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Research Article

Ranking of Key Components of CNC Machine Tools Based on Complex Network

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Complex networks have become a center of interdisciplinary research. The robustness and reliability of complex systems can be determined by analyzing the characteristics of networks. The computer numerical control machine tool (CNCMT) is a typical complex system, and reliability is the key factor that affects the processing quality and performance of the CNCMT. The process of quantitatively determining the key functional components of CNCMT and carrying out reliability growth experiments on them remains difficult. A new importance-ranking method for the key functional components of the CNCMT is proposed in this study. First, the real characteristics of the CNCMT are analyzed, and the complex network of the CNCMT is constructed. Then, we study various indicators of the network and determine that the network has small-world characteristics. Finally, a variety of complex network characteristic indicators are fused, the weight of each indicator is determined based on the analytic hierarchy process (AHP), the importance of each node is quantitatively determined, and the fused indicators are compared with a single indicator.

1. Introduction

As an industrial machine tool, the CNCMT is of great significance in the manufacturing industry. It is a strategic piece of equipment that affects the development of industrialization and national defense security. Modern CNCMTs exhibit improved machining accuracy, machining speed, multiaxis linkage, and intelligent machining, but the key factor restricting their further development is reliability. Traditional CNCMT reliability analyses primarily consider user feedback and results of accelerated life tests to expose failures and establish mathematical models to analyze and predict faults. Li [1] et al. published an improved four-parameter nonhomogeneous Poisson process reliability-modeling method based on meta-action and a comprehensive method of assessing system reliability. To comprehensively evaluate the reliability of the five-axis CNCMT, Wang [2] et al. applied the matter-element theory in extension to establish the matter-element model of reliability evaluation and fully established the reliability evaluation index system. Mu [3] et al. used radial basis function (RBF) neural networks to model the mapping between mission profile and load profile and machine tool reliability. These methods consider the failure characteristics of the CNCMT and build a reliability model based on time data. Because CNCMTs are complex electromechanical equipment with multisystem coupling, it is difficult to explore the potential factors of multisystem interaction failure using these methods.

With the rapid development of information technology, the applications of complex networks are becoming increasingly diverse [4], including disease transmission networks [4, 5], transportation networks [6–8], social networks [10], information networks [11], and supply chains [12]. The robustness of a complex network mainly depends on the reliability of nodes. Finding a group of optimal nodes in the network and activating them can greatly enhance the robustness of the network. Many scholars have conducted research on finding the key nodes of networks. Fan [13] et al. introduced FINDER, a deep reinforcement learning framework that can be trained on small synthetic networks generated by toy models before being applied to a wide spectrum of application scenarios. Wen [14] et al. proposed a method based on the least square support vector machine (which allows the user to find the mapping rules between simple indicators and AHP evaluation) and showed the validity of the method in experiments on artificial and real networks. Zhao [15] et al. proposed an important node mining method based on distance distribution and multi-index fusion (DDMF) to surpass the limitations of existing algorithms. In addition, the topology of the network impacts its stability. Liu [16] et al. proposed a family of nested weighted n-polygon networks to study the coherence of the networks based on their Kirchhoff indices, mean first-passage time, and the average path length. Liu [17] et al. considered several types of the generalized Sierpiński networks and investigated the explicit expressions of some well-known valency-based topological indices to determine the average degree based on other structural characteristics of generalized Sierpiński networks.

This paper analyzes the basic structural characteristics of the CNCMT, determines the connectivity between its relevant parts, establishes a complex network model of a CNCMT by constructing an adjacency matrix, and calculates several key features of that network. The network is then analyzed by calculating its node importance evaluation index, determining the index ranking, constructing the judgment matrix by using the analytic hierarchy process, and obtaining the key feature weight. Finally, the importance of the identified key nodes is verified using an empirical data set in the laboratory.

2. Construction and Analysis of Complex Network for CNCMT

2.1. Description of the Basic Characteristics of CNCMT Network. The CNCMT is a complex device coupled by mechanical, electrical, hydraulic, and other components. Its reliability and equipment diagnostic analysis methods are complex, so its key functional components should be explored. This study proposes an initial method to construct the coupling relationship network of a CNCMT to study the importance ranking of its key functional components. The division results are shown in Figure 1. This paper uses a modular division method to divide the CNCMT into modules based on the following principles:

(1) Principle of independent function of components. The component unit has certain mechanical, electrical, or information functions. It is an independent functional part in the CNCMT and is a necessary component.

(2) Principle of functional indivisibility. When dividing component units, component functionality is not divided again in order to maximize the network size.

(3) Principle of component aggregation. When proximal independent component units have high reliability and none of the data samples fail, several components with functional connection or physical connection are considered as a whole so that node reliability can be calculated more efficiently.

(4) Principle of component difference. For the same parts in different components, module division is performed according to their functions, their connections to other components, and the effects of part fault on those components.

In this paper, the construction method of the complex network of a CNCMT is studied from the perspective of topological characteristics. It is divided into seven systems: the CNC system, the servo system, the electrical system, the feed system, the drive system, the auxiliary system, and basic parts.

The CNC system is the operative interface of the CNCMT. It is generally composed of input and output devices, controllers, arithmetic units, and other calibration components. In this study, it is divided into communication module, decoding module, CNC interpolation module, position control mode, main memory mode, PLC mode, CRT mode, edit panel, and operation panel. The servo system is responsible for the control of moving parts within the CNCMT. In this study, it is divided into spindle servo motor, spindle servo drive, feed servo motor, feed servo drive, photoelectric pulse encoder, brake resistor, and air-cooled motor. The electrical system is the fundamental power source for the normal machining operation of the CNCMT. In this paper, it is divided into magnetic contactor, relay, master switches, fuse, circuit breaker, transformers, switches, DC power supply, and AC reactor. Master switches can be divided into control button, LED, proximity switch, and travel switch; switches are divided into knife switch and combination switch. The feed system is an executive part driven by the servo system through the mechanical transmission mechanism. Its accuracy and stability play decisive roles in the final machining quality and surface accuracy of the workpiece. Components in this system include workbench, rolling guide, transport ball screw, installation seat, ball screw bearing, and grating ruler. The drive system completes the cutting of the tool on the spindle, and its accuracy determines the machining accuracy of the part. This system includes spindle, spindle bearing, automatic tool clamping device, automatic stop device, spindle hole cleaning device, main spindle box, and spindle drive. The auxiliary system and basic parts improve the machining efficiency and ensure the machining accuracy of the machine tool. These are mainly composed of automatic tool changers, cooling and lube devices, and machine bed.

2.2. Characteristics of Complex Network Structure of CNCMT

2.2.1. Definition of Network. Based on the division of CNCMT structure in the previous section, this paper considers the CNCMT as a complex network (MTCN) and defines it as follows:

$$MTCN = (V, E), \tag{1}$$

where V is the node set (a nonempty finite set), E is the relative (edge set) between nodes, and $V \subseteq \{(u, v) | u, v \in V\}$.

Figure 1: Division results of CNCMT module.

The coupling relationship among the n components of the CNCMT is then analyzed to construct its adjacency matrix:

$$\mathrm{MT\_Adj}(i, j) = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \quad (2)$$

where i and j represent different components and a_{ij} is the connection strength between components i and j. When $a_{ij} = 0$, it means that the components are not connected; when $a_{ij} = 1$, it means that they are not connected. Since the components of the CNCMT cannot be connected by themselves, when $i = j$, $a_{ij} = 0$.

2.2.2. Network Construction. The nodes of the network are the basic components of the CNCMT complex network. The network attributes of the CNCMT are mainly reflected in the numbering, connection, and other aspects. In the network construction of this paper, each edge of the CNCMT network is defined as a_{ij}, which is represented by positive integer numbers corresponding to these nodes.

The nodes in the network transmit power and information through edges. Considering the actual characteristics of the CNCMT, the edge connection is divided into four aspects: mechanical connection, electrical connection, pipe connection, and functional connection. Mechanical connections involve physical contact between part surfaces, electrical connections involve electrical current, pipeline connections involve the controlled transmission of fluid, and functional connections involve the part being machined. Functional connections can be separated into noncontact connections and contact connections.

Differences in topology have a significant impact on the characteristics of the network. After the components and connection modes of the complex network of the CNCMT are determined, the topology of the network as a whole must be examined. Because the CNCMT needs to have high reliability and long life, it is necessary to plan the network in detail. The specific steps are as follows:

(1) Disassemble the structure of the CNCMT to ensure that the components no longer have functional coupling.

(2) Determine the connection mode among various components and build the adjacency table.

(3) An adjacency matrix is constructed according to the adjacency table, and the written program is run in Python to realize the construction of the CNCMT's complex network.

2.2.3. Basic Topological Properties of the Network. In the process of evaluating complex networks, the importance of a node is usually measured by its position in the network topology. The complex coupling relationship among the components of the CNCMT determines the existence of mutual promotion and mutual inhibition among the components. If the reliability of a part is improved or reduced, the reliability of adjacent components and even the whole system will be affected. Therefore, this study selects five indicators: node degree, the average path length, clustering coefficient, degree distribution, and betweenness to analyze the complex network of the CNCMT and explore the characteristics of the network.

1. *Node degree*. The node degree, which refers to the number of nodes connected to a node, reflects the importance of the node in the network. It is defined as follows:

$$D_i = \sum_{j=1}^{n} a_{\mathrm{ij}}, \tag{3}$$

where D_i is the degree of nodes i and a_{ij} represents the edge between nodes i *and* j.

The average node degree is defined as follows:

$$D_A = \frac{1}{N}\sum_{i=1}^{N} D_i, \tag{4}$$

where D_A is the average node degree, N is the sum of nodes, and D_i represents the nodal degree of the i^{th} node.

2. *Network diameter and average path length*. The distance of the network is the number of shortest path edges between two nodes, and its maximum value is the diameter of the network, which is defined as follows:

$$D_{\max} = \max_{i,j\in V}\left(d_{ij}\right), \tag{5}$$

where $D_{\max}$ is the diameter of the network and d_{ij} is the distance between nodes i and j.

The average path length of the network is the average value of the total distance, which is defined as follows:

$$L = \frac{2}{N(N-1)}\sum_{i\geq j} d_{\mathrm{ij}}, \tag{6}$$

where L is the average path length of the network, N is the number of network nodes, and d_{ij} is the distance between nodes i and j.

If the network has a large-scale (number of network nodes), but its average path length is small, the network has small-world characteristics. A small average path length can accelerate the flow rate of information in the network. However, the failure of a single component in such a system may cause great damage to the CNCMT in a short time due to the acceleration of information flow.

3. *Clustering coefficient*. The clustering coefficient is used to analyze the association strength between network nodes, which reflects the cluster characteristics of the network. This coefficient is represented with the letter C. Assuming that the degree of node i is D_i (i.e., there are D_i nodes connected to it in the network), there are at most $D_i(D_i-1)/2$ edges. The proportion of the actual number of edges E_i between D_i nodes in the maximum number of edges $D_i(D_i-1)/2$ is the clustering coefficient of node i, which is expressed as follows:

$$\begin{aligned} C_{\mathrm{i}} &= \frac{E_i}{D_i(D_i-1)/2}, \\ &= \frac{2E_i}{D_i(D_i-1)}, \end{aligned} \tag{7}$$

where C_i is the clustering coefficient of the i^{th} node $(0 \leq C_i \leq 1)$ and E_i is the actual number of edges among D_i adjacent nodes of node i. If node i has only one adjacent node or no adjacent node, then $C_i = 0$.

From a geometric point of view, since E_i is the number of triangles with node i as the vertex, we may state:

$$C_{\mathrm{i}} = \frac{\text{Number of triangles containing node } i}{\text{Number of connected triples centered on node } i}. \tag{8}$$

Given adjacency matrix $\mathrm{MT\_Adj}(i,j) = (a_{ij})_{N\times N}$, then:

$$C_i = \frac{E_i}{D_i(D_i-1)/2}, \\ = \frac{2E_i}{D_i(D_i-1)}, \\ = \frac{\sum_{j,k=1}^{N} a_{ij}a_{jk}a_{ki}}{D_i(D_i-1)}, \\ = \frac{\sum_{j\neq i,k\neq j,k\neq i}^{N} a_{ij}a_{ik}a_{jk}}{\sum_{j\neq i,k\neq j,k\neq i}^{N} a_{ij}a_{ik}}. \tag{9}$$

The clustering coefficient of the whole network is the average clustering coefficient of the network, and the expression is as follows:

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i, \tag{10}$$

where C is the clustering coefficient of the network and N is the number of nodes.

4. *Degree distribution*. The degree distribution of the network refers to the distribution of the number of degrees of each node in the network. The most common distribution is the normal distribution (Gaussian distribution), which is expressed as follows:

$$\xi - N(\mu, \sigma^2), \tag{11}$$

where μ is the mean and σ^2 is the variance. The mean determines the central value of the normal distribution, and the variance determines the shape of the normal distribution.

Normal distribution indicates continuous data distribution, but the degree of nodes in the network is discrete. Common discrete distributions include the hypergeometric, binomial, and Poisson distributions. Under certain conditions, these can be regarded as the discretization of the normal distribution and satisfy the Poisson distribution as follows:

$$P(k) = \frac{\lambda^k e^{-\lambda}}{k_!}, \tag{12}$$

where $\lambda > 0$ and the mean and variance of Poisson distribution are bothλ. Sufficiently large values for λ approximate the normal distribution curve. Poisson distribution of different parameters is shown in Figure 2:

In addition, in some networks, the majority of nodes have a small degree and a small number of nodes have a large degree. In these cases, the network is more in line with the long-tail distribution and is called a free standard network.

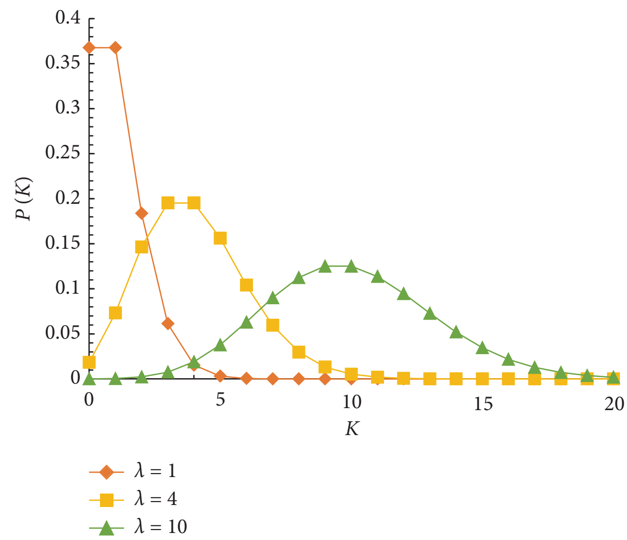

Figure 2: Poisson distribution with different parameters.

2.3. Importance Ranking of Network Key Nodes Based on AHP.

A group of optimal nodes in a complex network is called key participants. Their activity can greatly enhance the stability and robustness of the system. By evaluating the importance of nodes in the complex network of CNCMT, we can quickly and accurately find the key nodes in the large-scale and complex network. According to the evaluation results of node importance, preventive maintenance can be carried out for key nodes to further improve the reliability of CNCMTs, which reduces operational cost and production errors. The evaluation of the key nodes in the complex network in this study chiefly considers the following key indicators:

2.3.1. Degree Centrality. Degree centrality is a direct measure of network key nodes. The greater the degree of a node, the more important the node is. For a network with N nodes, the maximum node degree is $N-1$. Degree centrality is defined as follows:

$$\mathrm{DC}_i = D_i, \tag{13}$$

where D_i is the degree of the node.

2.3.2. Betweenness Centrality. The betweenness centrality of a node is shown as its load capacity between other nodes, as defined below:

$$\mathrm{BC}_i = \sum_{s\neq i\neq t} \frac{n_{st}^i}{g_{st}}, \tag{14}$$

where g_{st} is the number of shortest paths from node s to node t and n_{st}^i is the number of those shortest paths passing through node ig_{st}.

2.3.3. Closeness Centrality. Closeness centrality reflects the relative importance of nodes in the network.

$$\mathrm{CC}_i = \frac{1}{\mathrm{d}_i} = \frac{N}{\sum_{j=1}^{N} d_{ij}}, \tag{15}$$

where d_i represents the average distance from node i to other nodes in the network, d_{ij} represents the distance from node i to node j, and N is the total number of nodes. A larger CC_i

Table 1: Scale and meaning of judgment matrix.

Scale	Meaning
0	The latter is more important than the former.
1	Indicates that two factors have the same importance
2	The former is more important than the latter

represents a node being closer to the network center, which corresponds to node importance.

2.3.4. Network Efficiency. Network efficiency refers to the mean value of all node pairs' distance reciprocal sum, used to reflect the extent of difficulty in transmitting information in the network. The larger the network efficiency value, the easier it is for the information to transmit in the network. This value, E, is defined below:

$$E = \frac{1}{N(N-1)} \sum_{i=j}^{N} d_{ij}, \tag{16}$$

where N is the total number of nodes included in the network.

Network vulnerability, V_i, is defined as follows:

$$V_i = \frac{E - E_i}{E}, \tag{17}$$

where V_i, E_i represents the efficiency of the network after removing the ith node. A larger V_i means that the removed node is more important.

Normalization of the abovementioned indicators by min-max normalization is as follows:

$$\mathrm{DC}_i = \frac{\mathrm{DC}_i - \min \mathrm{DC}_i}{\max \mathrm{DC}_i - \min \mathrm{DC}_i}. \tag{18}$$

BC, *CC,* and *VV* may be normalized in the same way.

In this paper, each node is taken as the evaluation object, and its importance can be evaluated by the four abovementioned indicators. This is a multiattribute ranking problem. In this study, the analytic hierarchy process is used to analyze and construct the judgment matrix $B = (b_{ij})_{n\times n}$, and the scale of judgment matrix elements is given, as shown in Table 1:

According to the relevant theories of complex networks, the order of importance of the above factors is as follows: $DC > BC > CC = V$, and the index results are shown in Table 2.

The judgment matrix is as follows:

$$B = \begin{bmatrix} 1 & 2 & 2 & 2 \\ \frac{1}{2} & 1 & 2 & 2 \\ \frac{1}{2} & \frac{1}{2} & 1 & 1 \\ \frac{1}{2} & \frac{1}{2} & 1 & 1 \end{bmatrix}. \tag{19}$$

Table 2: Scaling results of parameters.

	DC	BC	CC	V	Sum
DC	1	2	2	2	7
BC	0	1	2	2	5
CC	0	0	1	1	2
V	0	0	1	1	2

Table 3: Key functional components and numbers of CNCMT.

Subsystem	Part name	Number
CNC system	PLC module	1
	Operation panel	2
	CRT module	3
	Automatic programming module	4
	CNC management module	5
	CNC interpolation module	6
	Position control mode	7
	Spindle control module	8
	Main memory mode	9
Feed system	Guide	10
	Ball screw	11
	Nut	12
	Ball	13
	Ball screw bearing	14
	Detection feedback device	15
	Workbench	16
	Transmission mechanism	17
Servo system	Feed servo motor	18
	Spindle servo motor	19
	Servo motor	20
	Spindle servo drive	21
	Feed servo drive	22
Electrical system	Magnetic contactor	23
	Relay	24
	Circuit breaker	25
	Fuse	26
	Control button	27
	LED	28
	Travel switch	29
	Proximity switch	30
	Transformers	31
	Switches	32
	Braking resistance	33
	DC power supply	34
Drive system	Headstock	35
	Spindle	36
	Spindle bearing	37
	Automatic tool clamping device	38
	Automatic stop device	39
	Spindle hole cleaning device	40
Auxiliary system	Tool magazine	41
	Manipulator	42
	Lubrication cooling system	43
	Chip removal device	44
	Vise	45
	Shank	46
	Hydraulic device	47
	Pneumatic device	48
Basic part	Machine bed	49
	Machine column	50

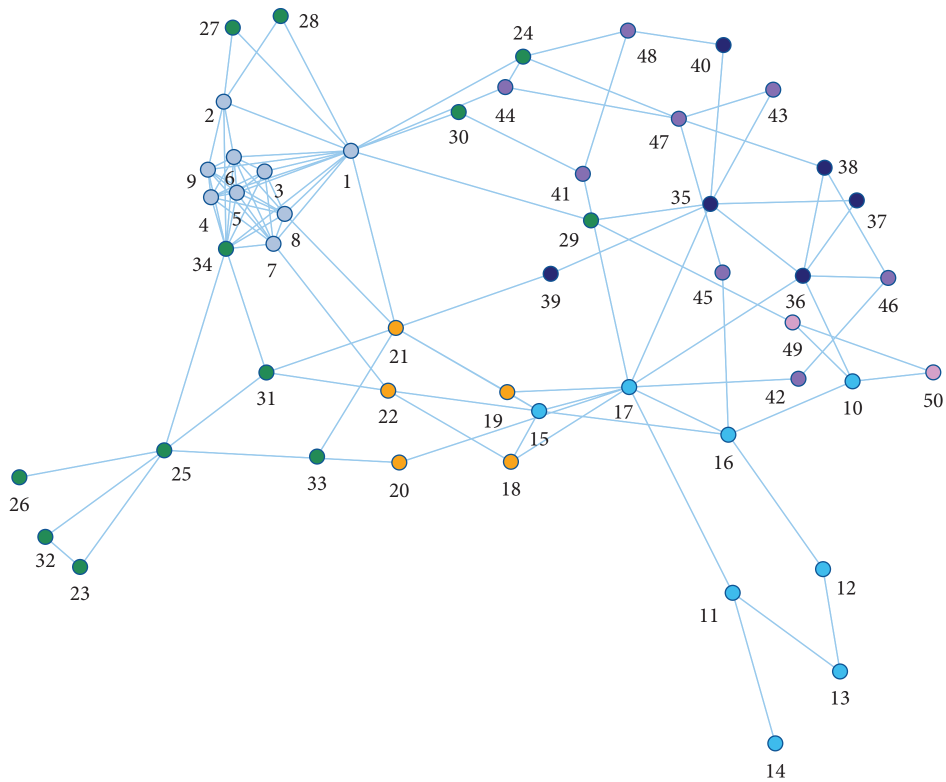

Figure 3: Complex network of CNCMT.

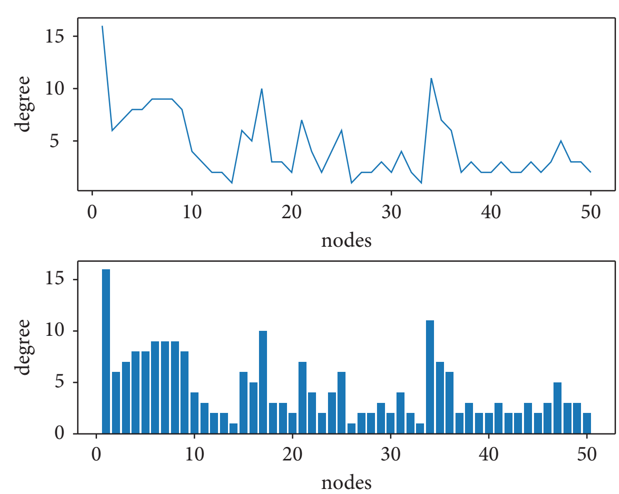

Figure 4: Node degree of complex network of CNCMT.

The weight vector obtained by the feature method is as follows:

$$\overline{W} = [0.4032\ 0.2581\ 0.1694\ 0.1694]. \tag{20}$$

The expression for calculating the importance of nodes is as follows:

$$Y_i = 0.4032 \times DC_i + 0.2581 \times BC_i + 0.1694 \times CC_i + 0.1694 \times V_i. \tag{21}$$

3. Experiments and Results

3.1. Construction of the Complex Network for CNCMT. The connection modes among the components of the CNCMT can be divided into four groups: mechanical connection, electrical connection, pipe connection, and functional connection. By analyzing the connection characteristics and coupling relationship of each part, 50 CNCMT components are selected and numbered, as shown

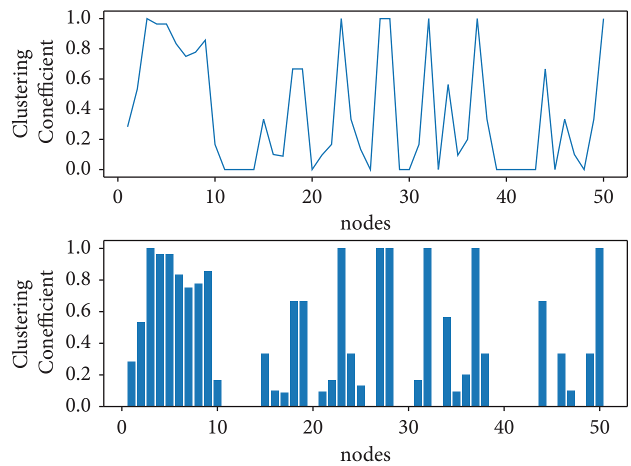

Figure 5: Clustering coefficient of complex network of CNCMT.

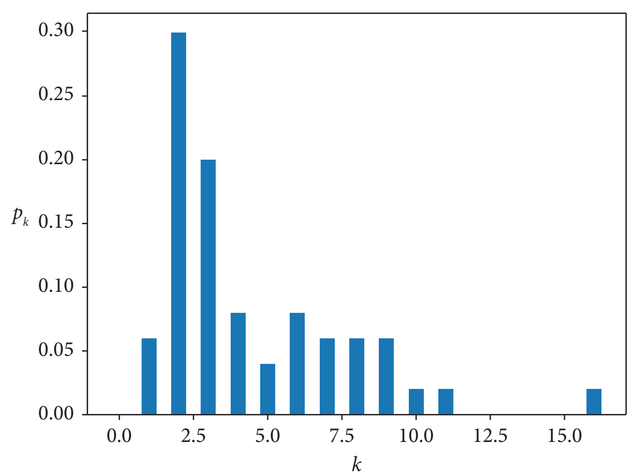

Figure 6: Degree distribution of complex network of CNCMT.

Table 4: Comparison of complex network related parameters.

Network type	Nodes	Average degree	Clustering coefficient	Average path length
MTCN	50	4.44	0.370	3.0645
ER			0.091	2.86

in the following Table 3. The complex network considered in this paper consists of the connections between all parts shown in Figure 3. It can be seen that the various subsystems of CNC machine tools are closely linked through one or more specific functional components for interconnection; the CNC system, as the most core subsystem of CNC machine tools, shows a high degree of connectivity.

3.2. Analysis Results of MTCN. Node degree K_i, which refers to the number of nodes connected to the node, reflects the importance of the node in the network. The network node degree of this study is shown in Figure 4. The average node degree is calculated to be 4.44.

Through the analysis of the figure, it can be found that the node degrees of nodes 1, 17, and 34 are notably high. These correspond to the PLC function module, transmission mechanism, and DC-regulated power supply, respectively, and undertake multiple execution tasks, display tasks, and information exchange tasks in the CNCMT. From this perspective, the most critical component of the CNCMT appears to be the PLC function module.

The clustering coefficient describes the aggregation tightness of the network. The clustering coefficient of each node is shown in Figure 5.

The node degree distribution is shown in Figure 6. It can be found that the node degree distribution of the network conforms to the Poisson distribution.

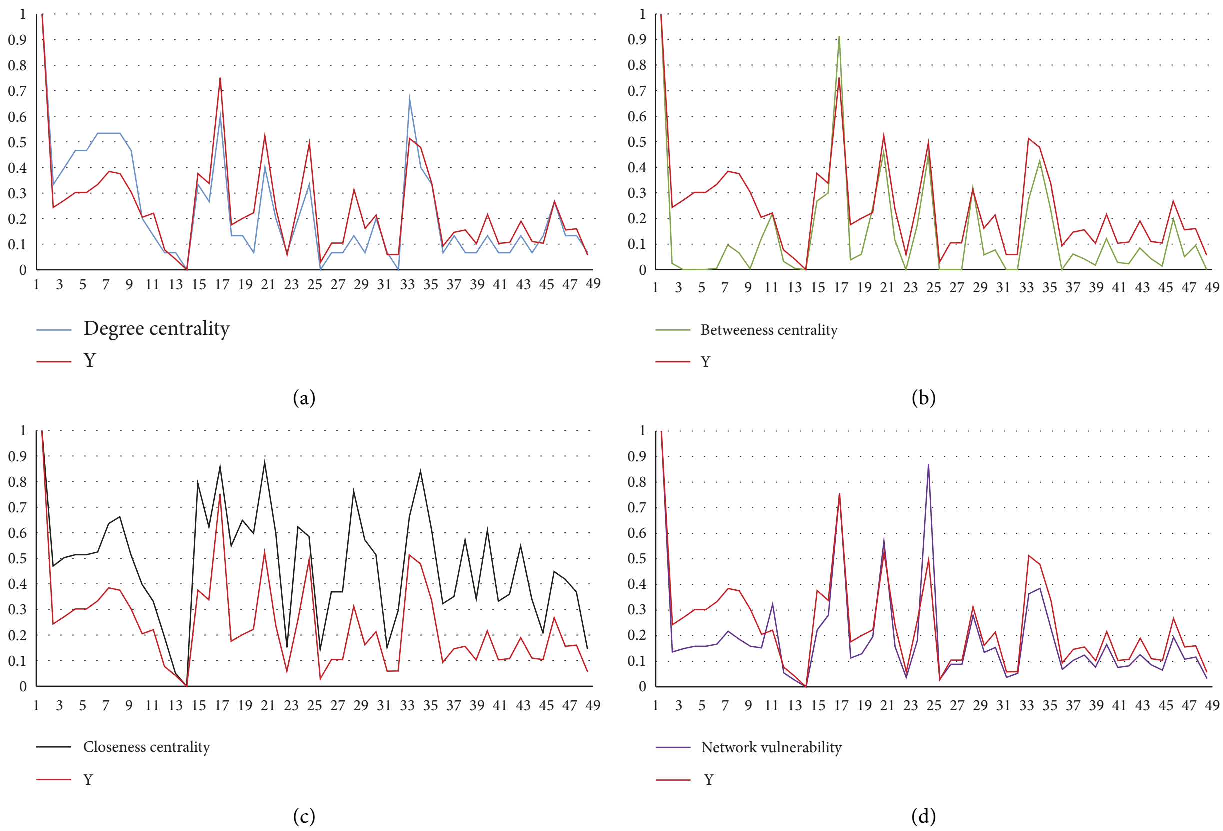

Figure 7: Comparison of node importance between multiparameter and single-parameter networks.

An ER random network with the same number of nodes and average degree is constructed. The calculation results of the abovementioned indicators of the network are compared with the relevant indicators of the constructed ER random network. The results are shown in Table 4.

A comparison of the abovementioned results shows that the clustering coefficient and average path length of the constructed CNCMT complex network are greater than those of the ER random network with the same number of nodes and average node degree. This demonstrates that the CNCMT complex network has small-world characteristics, and there is a close connection between nodes.

The comparison between the results of the importance of nodes in the complex network of CNCMT using the analytic hierarchy process and the results of a single parameter is shown in Figure 7.

4. Conclusion

In this study, a complex network is introduced into the analysis of the key functional components of the CNCMT to construct the complex network of the CNCMT. An analysis of the characteristics of the node degree and the clustering coefficient of the network reveals that the network has small-world characteristics. The model presented in this study considers the degree centrality, betweenness centrality, closeness centrality, and network vulnerability of nodes. The use of the analytic hierarchy process to determine node importance and the application of min-max normalization reduce the influence of previous model biases. It is found that the calculation results of the complex network of the CNCMT with multiple parameters are more consistent with fault history data obtained in the laboratory than those with single parameters [9].

Data Availability

The datasets used in the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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