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Research Article

Mathematical Model Construction of the Production Workshop Based on the Complex Network and Markov Theory

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Because of the advantages of the complex network in describing the interaction between nodes, the complex network theory is introduced into the production process of the modern workshop in this paper. According to the characteristics of the workshop, based on extracted key nodes, the complex network model of the workshop is constructed to realize the mathematical description of the production process of the workshop. Aiming at the multidisturbance factors in the production process of the workshop, the key disturbance factors are predicted based on the Markov method, and the propagation dynamics model close to the actual production of the workshop is established. Finally, the bottleneck prediction model of the workshop under the disturbance environment is established. The simulation results show that the proposed prediction model is in good agreement with the actual data, and the coincidence rate is as high as 93.7%.

1. Introduction

Production workshop is the basic unit of manufacturing enterprises, which consists of equipment, personnel, departments, and various workpieces. In the production workshop, the workpiece is processed to the final product according to the established process route, and the process is accompanied by many uncertain factors. These disturbance factors lead to the generation, transfer, and disappearance of the bottleneck in the workshop, and the bottleneck unit restricts the effective output of the production system. Therefore, it is necessary to study the dynamic prediction of the bottleneck in the workshop under the disturbance environment for improving the management of the production system.

In the manufacturing process, how to establish a reasonable and accurate mathematical model to identify and predict bottlenecks can provide a theoretical basis for enterprises to make production plans and management. Wu et al. [1] thought that, from the point of view of complex network statistical parameters, the cooperation, supply and demand, information transmission, and other aspects between production enterprises show self-similar characteristics. Hao et al. [2] used simulation software to simulate and analyze the production process of the production system. The research showed that the evolution process of the production system was extremely sensitive to the system parameters. Sun and Bin [3] analyzed that all kinds of manufacturing workshop cell network, mould manufacturing network, and all kinds of supply chain network show small-world characteristics.

In recent years, more and more researchers have applied the complex network theory to the manufacturing industry in order to make new breakthroughs in complex product development, supply chain optimization, and enterprise production management and optimization. Ma et al. [4] proposed the concept of collaborative manufacturing chain based on the complex network theory for the effective utilization of resources in the complex environment and finally realized the optimal utilization of resources. Cao et al. [5] modelled the production process of the product with the modular network, analyzed the evolution of the product

module by using the brittleness theory of the complex network, and improved the antirisk ability of the modular product network. Funke and Becker [6] analyzed the application of the complex network theory in the manufacturing system and provided a new method for network modelling of the manufacturing system. Giret et al. [7] applied the complex network theory to the service-oriented manufacturing network and analyzed the network structure and statistical parameters of the service-oriented manufacturing network.

Nowadays, artificial intelligent algorithms had been applied in the construction for different applications. Kea et al. [8] proposed a new model to estimate the disc cutter life by integrating a group method of data handling- (GMDH-) type neural network with a genetic algorithm. Wei et al. [9] proposed an analytical method for estimating the horizontal transition probability matrix, which is one of the important input parameters for the coupled Markov chain model. Shen et al. [10] presented an automatic pumping-recharge system to maintain groundwater balance during dewatering. Lin et al. [11] presented an approach for eutrophication evaluation based on the technique for order preference. Zhang et al. [12] proposed an artificial intelligence model to predict ground settlement. Ssl et al. [13] proposed an intelligent framework for predicting the advancing speed during earth pressure balance.

The definition and classification of bottlenecks are different according to different research objects, different methods, and different observation angles. Wang et al. [14] regarded the queuing number of parts in the processing area as the bottleneck identification index, and the bottleneck is the one with the largest queuing number. Samouei et al. [15] studied the bottleneck in the workshop from various aspects of the equipment parameters and identified the bottleneck unit by building a time-based mathematical model. Azadeh and Shoja [16] proposed a network model of bottleneck identification, which converted the main units of the workshop into a network model to identify the bottleneck location from the perspective of the system. Rui and Cheng [17] studied the workshop of the assembly line production mode, constructed a mathematical model based on the balance rate of the production line, and identified the bottleneck in real time. Based on the TOC constraint theory, Bin and Sun [18] combined with the intelligent algorithm and improved some processes of the previous genetic algorithm, so as to optimize the bottleneck identification method. According to the linear programming method, Brucker et al. [19] constructed a programming model for the objective function and constraints of the production workshop to identify the bottleneck unit of the production system. Masoud et al. [20] used the model graph and network model construction algorithm to identify the real-time bottleneck in the production workshop. Thurer and Stevenson [21] used simulation software to simulate the main production factors of the production system and compared the simulation data with the theoretical model and workshop data to identify the real-time bottleneck. Sweeney et al. [22] carried out orthogonal experiments on the factors that affect the output target of the system in the production workshop, compared with the mobile bottleneck generator, and verified the superiority of the orthogonal experiment bottleneck identification method.

The existing bottleneck research methods are limited to a specific parameter index, such as equipment, station, personnel, and materials, which lack systematic thinking. The bottleneck identification method in this paper is based on the complex network theory, the Markov model is simple, and it can be used to describe complex random phenomena. Markov process is used to analyze the disturbance factors, and the state transition probability and steady distribution of the Markov chain are obtained; it provides a way for the quantitative analysis of the disturbance factors in the production workshop. From the perspective of the complex network, all production factors are considered to identify and predict the bottleneck. And then, the accuracy and effectiveness of the proposed method are verified by the actual data of the workshop and simulation software.

2. Disturbance Factors' Analysis of the Production Workshop Based on the Markov Model

In this paper, Markov model is used to evaluate and predict the intensity of disturbance factors. The method has a good effect on process state prediction, and it can be used for production site state prediction. However, it is not suitable for medium- and long-term system prediction. From the perspective of the production process, the disturbance factors of the workshop are analyzed, the disturbance factor intensity matrix is constructed, the relationship between the matrix and disturbance factor intensity is simulated, and the Markov chain prediction model is established to predict the change of disturbance factor intensity, so as to determine the key disturbance factors and their occurrence probability. The flowchart indicating the bottleneck prediction of the production workshop is shown in Figure 1.

In each link of the workshop, there will be a variety of disturbance factors, such as demand change, emergency order insertion, equipment failure, machining accuracy, and personnel absence. At the same time, there will be a lot of inaccurate information, such as material arrival time, manual clamping time, and auxiliary processing time. The existence of these disturbance factors will make the workshop conditions change dynamically and seriously affect the normal production activities.

The disturbance in the workshop mainly refers to the factors that affect the effective output of production units such as equipment, personnel, process, and department. Disturbance factors can be divided into the following four categories: internal production environment, external environment, monitoring technology, and human factors. Disturbance factors caused by the internal production environment: although the production in the manufacturing workshop has been oriented to standardization and precision, the microdifferences and randomness in time cannot be eliminated. These uncertainties are mostly related to the internal production

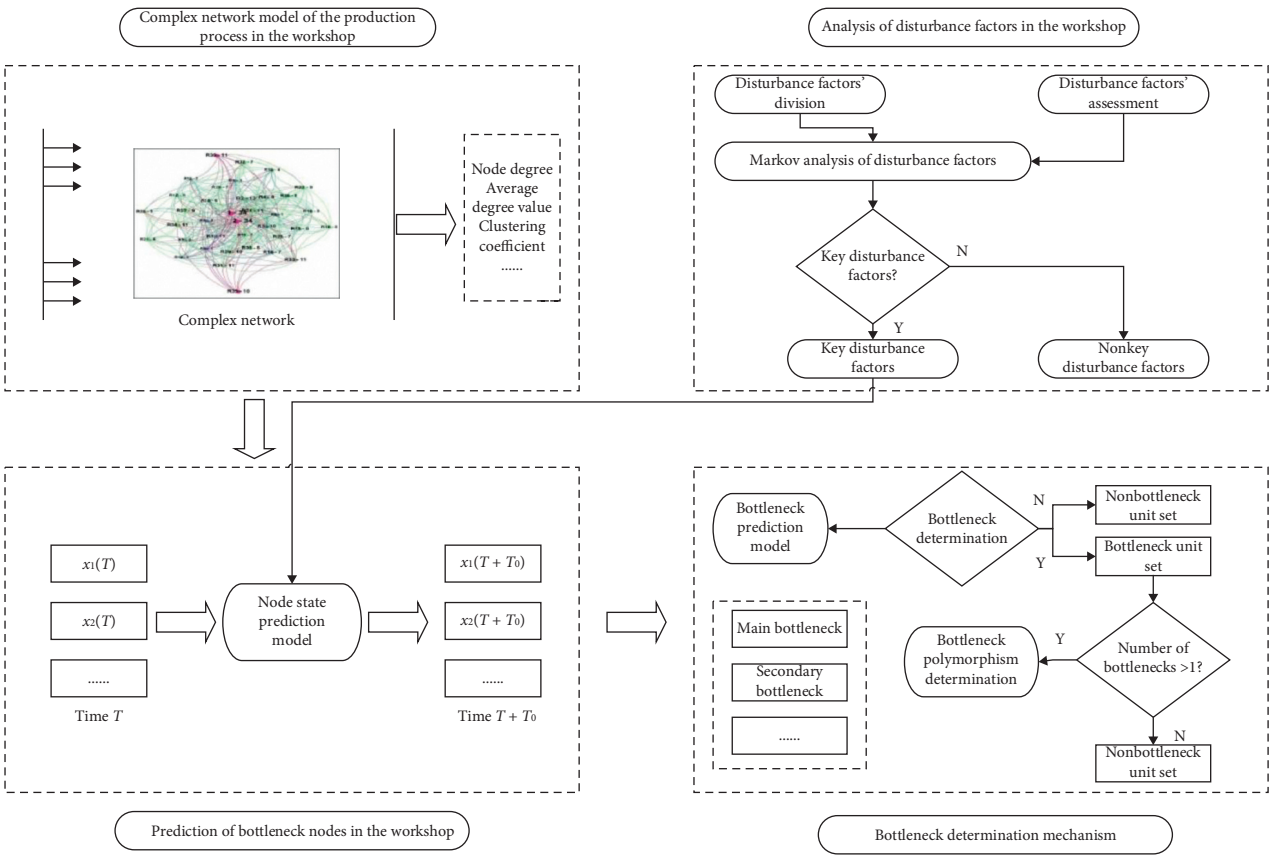

Figure 1: The flowchart indicating the bottleneck prediction of the production workshop.

environment, such as equipment random failure and equipment accuracy error. Disturbance factors caused by the external environment: they are materials not transported in place according to regulations, order changes, etc. The disturbance factors caused by the external environment will lead to the cancellation of existing production tasks or the change of production schedule, which is a kind of disturbance factors with great influence on the determination of results. The disturbance factors caused by monitoring technology include detection method, detection time, and detection environment. The influence of such disturbance factors is relatively weak. Disturbance factors caused by human factors mainly included workers absence, workers' proficiency, and workers' mood. These disturbance factors affect the quality and production schedule of the product directly.

The intensity of the disturbance factor is a quantitative description of the disturbance factor. The expression of disturbance factor intensity is different in different fields. The intensity of the disturbance factor reflects an inherent dynamic characteristic of the disturbance factor, which is used to describe the direct influence of the disturbance factor on the workshop network. The influence of different disturbance factors on the workshop is different; Chin et al. [23] classified the disturbance factors into four types: external disturbance, internal disturbance, monitoring disturbance, and human disturbance. The bottleneck influencing factor matrix is shown in Table 1.

There are various uncertain disturbance factors in the process of production and processing. The occurrence of disturbance factors may lead to the generation, transfer, increase, or decrease of bottlenecks in the production workshop. In this paper, the intensity of the disturbance factor is defined to express the comprehensive action degree of various disturbance factors in the process of production and processing. The intensity of the disturbance factor is expressed as follows:

$$I = \sum_{i=1}^{n} w_i d_i, \quad i = 1, 2, \ldots, n, \tag{1}$$

where w_i represents the importance of each disturbance factor and d_i represents the measurement indexes of the intensity of each human disturbance factor to the disturbance factor.

Because the intensity of disturbance factors in the production workshop is a comprehensive quantitative index of various disturbance factors and the intensity of disturbance factors is a fuzzy quantity, the intensity of disturbance factors in the production workshop can be measured by the fuzzy evaluation method at all levels, analytic hierarchy process, expert scoring, and other comprehensive methods. The specific steps are as follows:

(i) Step 1: the set of disturbance factors in the workshop is established. $D = \{d_1, d_2, d_3, d_4\}$ is the disturbance factors' set. Analytic hierarchy process

(AHP) is used to measure the disturbance intensity, $W = \{w_1, w_2, w_3, w_4\}$, $\sum_{i=1}^{4} w_i = 1$, $w_i \geq 0$. The weight of fuzzy subsets in D is $w_i = \{w_{i1}, w_{i1}, \ldots, w_{im}\}$, $\sum_{i=1}^{m} w_{im} = 1$, $w_{im} \geq 0$.

(ii) Step 2: the workshop influence evaluation set is established. By using the expert scoring method, the manufacturing workshop bottleneck research experts score the intensity of disturbance factors in the production workshop and grade different disturbance factors. Each disturbance factor is divided into five levels according to the influence level, and the level from low to high represents the influence degree. It is assumed that the evaluation set is $C = \{c_1, c_2, c_3, c_4, c_5\}$; c_i represents the influence of each disturbance factor on the intensity of the disturbance factor in the workshop.

(iii) Step 3: the evaluation of the disturbance factor to disturbance factor intensity is obtained by expert scoring, fuzzy function $f: D \longrightarrow F(V)$ is established, $F(V)$ is the fuzzy complete set of subset V, and $d_i \longrightarrow f(d_i) = (d_{i1}, d_{i2}, d_{i3}, d_{i4}, d_{i5})$ is the feedback of disturbance factor d_i in the workshop to the expert scoring system and evaluation set. It is assumed that the feedback vector of disturbance factors to bottleneck set V is $R_i = \{r_{i1}, r_{i2}, \ldots, r_{i5}\}$; after fuzzy transformation, the following formula can be obtained:

$$B_i = w_i \cdot R_i = (b_1, b_2, b_3, b_4, b_5). \tag{2}$$

The obtained values are imported into the upper layer by the analytic hierarchy process and then evaluated. Finally, the overall disturbance factor intensity is calculated as

$$D = W \cdot R = (D_1, D_2, D_3, D_4, D_5). \tag{3}$$

The bottleneck of the production workshop is produced in the production activities, and it is the result of the comprehensive effect of various disturbance factors in the production activities. The intensity of disturbance factors caused by human disturbance factors is divided into states. Markov model is used to predict the divided states. Finally, the probability of each state is obtained to predict the key disturbance factors.

In this paper, Markov chain is used to model the disturbance intensity caused by disturbance factors in the workshop. $S = \{s_1, s_2, \ldots, s_n\}$ represents the state set; it is the division of the disturbance factor intensity and the probability measure of the disturbance factor intensity under the comprehensive action of each disturbance factor in the production workshop. S can be preliminarily determined according to the historical data of disturbance factors in the production workshop. The state of disturbance factors is defined in Table 2.

The initial probability of the state set is determined by fitting the curve with the historical data of disturbance factors in the workshop. The probability of the initial state is expressed by vector a:

$$a = [a_1, a_2, \ldots, a_k], \tag{4}$$

where a_k represents the occurrence probability of state k.

In the Markov process, x_k is the state in time step t_k, $x_i(k) = P(x_k = i)$, the probability in matrix P_{ij} represents the probability that the state is i at this moment and j at the next moment. The matrix expression is as follows:

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix}, \tag{5}$$

where p_{ij} is defined as follows:

$$p_{ij} = \frac{N_{ij}}{\sum_{j=1}^{n} N_{ij}}, \tag{6}$$

and N_{ij} is the statistical historical data; it represents the number of times that the node state changes from i to j in the production activity of the workshop.

According to the Markov theory, the probability of the state of disturbance intensity in the workshop can be calculated as follows:

$$\widehat{p} = a \cdot p. \tag{7}$$

3. Bottleneck Prediction of the Production Workshop Based on the Complex Network under the Disturbance Environment

In a workshop, N workpieces are produced and processed on M sets of equipment, and workpieces of the same specification have their own process routes. It is assumed that the same equipment can only process one workpiece at the same time, and the processing sequence is first come first process. There are time constraints and process constraints in the processing of workpieces. Different equipment processes different workpieces with different times and processes. The variables are defined as follows.

The workpiece sequence is represented by $J = \{J_j | j = 1, 2, \ldots, N\}$, J_j represents the j-th workpiece, the equipment sequence is represented by $Q = \{Q_i | i = 1, 2, \ldots, M\}$, Q_i represents the i-th equipment, and the process sequence is represented by P_p; then, the process matrix of N workpieces produced and processed on M sets of equipment is defined as

$$P_p = \begin{bmatrix} P_{p1(1)} & \cdots & P_{p1(n)} \\ \vdots & \ddots & \vdots \\ P_{pj(1)} & \cdots & P_{pj(n)} \end{bmatrix}, \tag{8}$$

where n represents the number of processes and $P_{ij(n)}$ represents the n-th process of the j-th workpiece produced on the i-th equipment.

Machining time series of the workpiece is represented by T_i, which is defined as follows:

Table 1: The bottleneck influencing factor matrix.

Disturbance factors		Disturbance intensity level				
		Level 1 0-0.1	Level 2 0.1–0.3	Level 3 0.3–0.5	Level 4 0.5–0.8	Level 5 0.8–1.0
External disturbance factors	Order change				*	
	Material supply					*
	Production plan				*	
	Policy changes			*		
Internal disturbance factors	Equipment failure				*	
	Route change					*
	Machining accuracy	*				
	Dispatcher change		*			
Human factors	Personnel absence					*
	Proficiency				*	
Monitoring factors	Monitoring method		*			
	Monitoring technology	*				
	Monitoring environment			*		

$$T_i = \begin{bmatrix} T_{i1(1)} & \cdots & T_{i1(n)} \\ \vdots & \ddots & \vdots \\ T_{ij(1)} & \cdots & T_{ij(n)} \end{bmatrix}, \tag{9}$$

where $T_{ij(n)}$ represents the machining time of the n-th process of the j-th workpiece on the i-th equipment.

Each resource node (such as workshop department, equipment personnel, and tools) involved in the production process of a production workshop is regarded as a network node. The possible process routes and logistics paths between nodes are regarded as the connecting edges in the network. The direction of the connecting edges between nodes is determined by the priority relationship of processes; as the weight on the connected edge of the network, the device load is used to measure the closeness of the relationship between nodes. Therefore, each production process constitutes a complex multitask weighted directed network model. An example of a workshop network model is shown in Figure 2.

Figure 2 represents a workshop production process which consists of two workshops, node P represents the resources (equipment, personnel, departments, etc.) in the manufacturing system, the direction of the edge represents the flow direction of the logistics process, and the node state is represented by the load of the node. Thus, the disturbance factors can be described as follows:

$$\begin{cases} \overline{P_p} & = P_p + \Delta P_p, \\ \overline{x_i}(t) & = x_i(t) + \Delta x_i(t), \\ \overline{\vartheta} & = \vartheta + \Delta\vartheta, \end{cases} \tag{10}$$

where $\overline{P_p}$ represents changes in disturbance factors, ΔP_p represents the process matrix change increment, $\Delta x_i(t)$ represents the fluctuation of the node state caused by disturbance factors, and $\Delta\vartheta$ represents the influence of disturbance factors on network coupling strength.

Considering the interaction between nodes and the dynamic characteristics of nodes in the whole network, a coupled map lattice node state prediction model with the network scale of n is constructed in this paper.

$$x_i(t+1) = \left| (1-\overline{\vartheta}) f(x_i(t)) + \frac{\overline{\vartheta} \sum_{j=1, j\neq i}^{N} \left(a_{i,j} + r_{i,j}\right)}{k(i)} \right|, \tag{11}$$

where $x_i(t)$ represents the state value of node i at time t, $x_i(t+1)$ represents the calculated value of the next time step of the node, $k(i)$ represents the degree of node i in the complex network, $a_{i,j}$ represents the network connection matrix, ϑ represents the coupling strength between nodes, function f represents the dynamic behaviour of nodes, and $r_{i,j}$ represents the fluctuation of the connection matrix after disturbance.

In this paper, from the perspective of the complex system, considering the network characteristics such as node degree value and clustering coefficient, the bottleneck judgment standard is given. Finally, according to the judgment standard, the bottleneck classification is implemented, such as primary and secondary bottlenecks and nonbottlenecks [24]. Suppose the bottleneck criterion is τ; the calculation formula of τ is as follows:

$$\tau = \alpha C + \beta K + \gamma L, \tag{12}$$

where C represents the network clustering coefficient, K represents the node degree, L represents the node load, and α, β, and γ represent weights, and $\alpha + \beta + \gamma = 1$.

Therefore, the bottleneck identification formula in the network is defined as follows:

$$\begin{aligned} \mathrm{BS}_N &= \{X_i(t) \geq \tau\}, \\ \mathrm{BS}_{\mathrm{non}-N} &= \{0 < X_i(t) < \tau\}, \end{aligned} \tag{13}$$

where BS_N represents the bottleneck sequence and $\mathrm{BS}_{\mathrm{non}-N}$ represents the nonbottleneck sequence.

In order to analyze the fluctuation and influence of disturbance factors on the production process of the workshop, the load change rate F_i is defined to describe the fluctuation caused by disturbance factors:

Table 2: State of disturbance factors.

Frequency of disturbance factors	State
$F > 7$	s_5
$4 \le F < 7$	s_4
$2 \le F < 4$	s_3
$0 \le F < 2$	s_2
$F \ge 0$	s_1

$$F_i = \sum_{t=1}^{T} \lim_{\Delta t \longrightarrow 0} \frac{\left| x_i(t+1) - x_i(t) \right|}{\Delta t}, \tag{14}$$

where T represents the total simulation time.

4. Simulation Results and Discussion

4.1. Analysis of Disturbance Factors. In the experiment, the actual production workshop data of an automobile manufacturing enterprise [25] are taken as an example; Markov process is used to analyze the disturbance factors. Firstly, the analytic hierarchy process is used to analyze many disturbance factors and determine their respective weights, as shown in Table 3.

After classifying and subdividing the disturbance factors and calculating the weight, the occurrence frequency is fitted according to the historical data of the disturbance factors in the production workshop. The state probability transition matrix is determined according to Table 3, in which the state probability transition diagram and probability matrix are as follows:

$$P = \begin{bmatrix} 0.382 & 0.387 & 0.288 & 0 & 0 \\ 0.522 & 0.330 & 0.120 & 0.120 & 0 \\ 0.450 & 0.270 & 0.350 & 0.120 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \tag{15}$$

The production process parameters of the workshop are shown in Table 4.

According to Table 4, the node state transition frequency matrix in the process of production activities is calculated:

$$N = \begin{bmatrix} 6 & 6 & 4 & 0 & 0 \\ 6 & 3 & 2 & 1 & 0 \\ 3 & 2 & 3 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \tag{16}$$

According to the expert scoring method, the initial state probabilities of ten disturbance factors to the disturbance factor intensity are determined as follows:

$$a = \left[0.4 \;\; 0.3 \;\; 0.2 \;\; 0.1 \;\; 0.0 \right]. \tag{17}$$

In this way, the prediction probability of each node state S_i will be calculated as follows:

$$\widehat{p} = a \cdot p = \left[0.382 \;\; 0.380 \;\; 0.201 \;\; 0.027 \;\; 0 \right]. \tag{18}$$

It can be seen that, in the production process, in each state of 23 production process indicators, the key disturbance factors are equipment failure, material supply, order change, and so on, and the influence of the occurrence probability of these disturbance factors accounted for 86.2%.

4.2. Bottleneck Prediction Model Simulation. Aiming at an auto parts production workshop, the data of the production process are collected in hours by sensors on the production line. According to the working characteristics, resource flow, process constraints, information flow, and personnel allocation of the production workshop, the data are collected, and the key nodes are extracted, and the complex network model is constructed to realize the network mathematical description of the production process of the production workshop. The specific production data of 10 sets of equipment and 6 workpieces' sequence are shown in Table 5.

The layout of the workshop is shown in Figure 3.

After the initial state of each node is set, the subsequent state of each node is calculated according to the prediction model. The node state values without disturbance are shown in Table 6.

Table 6 shows that the state values of each node are basically stable without disturbance, and there is no bottleneck unit.

When the disturbance factor is added, the node state values of the workshop after 3 hours of disturbance are shown in Table 7.

According to the criterion of bottleneck judgment [26], the state value of each node is counted to judge the bottleneck. The results are shown in Table 8.

As shown in Tables 7 and 8, before the disturbance, the state value of the workshop nodes fluctuates little, and there is no bottleneck unit. After the disturbance factor is added, the state value of each node begins to be affected. Through simulation calculation, it is found that equipment P_6 is the primary bottleneck and equipment P_5 is the secondary bottleneck. Through the analysis of Table 8, it is found that the degree value and clustering coefficient of the bottleneck unit are larger than other nodes, and the bottleneck unit appears on the equipment directly affected by order insertion.

In order to verify the rationality and correctness of the model, the production process of the workshop is simulated and analyzed. Through the simulation analysis, when there is no disturbance factor, the production activities of the

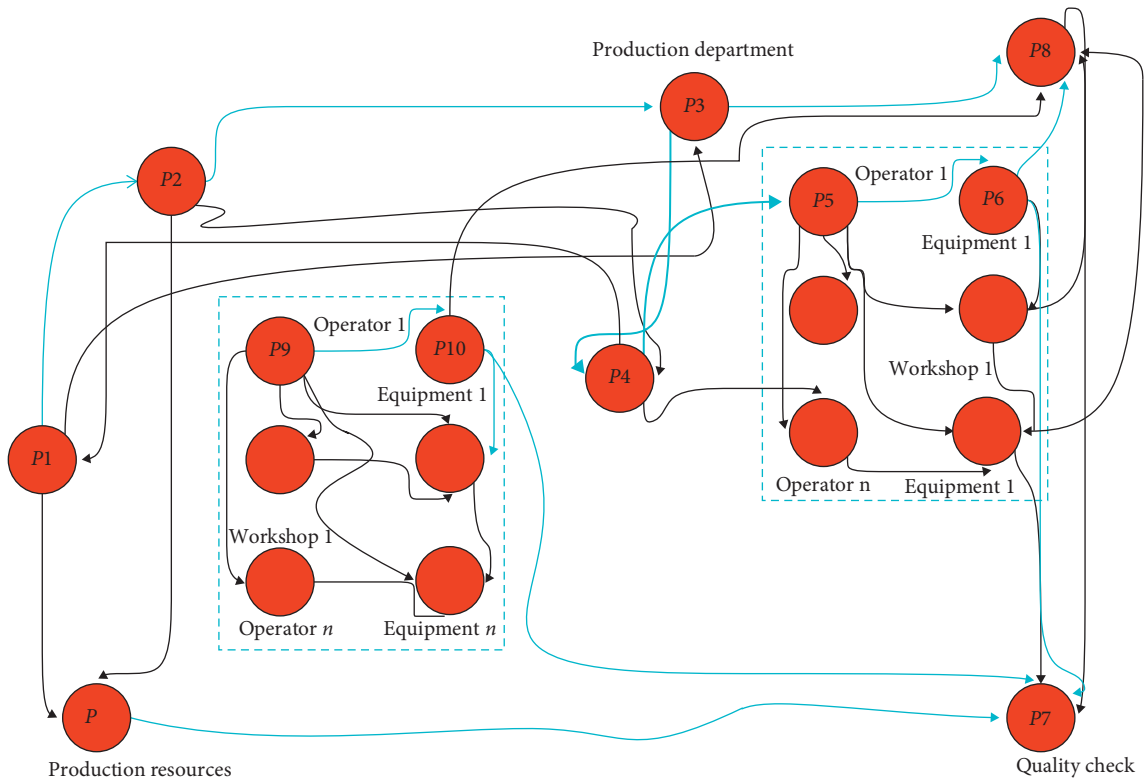

Figure 2: An example of a workshop production network model.

Table 3: Disturbance factors and their weights in the workshop.

Symbol	a_1	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
Disturbance factors	External disturbance	Order change	Material supply	Demand change	Policy change	Environment change
Weight	0.5637	0.1947	0.4628	0.1889	0.0725	0,.0733
Symbol	a_2	a_{21}	a_{22}	a_{23}	a_{24}	
Disturbance factors	Internal disturbance	Equipment failure	Process change	Machining accuracy	Workshop scheduling	
Weight	0.2631	0.2751	0.0643	0.5502	0.1236	
Symbol	a_3	a_{31}	a_{32}	a_{33}		
Disturbance factors	Human factor	Personnel absence	Skill level	Quality defects		
Weight	0.1202	0.0927	0.5201	0.3896		
Symbol	a_4	a_{41}	a_{42}	a_{43}		
Disturbance factors	Monitoring	Monitoring method	Monitoring technology	Monitoring environment		
Weight	0.0565	0.6386	0.1037	0.2579		

workshop are normal, and there is no bottleneck. With the input of the disturbance factor, the process matrix changes, resulting in the changes of the network topology, clustering coefficient, node degree value, node state, and process matrix. Accuracy index is used to verify the accuracy of the prediction model, and it is defined as follows:

$$\text{accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})}, \tag{19}$$

where TP represents true positive, FP represents false positive, FN represents false negative, and TN represents true negative.

The fluctuation caused by disturbance is positively correlated with the degree value, but not with betweenness and clustering coefficient. After the disturbance, the proposed prediction method in this paper is in good agreement with the actual data, and the coincidence rate is as high as 93.7%. The coincidence rate with other prediction methods

Table 4: The production process parameters of the workshop.

A_i	D_i	F_i	S_i
A_1 (order information)	0.2652	1	S_1
A_2 (material purchasing plan)	0.3275	0	S_1
A_3 (demand risk analysis)	0.1861	1	S_1
A_4 (initial data)	0.3785	1	S_2
A_5 (material arrival time)	0.3952	0	S_2
A_6 (manual clamping time)	0.3562	1	S_1
A_7 (auxiliary processing time)	0.3283	0	S_1
A_8 (industry policy changes)	0.3183	1	S_2
A_9 (market environment changes)	0.5902	3	S_3
A_{10} (equipment failure rate)	0.3392	0	S_2
A_{11} (aging degree of equipment)	0.3287	1	S_1
A_{12} (importance of equipment)	0.3916	1	S_3
A_{13} (route layout)	0.3285	1	S_2
A_{14} (process constraints)	0.3852	0	S_2
A_{15} (accuracy of machining different parts)	0.3907	1	S_2
A_{16} (selection of the production scheduling mode)	0.5589	2	S_3
A_{17} (scheduling objectives)	03205	0	S_1
A_{18} (staff leave rate)	0.5960	3	S_3
A_{19} (processing pass rate)	0.2298	2	S_3
A_{20} (time required for monitoring)	0.3805	5	S_4
A_{21} (monitoring environmental impacts)	0.3607	3	S_4
A_{22} (production line balance rate)	0.2385	1	S_2
A_{23} (change of delivery date)	0.3762	2	S_3

Table 5: Original data of workpiece production.

Workpiece	Process route/arrival rate per unit time/processing rate per unit time					
J_1	$P1/35/120$	$P2/40/110$	$P3/40/90$	$P4/35/100$	$P5/35/130$	—
J_2	$P10/35/100$	$P9/40/100$	$P8/30/90$	$P7/40/80$	$P6/40/110$	—
J_3	$P10/25/100$	$P3/35/80$	$P6/30/90$	—	—	—
J_4	$P1/30/110$	$P8/30/120$	$P5/30/80$	—	—	—
J_5	$P1/45/120$	$P4/45/150$	$P6/40/160$	—	—	—
J_6	$P10/45/110$	$P2/55/100$	$P8/55/120$	$P6/45/130$	$P5/55/110$	—

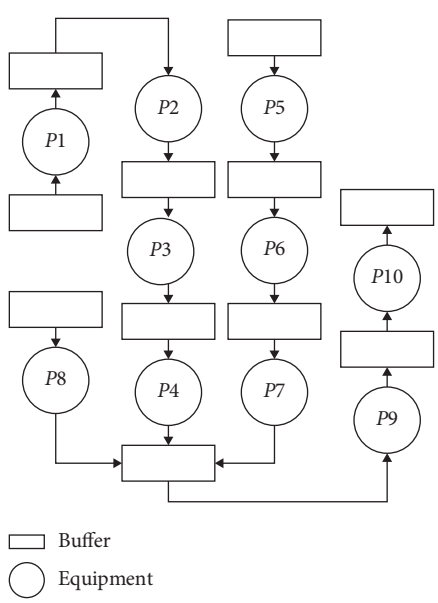

Figure 3: The layout of the workshop.

Table 6: Node state values without disturbance.

Time (d)	Node state values									
	$P1$	$P2$	$P3$	$P4$	$P5$	$P6$	$P7$	$P8$	$P9$	$P10$
1	0.875	0.400	0.875	0.625	0.538	0.763	0.429	0.542	0.365	0.625
2	0.677	0.706	0.687	0.809	0.925	0,.736	0.659	0.980	0.937	0.836
3	0.675	0.833	0.738	0.639	0.206	0.755	0.482	0.196	0.286	0.569
4	0.565	0.686	0.737	0.579	0.198	0.859	0.783	0.837	0.691	0.896
5	0.763	0.902	0.849	0.782	0.390	0.491	0.509	0.359	0.425	0.739
6	0.803	0.285	0.729	0.832	0.849	0.729	0.492	0.401	0.839	0.685
7	0.586	0.339	0.605	0.572	0.449	0.839	0.837	0.938	0.729	0.817
8	0.806	0.839	0.358	0.609	0.362	0.937	0.885	0.829	0.582	0.606

Table 7: Node state values after 3 hours of disturbance.

Time (d)	Node state values									
	$P1$	$P2$	$P3$	$P4$	$P5$	$P6$	$P7$	$P8$	$P9$	$P10$
1	0.875	0.400	0.875	0.625	0.538	0.763	0.429	0.542	0.365	0.625
2	0.677	0.706	0.687	0.809	0.925	0,.736	0.659	0.980	0.937	0.836
3	0.875	0.952	0.896	1.000	0.984	1.255	0.482	1.000	0.325	1.000
4	0.865	0.977	0.904	0.892	0.795	1.389	0.886	0.949	0.892	0.916
5	0.763	0.902	0.849	0.782	1.286	0.695	0.616	0.479	0.495	0.739
6	0.933	0.858	0.786	0.897	1.497	0.881	0.797	0.771	0.739	0.657
7	0.266	0.217	0.605	0.572	1.930	0.780	0.633	0.814	0.796	0.817
8	0.766	0.583	0.658	0.509	3.362	0.837	0.775	0.626	0.594	0.316

Table 8: Statistics of workshop network parameters.

Node	Node degree	Clustering coefficient	State fluctuation rate	Node average state value	Bottleneck node
$P1$	3	0.667	0.196	0.722	—
$P2$	4	0.333	0.175	0.672	—
$P3$	4	0.167	0.189	0.736	—
$P4$	5	0.500	0.072	0.741	—
$P5$	3	0.333	1.020	1.106	Secondary bottleneck
$P6$	6	0.667	1.108	1.528	Primary bottleneck
$P7$	2	0.167	0.207	0.532	—
$P8$	3	0.200	0.433	0.602	—
$P9$	4	0.500	0.051	0.622	—
$P10$	3	0.333	0.176	0.752	—

[27, 28] is also high; it shows that the theoretical analysis of the disturbance factors in the proposed prediction model is consistent with the simulation results, which verifies the correctness and rationality of the proposed model.

5. Conclusions

In this paper, a complex network is introduced into the production process of the production workshop. According to the characteristics of the production workshop, such as the working characteristics, resource flow, process constraints, information flow, and personnel allocation, the data are collected, and the key nodes are extracted, and then the complex network model is constructed to realize the network mathematical description of the production process of the production workshop. The disturbance factors are described mathematically, and the mechanism of the disturbance factors in the complex network system is constructed, so as to identify the bottleneck position of the production workshop under the disturbance factors.

Data Availability

The basic data used in this article are downloaded from the online public dataset weighted tardiness (http://people.brunel.ac.uk/~mastjjb/jeb/info.htm).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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