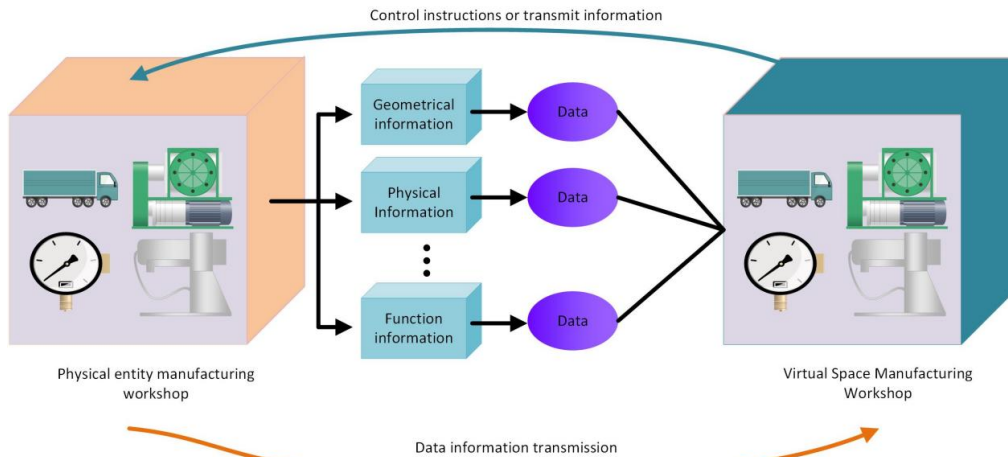


Fig. 4 Twin workshop information model

In the twin workshop, the information features that need to be extracted include labour, materials, equipment, production environment, and production knowledge. Based on this, key data for information fusion is constructed, as shown in Eq. 7 [20].

$$DT = DT_{cq} \cup DT_{pr} \cup DT_{pe} \cup DT_{cn} \cup DT_{kn} \quad (7)$$

In Eq. 7, DT_{eq} represents device information. DT_{pr} represents material information. DT_{pe} represents personnel information. DT_{en} represents environmental information. DT_{kn} represents production knowledge information. Among them, DT_{kn} information contains the entire workshop workpiece processing process information, which needs to be optimized starting from it. After obtaining the fused data, an improved CSO model is used to solve the scheduling problem.

CSO is a search algorithm derived from particle swarm optimization without memory, which has excellent optimization performance and strong convergence. CSO selects the optimal individual through competitive relationships. The CSO algorithm is updated, as shown in Eq. 8.

$$v_1(t+1) = R_1 v_1(t) + R_2 [x_w(t) - x_t(t)] + \varphi R_3 [\bar{x}(t) - x_t(t)] \quad (8)$$

In Eq. 8, $x_w(t)$ represents the dimensional vector of the winning individual after t rounds of competition. $x_t(t)$ is the dimension vector of the failed individual. $\bar{x}(t)$ represents the random position value of individuals competing t times. R_1 , R_2 and R_3 are all representative interval distributed random vectors. φ represents updated the influencing parameters. $v_1(t)$ represents the updated strategy. In CSO updates, population diversity is improved by half updating, but it can easily lead to a decrease in inter population searchability. Therefore, two encoding segments are introduced to improve CSO. Among them, circular and cross topology structures are added to the positions of the winning individuals, and the top 20 % of individuals are selected for neighborhood search to improve the overall optimization performance of the model. In addition, it is also considering that the circular topology structure allows encoding adjacent individuals to be connected to each other. But the expansion of the radius slows down information transmission and limit information sharing. Therefore, a Precedence Operation Crossover (POX) algorithm is adopted to integrate into the circular structure. Individuals and adjacent excellent individuals are selected as the subsequent crossover parents, and excellent individuals are selected from the iterative offspring to replace the current individual, achieving model improvement [21]. The crossover probability is shown in Eq. 9.

$$p_c = p_0 \times \frac{t_{rmax} - t_r}{t_{rmax}} \quad (9)$$

In Eq. 9, p_0 represent the initial values, while t_{rmax} denotes the maximum iteration, and t_r represents the current iteration count.

3.3 Modelling of workshop dynamic scheduling mechanism based on SN

In actual manufacturing workshops, different processes can lead to problems such as overlapping and scheduling errors in a certain link. To solve this problem, a workshop dynamic scheduling mechanism based on SN is proposed to address the scheduling disturbances in manufacturing workshops. SN is a coupled deep learning framework composed of multiple identical structures. The core of the SN is to use multiple sub networks to simultaneously train and compare parameter similarities and differences [22]. Based on this study, SN network is used to identify abnormal disturbances between physical and virtual workshops in digital twins. Cumulative disturbances are determined, and scheduling is adjusted by mining historical workshop data. At the same time, the impact of updated scheduling on actual workshop manufacturing is compared. Continuous iterations are repeated to approach the optimal workshop scheduling, achieving workshop scheduling disturbance optimization [23]. In the study, the loss function of the SN network is selected as Binary Cross Entropy, which has better stability, as displayed Eq. 10.

$$loss(y_o, t_r) = -[t_r \log(y_o) + (1 - t_r) \log(1 - y_o)] \quad (10)$$

In Eq. 10, t_r represents the label, while y_o denotes network output. In the sub networks of SN, Visual Geometry Group (VGG) has excellent application effects in the field of image feature processing. Therefore, with the help of VGG features, 3×1 convolution is introduced to design the sub network. At the same time, the Sigmoid function is selected as the network activation function, which has excellent performance in handling binary classification problems and is more advantageous for handling features with obvious differences, meeting the requirements of digital twin feature data processing. Therefore, the Sigmoid function is expressed as shown in Eq. 11.

$$f(x) = \frac{1}{1 + e^{-x}} \quad (11)$$

When processing data that is too large or too small, SN is prone to gradient vanishing problems, which can affect network training. Therefore, Batch Normalization (BN) is applied to address gradient vanishing problems. Increasing the BN layer after each convolution improves the

training speed of the network. The BN layer transformation is shown in Eq. 12.

$$\begin{cases} \hat{x}^{(i)} = \frac{x' - E[x^{(i)}]}{\sqrt{Var[x^{(i)}]}} \\ y^{(i)} = \gamma^{(i)} \hat{x}^{(i)} + \beta^{(i)} \end{cases} \quad (12)$$

In Eq. 12, $E[x^{(i)}]$ represents the mean, while $\sqrt{Var[x^{(i)}]}$ represents the standard deviation. $\gamma^{(i)}$ corresponds to the learning scaling parameters, and $\beta^{(i)}$ represents the offset parameter. $y^{(i)}$ is the output of neurons, and $x^{(i)}$ is the input vector. Finally, $\hat{x}^{(i)}$ represents transformed input vector. To enhance the ability of the SN model to extract workshop feature data, the study employs a double-layer VGG convolutional network structure. This includes various layers such as activation and pooling layers, designed for extracting features that capture differences in twin workshop information. Multiple similar structures are combined to form the SN model. The SN structure is shown in Fig. 5 [24].

After constructing the SN, it is necessary to select important feature data from the digital twin system as the output of the SN, such as processing time, production machine processes, process constraints, etc. Therefore, Table 1 data are taken as status characteristics.

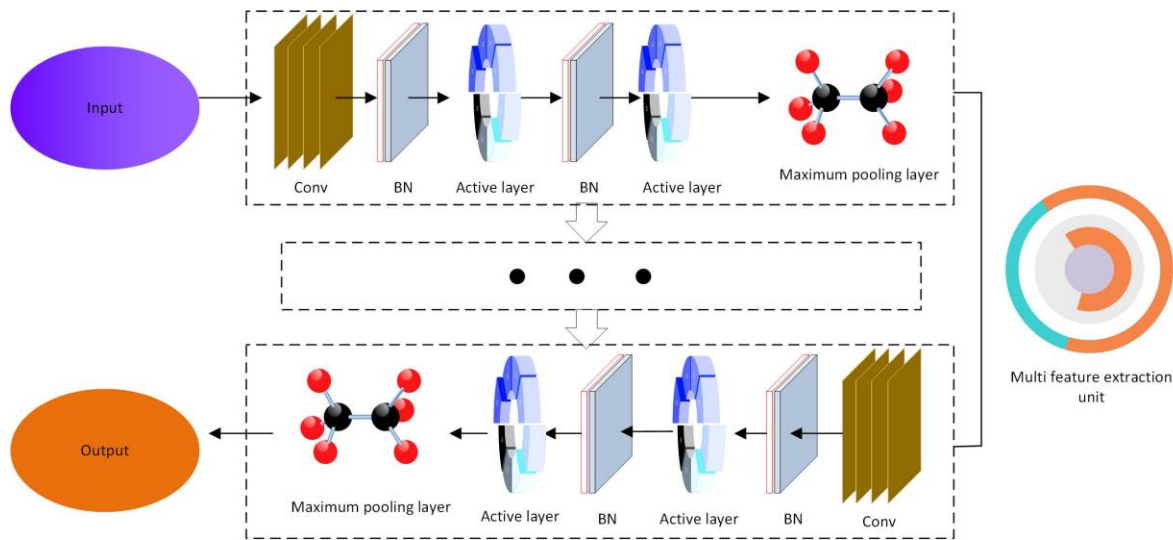


Fig. 5 SN sub network structure

Table 1 Status characteristics of digital twin manufacturing workshop

Signature sequence	Characterization
1	The total duration of workpiece processing
2	The number of processes in which the workpiece has been processed
3	The number of idle workpieces in the workshop
4	Number of idle machines in the workshop
5	The number of processes that the machine has not yet processed
6	The number of machines being processed in the workshop
7	The total duration of machine processing
8	Total idle time of the machine
9	The number of processes where the workpiece has not been processed yet
10	Number of processes for the workpiece
11	The number of processes to be processed by the machine
12	The machine number of the workpiece being processed
13	Total idle time of workpieces
14	The number of processes already processed by the machine

The min-max standard is used to preprocess selected data and improve the accuracy of network training. In actual training, if the SN output label is selected based on the accumulated disturbance time point, the output label of the data state before the accumulated disturbance is

determined to be 0. The output label of the data state after the accumulated disturbance point is determined to be 1. In addition, for traditional manufacturing workshops with a single scheduling rule, SN cannot provide good scheduling decisions. Therefore, a pseudo-SN is added to the SN to learn features, which simplifies the structural process, uses simplified convolutions as sub networks, and mines the mapping relationship between processes and machine scheduling. The connection layer of the network achieves feature fusion through concatenation, followed by the simplified double convolution to enhance feature extraction. Through the above research, the dynamic scheduling mechanism for manufacturing workshops is completed.

4. Results and discussion

4.1 Experimental analysis of workshop scheduling effect

To test the manufacturing workshop scheduling technology, corresponding experiments are conducted to verify the reliability of the technology. Firstly, the experimental environment is built. In the experiment, a flexible workshop for electrical manufacturing is taken as the research object. The workshop has a total of 26 production and manufacturing processes, several machines, and 6 workpieces. The workshop scheduling solution adopts an improved COS model and a SN scheduling mechanism to solve the dynamic scheduling disturbance problem caused by the accumulation of hidden disturbances in the workshop. In the digital twin workshop, the improved CSO algorithm is set to have 100 iterations, a population size of 60, and a crossover rate of 0.8. Simultaneously, the Genetic Optimization-Particle Swarm Optimization Algorithm (GA-PSO) and standard CSO algorithm are introduced for comparison. Sphere function and Griebank function are taken to test the performance of different scheduling models, as shown in Fig. 6.

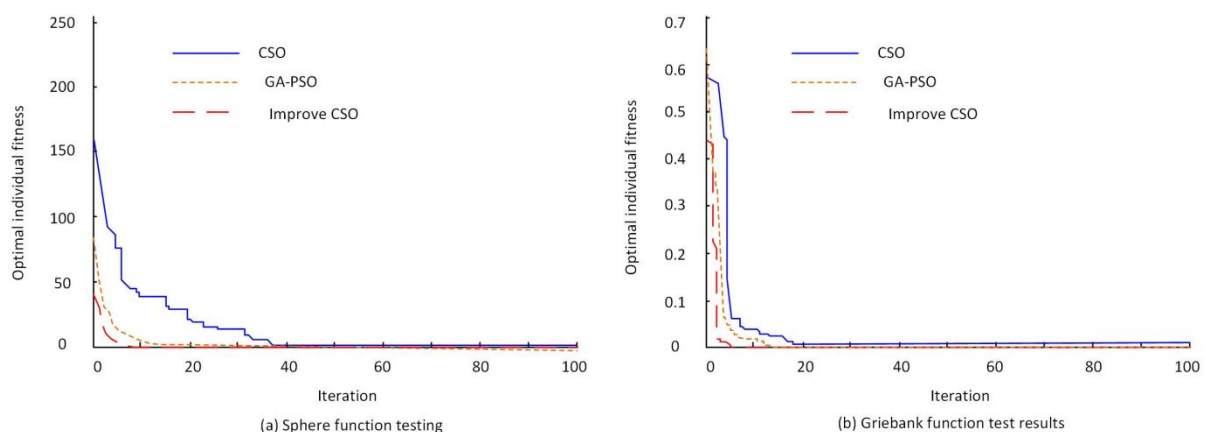


Fig. 6 Comparison of optimization performance of different scheduling models

Fig. 6(a) and 6(b) show the optimization test results of Sphere function and Griebank function, respectively. According to the test results, the improved CSO converged faster and was closer to the optimal value of the function compared with GA-PSO and CSO. In the Sphere function, the improved CSO converged 9 times, achieving an optimal fitness value of 0.025. In comparison, the GA-PSO converged 18 times, with a final fitness value of 0.156, while the standard CSO converged 38 times, reaching an optimal fitness value of 0.186. In the Griebank function, the improved CSO still performed better, with a 5.38 % and 11.25 % improvement in optimization ability compared with GA-PSO and CSO.

Next, the training results of the objective function for different scheduling models are shown in Fig. 7. This figure shows the results of solving scheduling objectives for different scheduling models. The standard CSO scheduling model performed the worst overall. According to the test curve, although the standard CSO model had an advantage in population diversity in the early stages of training, its search performance decreased in the later stages of training, and the model fell into local convergence. Its maximum completion time was ultimately 264.5 minutes. In contrast, GA-PSO had better optimization performance and convergence effect, but due to the influ-

ence of genetic algorithm parameters, premature convergence phenomenon occurred when processing high-dimensional data. Its maximum completion time was 249.2 minutes, which was better than the standard CSO model. The overall best performance is the improved CSO model, with a final target value of 244.8 minutes. It enhances the information communication between individuals through neighbourhood structure, avoids local optima, and has more advantages in convergence. Next, the scheduling Gantt chart results of different models are compared, as shown in Fig. 8.

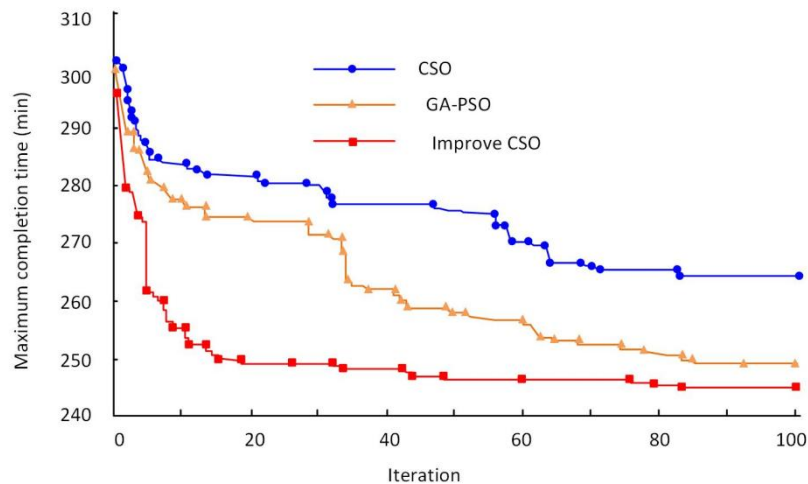


Fig. 7 Results of solving scheduling objectives for different scheduling models

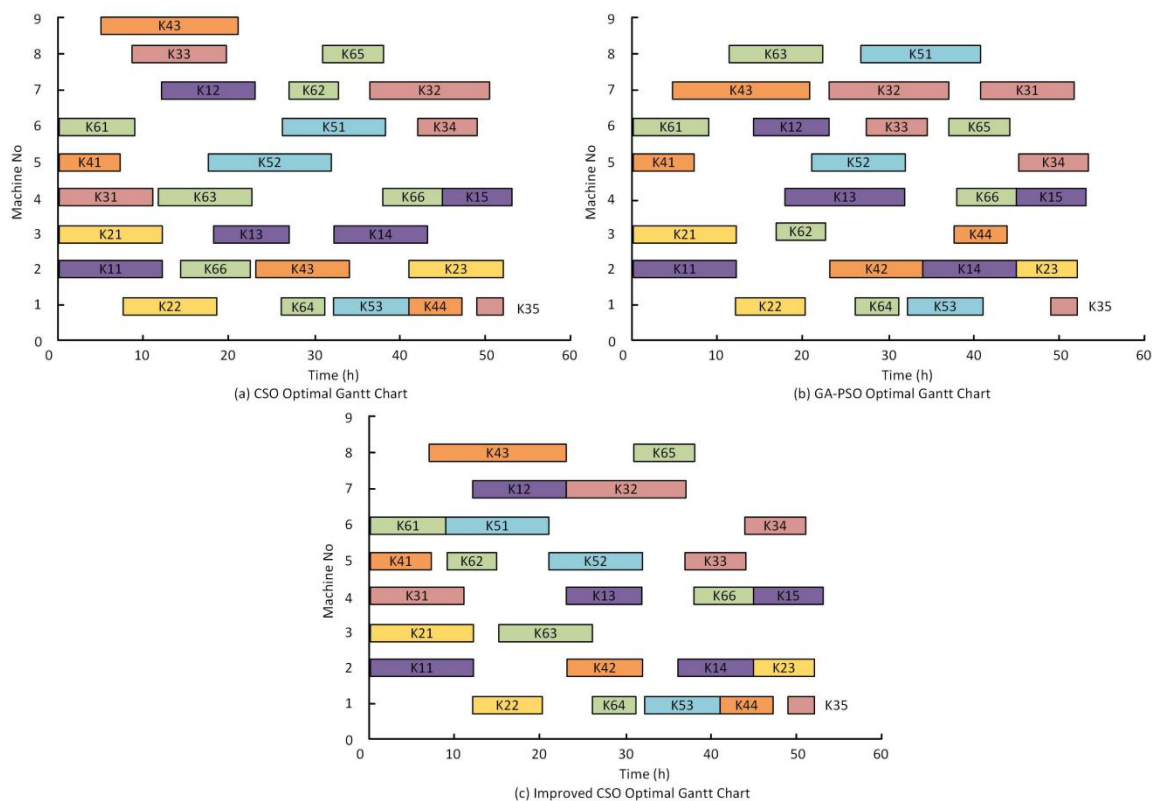


Fig. 8 Optimal Gantt chart results for different scheduling models

Fig. 8(a) shows the optimal result of the CSO Gantt chart. The number of processing machines under CSO training was 9, the number of processed workpieces was 6, and convergence was achieved after 84 iterations. The average processing time for a single workpiece was 59.2 minutes. Fig. 8 shows the optimal result of the GA-PSO Gantt chart. GA-PSO scheduling optimization was better. The processing machine consisted of 8 units and processed 6 workpieces. It

converged after 85 iterations, with an average processing time of 55.25 minutes for a single workpiece. Fig. 8(c) shows the optimal result of the improved CSO Gantt chart, which converged after 82 iterations. The number of processing machines was 8, the number of processed workpieces was 6, and the average processing time for a single workpiece was 52.2 minutes.

4.2 Experimental analysis of workshop scheduling based on SN

To test the application effect of SN in scheduling rules, the improved CSO model scheduling results are selected as a case study for analysis. Among them, there are 26 workshop processes, 8 machines, and 6 workpieces. In the experiment, the convolution kernel of the SN is set to 3×1 , with 5 feature extraction units, a sliding step size of 2, and an optimizer of Adam. In the experiment, the process code is set as K, the workpiece code is C, and the mechanical code is D. Table 2 shows the corresponding machining machine information for the manufacturing and processing process of this electrical appliance.

Table 2 Electrical manufacturing and processing information of a manufacturing workshop (Time/h)

Workpiece	C1				C2				C3				
Production processes	K11	K12	K13	K14	K15	K21	K22	K23	K31	K32	K33	K34	K35
D1	-	18	-	-	15	-	8	16	-	-	9	-	3
D2	12	-	-	11	-	-	-	7	-	-	-	12	-
D3	-	-	14	-	-	12	-	-	-	12	-	-	-
D4	-	19	9	-	8	19	9	-	11	18	15	-	4
D5	14	-	-	0.9	-	14	-	-	10	-0:	7	-	-
D6	-	-	17	-	-	-	-	9	-	-	-	5	8
D7	20	11	-	-	-	-	15	-	-	14	-	-	-
D8	-	-	-	12	18	-	-	-	13	-	-	9	-
Workpiece	C4				C5				C6				
Production processes	K41	K42	K43	K44	K51	K52	K53	K61	K62	K63	K64	K65	K66
D1	-	-	-	6	-	-	9	-	8	-	5	-	19
D2	19	-	11	-	-	18	-	11	-	-	-	11	-
D3	-	8	-	-	-	-	12	-	-	11	-	-	-
D4	-	-	8	-	22	-	-	-	-	-	15	-	7
D5	7	11	-	-	-	11	-	-	6	17	-	-	-
D6	-	-	-	-	12	-	-	9	-	-	-	8	15
D7	13	-	18	14	17	-	-	14	-	-	7	-	-

The scheduling results in Table 2 are obtained from the training of the improved CSO scheduling model. In the improved CSO model, the planned completion time was 52.2 min. The disturbance was added in the subsequent experiments to simulate the disturbance of different process abnormal states in scheduling. The scheduling data are input into the digital twin scheduling system and 21.2 min perturbations are added. Whether the system disturbance has been triggered is checked, as shown in Fig. 9. This figure shows the results of the disturbance effect test. According to the results, disturbance is added at 24.1 minutes of scheduling, as indicated by the red line in Fig. 9(b). Compared with the simulated output value of 0.523 at 24.1 minutes in Fig. 9(c), it exceeded the system's specified disturbance standard value of 0.5, indicating successful triggering. Next, the effect of different models on post disturbance scheduling adjustment is compared.

The disturbance time point is 37.1 min, and the results are shown in Fig. 10. Fig. 10(a) to 10(d) show the original scheduled scheduling, perturbed unadjusted scheduling, pseudo-SN scheduling, and SN scheduling, respectively. According to the test results, the original workshop's planned completion time for the workpiece was 52.2 minutes. After disturbance, its maximum completion time in its unadjusted state became 58.5 minutes. After using pseudo-SN and SN for disturbance adjustment, the maximum completion time of both models was adjusted to 56.4 minutes and 54.2 minutes, respectively. Both models improved the scheduling deviation after disturbance, while the SN performed the best, reducing the unadjusted state time by 4.3 minutes, which was better than the pseudo-SN's 2.1 minutes. The SN dynamic scheduling mechanism can effectively suppress disturbances and meet the scheduling requirements of the manufacturing workshop.

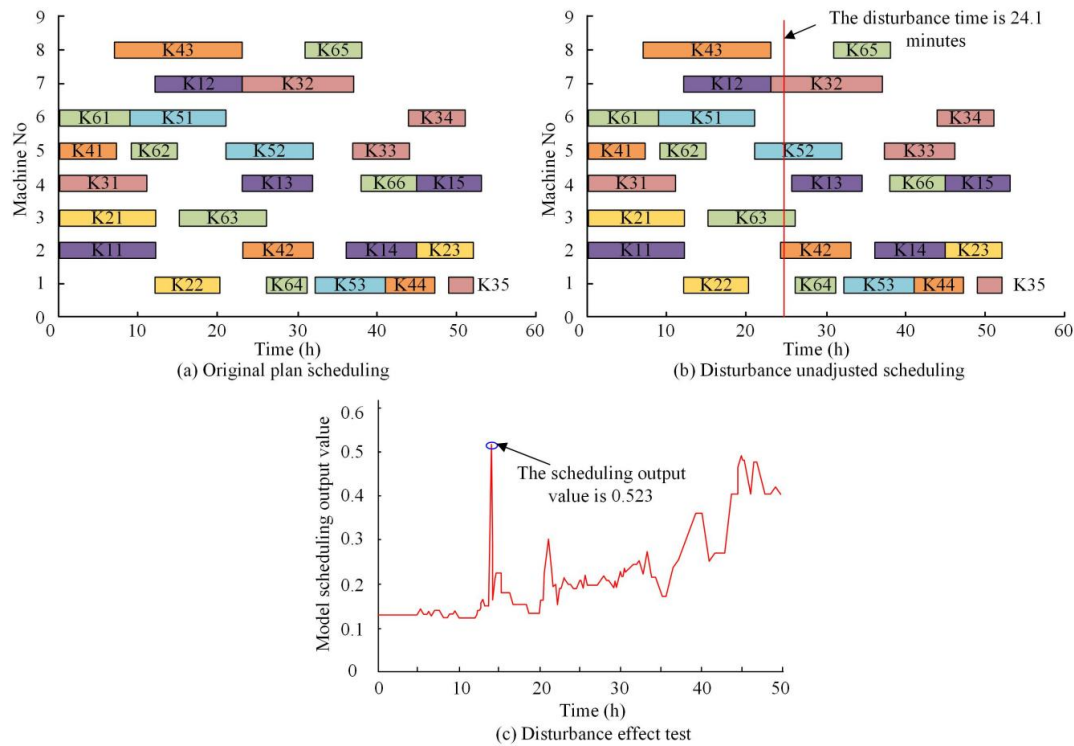


Fig. 9 Disturbance trigger test

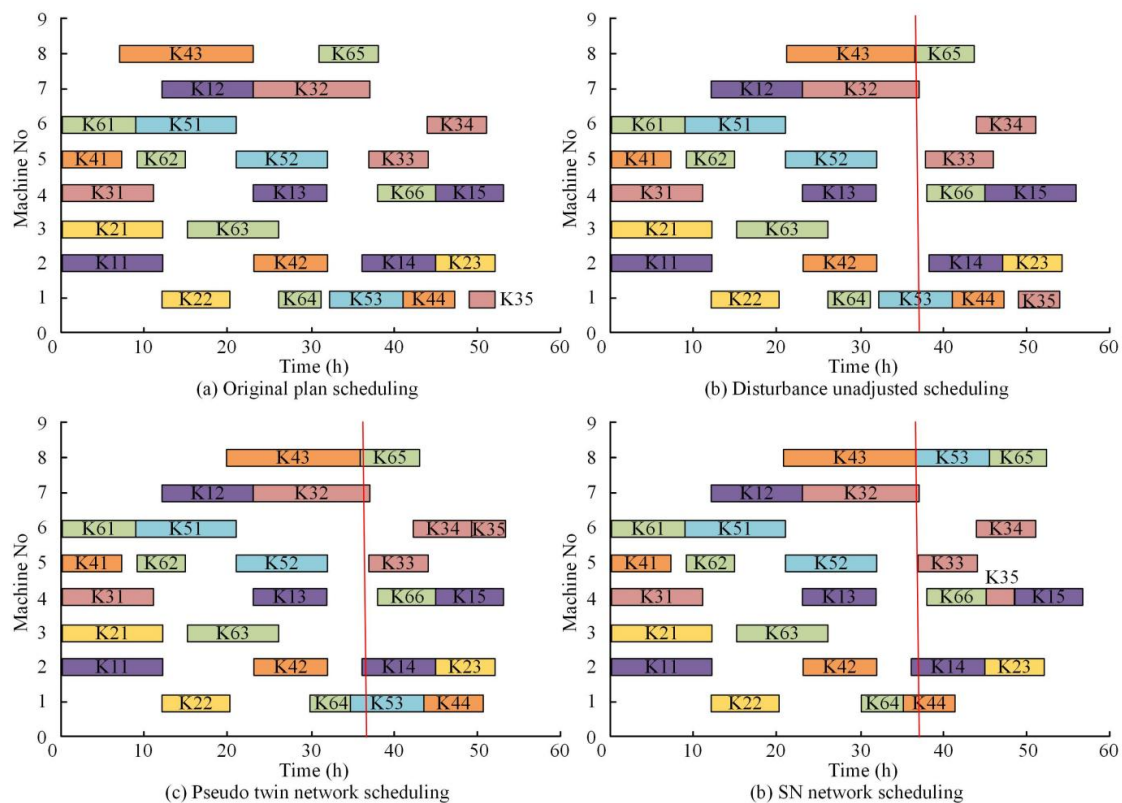


Fig. 10 Scheduling effects of different models after adding perturbations

In addition, studying the same process and increasing complexity to compare the effects of different technologies is shown in Table 3. This table shows the scheduling situation in complex scenarios, with each scenario repeated three times. According to the results, the overall performance of SN scheduling is better, with a typical mid-term disturbance time of 55.6 minutes,

pseudo-SN time of 57.5 minutes, and the original scheduling time of 60.5 minutes. In more complex repeated disturbances, the pseudo-SN has a large deviation from the original scheduling time, while the SN scheduling time is the shortest and the three times of time are close. From this, it can be seen that SN scheduling also has excellent performance and better stability in more complex scenarios.

Table 3 Time consumption for scheduling more complex scenarios

Scheduling scenario	Experiment number	Original scheduling (min)	Pseudo-SN scheduling (min)	SN scheduling (min)
General disturbance	1	60.5	57.5	55.6
	2	61.2	58.6	56.4
	3	60.8	57.8	55.4
Mild disturbance	4	71.3	66.5	61.2
	5	70.2	67.2	60.3
	6	72.5	66.9	61.2
Repeated disturbances multiple times	7	112.5	91.2	76.5
	8	109.5	95.2	78.5
	9	110.5	94.5	77.5

5. Conclusion

With the rapid development of digital industrialization, intelligent and automated manufacturing has become the key to the transformation of traditional manufacturing industry. However, in actual manufacturing workshops, many enterprises face insufficient workshop scheduling. To solve this problem, an intelligent scheduling mechanism was proposed based on a flexible production workshop. Firstly, the characteristics of workshop scheduling were analysed to construct a scheduling problem model. Considering the data scheduling and solving in discrete workshops, this study introduced an improved CSO algorithm based on digital twin technology to construct a scheduling model. Finally, the SN was introduced to construct a dynamic scheduling mechanism for manufacturing workshops, optimizing workshop scheduling disturbances. In the Griewank function scheduling performance test, the improved CSO showed a 5.38 % and 11.25 % improvement in optimization ability compared with GA-PSO and CSO, respectively. In the training of the objective function of the scheduling model, the maximum completion time of the improved CSO was 244.8 minutes, which was better than the 264.5 minutes and 249.2 minutes of CSO and GA-PSO. In the SN scheduling experiment, a disturbance was set at 37.1 minutes, and the maximum completion time of the SN after disturbance optimization was 54.2 minutes, while the pseudo-SN was 56.4 minutes. Compared with the unadjusted state of the disturbance, the maximum completion time of the SN was reduced by 4.3 minutes, and the optimization effect was the best. The workshop scheduling technology has good application effects. However, there are also shortcomings in the research. Due to the complexity of discrete workshop scheduling, only the shortest completion time is considered as the sole objective. In the future, cost, equipment load and other objectives can be considered to improve the practical application effect of the technology.

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