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Evaluation of Node Importance in Collaborative Network of Traditional Manufacturing Enterprises Based on Multiple Attribute Decision Making

Tao Yang[1,2], Yihuan Ding[1,*], Fang Jiang[1]

[1] School of Business Administration, Chongqing Technology and Business University, Chongqing 400067, China
[2] School of Economics and Management, University of Electronic Science and Technology of China, Chengdu 611731, China

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ABSTRACT

The construction and operation of collaborative production networks based on multi-subject collaboration is an important path and means for enterprises to adapt to personalized, diversified, and differentiated market demand. It is of great practical significance to identify the key collaborative subjects in the collaborative network and protect and maintain them to ensure its normal operation. To identify the key collaborative subjects in the collaborative network of traditional manufacturing enterprises, this paper proposes a method for identifying and evaluating the importance of nodes in traditional manufacturing enterprise collaborative networks. Firstly, the method uses four parameters, degree centrality, betweenness centrality, closeness centrality, and subgraph centrality, as node importance evaluation indexes, based on complex network theory. Secondly, the coefficient of variation method (CVM) is used to calculate the weights of evaluation indexes. The Multiple Attribute Decision Making (MADM) based on the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is then used to comprehensively evaluate node importance and identify key nodes (key collaborative subjects) in the network. Finally, the proposed method's effectiveness, rationality, and scientific nature are verified by using the measurement index of network connectivity in combination with specific enterprise cases. The results show that the failure of key nodes has a more significant impact on network connectivity. Therefore, the node importance evaluation method based on Multiple Attribute Decision Making has better performance. It helps traditional manufacturing enterprises to focus on the protection and maintenance of the key collaborative subjects when coping with the competitive environment of the external market and provides a valuable reference for the normal operation of collaborative network organizations.

1. Introduction

Currently, advanced digital technologies such as big data, cloud computing, artificial intelligence, and blockchain have significantly evolved. These technologies have led to the growth of the

* *Corresponding author.*
E-mail address: dingyihuan@ctbu.edu.cn

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intelligent industry and the digital economy, while also promoting the close fusion of information technology and traditional manufacturing industry [1-7]. Moreover, with the rapid advancement of economic globalization, the division of labor within society is becoming increasingly specialized. As a result, enterprises are also becoming more specialized, making it challenging for traditional manufacturing enterprises to rely solely on their abilities to compete in the fierce market environment. The traditional reliance on the profitability of the market share has been unable to ensure the sustained growth of its profits, and China's traditional manufacturing enterprises are still at the rough management level when compared to developed nations. These enterprises are facing pressures such as rising costs, declining profits, diminishing competitive advantage, the increasingly shortened product life cycle, increasing customer demand diversification and personalization, and many other pressures. To deal with the external competitive environment, inter-enterprise cooperation between multi-principal synergy and production collaboration has become a traditional manufacturing business in China [8]. A variety of collaborative network organizations also emerged [9].

Collaborative network organizations are formed by manufacturing enterprises to deal with the increasingly fierce competition. This is achieved by sharing resources, risks, and results, with each collaborative body working towards achieving common goals and benefits [10]. In reality, through deep integration with collaborative partners, traditional manufacturing enterprises can achieve comprehensive and complete intelligent and flexible development, which is essential to adapt to the constantly upgrading consumer demand and changing development patterns. It is also a vital means to achieve innovation and development for traditional manufacturing enterprises [11]. However, many actual cases have shown that while traditional manufacturing enterprises gain competitive advantages through multi-subject collaboration, they also face new risks and challenges. i.e., the failure or abnormality of the collaborative partners will have an impact on the network organization of other collaborative subjects, or even the regular operation of the entire collaborative network. Consequently, how to evaluate the importance of the nodes in the enterprise collaborative network, identify the key collaborative subjects, and focus on the protection and maintenance of the key collaborative subjects, is of great practical significance for the normal operation of collaborative network organizations, and has become the focus of current research in the industry and the theoretical community. As the network node importance evaluation belongs to the typical multi-attribute integrated decision-making problem, it is a multi-objective, multi-level, uncertain, and complex decision-making process due to the influence of various factors, such as the uncertainty of index weights, diversity of judging criteria, and ambiguity of evaluation information. In this regard, based on complex network theory, this paper proposes a method to evaluate the importance of collaborative network nodes using Multiple Attribute Decision Making and realizes the research objectives through the processes such as network node importance evaluation attribute determination, importance calculation, and comprehensive ranking.

Complex network theory was first applied to graph theory and topology in the field of mathematics. The stochastic network theory proposed by Erdős and Renyi [12] laid an important theoretical foundation for the subsequent research on complex networks, and the small-world network model proposed by Watts and Strogatz [13] and the scale-free network evolution model proposed by Barabási and Albert [14] marked a new era in the research of complex network theory. Due to the cross-disciplinary nature of complex network theory, it is now widely used in various disciplines and provides new ideas for solving network organization problems [15-18]. Scholars have researched the related networks and developed network models. Sheikh et al., [19] constructed an innovation ecosystem network, and the results of the research show that resource integration can partially regulate the mediating role of knowledge synergy between innovation ecosystems and corporate innovation. Al-Omoush et al., [20] constructed a corporate collaborative innovation network to examine the causal relationship between e-supply chain collaboration, supply chain agility, collaborative innovation, and value co-creation in key industries. Zhang et al., [21] constructed a collaborative production network and analyzed the grid structure and functional characteristics of a typical heavy chemical enterprise collaborative production system. Yu et al., [22] constructed a customer collaborative product innovation network from the customer's perspective and analyzed the system characteristics. Wang and Chen [23] verified that the complex network model is suitable for studying supply chain networks, and the established complex supply chain network has scale-free characteristics.

In addition, some scholars have conducted relevant research on complex network characteristics based on complex network construction. Some of the notable research works are as follows: Chen et al., [24] studied the network topology characteristics of multimodal transportation networks and the vulnerability of the network in the event of network node failure. Azadegan and Dooley [25] constructed a supply chain network to investigate its disaster resilience in responding to significant supply and demand disruptions from a network-level perspective. Ma et al., [26] evaluated the network resilience of an urban road network by assessing its ability to cope with heavy rainfall and flooding disasters. Wang et al., [27] constructed a power grid model, focusing on evaluating and examining the performance and resilience of the network from both structural and functional perspectives. Li and Fu [28] analyzed the optimization method of wireless sensor network destruction resistance from the aspects of network reconfiguration and topology evolution. An et al., [29] quantified the destruction resistances of different regional network topologies in terms of internal topology and external communication, ranked them, and found the destruction resistance differences between regional network topologies. As for node importance identification, individual scholars have conducted relevant research. Fu et al., [30] proposed a node importance evaluation matrix method by considering the node position and the contribution information of neighboring nodes. Hu et al., [31] proposed a network node importance identification method based on the information entropy method by studying the correlation relationship between nodes and their direct and indirect neighboring nodes. Cui et al., [32] proposed a network node importance identification method based on the contribution matrix method and applied it to the identification of key stations in urban rail transit.

After analyzing the existing literatures, it was found that the current research mainly concentrates on the construction of the multi-subject collaborative network model and the analysis of the fundamental characteristics of the network. Most of the few studies that address the identification of network node importance use a single attribute metric, which has significant limitations when performing node importance assessment in a network, or even if multiple metrics are adopted for judging, they do not provide a comprehensive consideration of the network's global structure. However, there is a lack of in-depth analysis of the significance of the network collaborative subjects. The identification of critical nodes plays a pivotal role in the stability of the overall network and has a crucial impact on the transmission of network information and the reliability of network operation.

To summarize, for the identification of key collaborative subjects in the collaborative network of traditional manufacturing enterprises, this paper takes the traditional manufacturing enterprise collaborative network as the research object, and employs, based on the complex network theory, the coefficient of variation method (CVM) to calculate the weight of each evaluation index in importance evaluation. Then, by comprehensively evaluating the importance of nodes and finding the key nodes through the Multiple Attribute Decision Making method based on the Technique for

Order Preference by Similarity to an Ideal Solution (TOPSIS), the importance of each collaborative subject in the collaborative network is evaluated and the key nodes (key collaborative subjects) in the collaborative network are determined. The results of this research can provide a methodology to support the effective operation of collaborative production networks in traditional manufacturing enterprises.

2. Evaluation Model Construction of Importance of Collaborative Network Nodes in Traditional Manufacturing Enterprises

A traditional manufacturing enterprise collaborative network was established as a result of various business connections (materials, information, technology, services, etc.) between enterprises, and it can be visualized as an undirected, unweighted network G with n nodes and m edges. In this network, the collaborative subjects are regarded as network nodes, and the stable collaborative relationships between the collaborative subjects are regarded as the edges of the network. Let the graph $G = G(V, E)$ be an undirected and unweighted network, where $V = \{v_1, v_2, v_3, \dots, v_n\}$ is the set of all the nodes in the network, $v_i(i = 1,2, \dots, n)$ is an individual node in the network, and n is the number of nodes in the network; and $E = \{e_1, e_2, e_3, \dots, e_m\} \subseteq V \times V$ is the set of connecting edges between nodes, $e_i(i = 1,2,3, \dots, m)$ is the exchange line where nodes are connected, and m is the number of lines. Four parameters—degree centrality, closeness centrality, betweenness centrality, and subgraph centrality—are chosen as the node importance evaluation indexes after the collaborative network of traditional manufacturing enterprises is constructed. The coefficient of variation method (CVM) is then used to determine the weights of the evaluation indexes, and based on this, the comprehensive evaluation of node importance is carried out by the Multiple Attribute Decision Making method based on the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), to search for the key collaboration subjects in the collaborative network. Based on the above analysis, this paper proposes a process research model for identifying the key nodes in the collaborative networks of traditional manufacturing enterprises based on Multiple Attribute Decision Making, as illustrated in Figure 1.

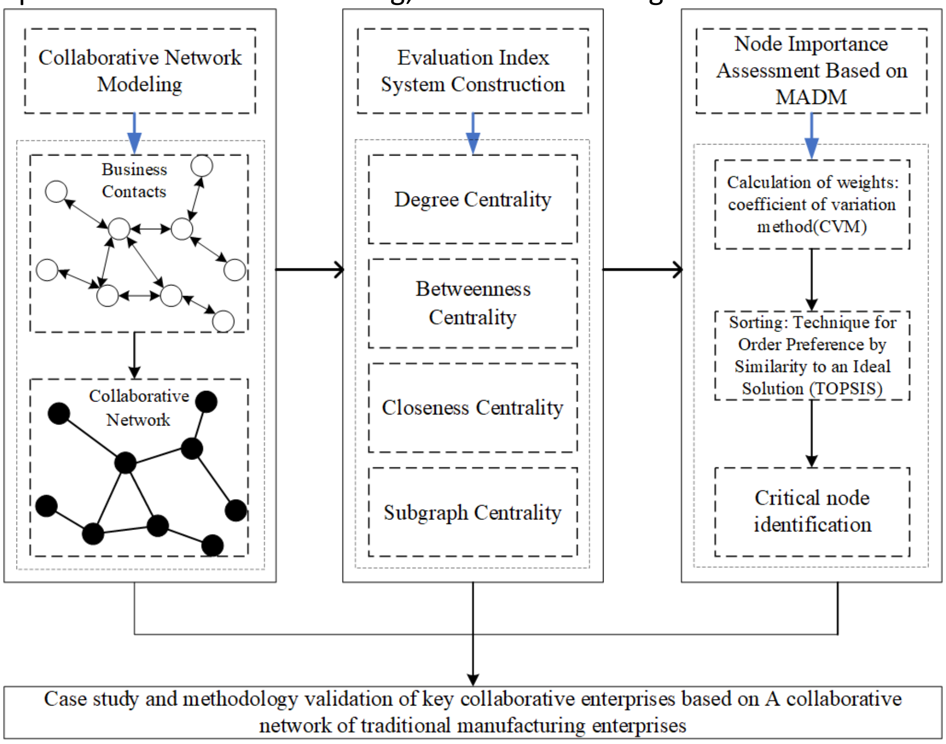


Fig. 1. A model for studying the process of identifying key nodes of a network based on MADM

3. Construction of an Evaluation Index System based on Multiple Attribute Decision Making

Due to the ever-changing nature of traditional collaborative networks of manufacturing enterprises in actual operation, as well as the fact that different indexes emphasize the importance of nodes in the network from different perspectives, relying only on a single index to judge the importance of a node in the network is highly one-sided. Based on this, this paper proposes Multiple Attribute Decision Making (MADM), which evaluates the network nodes comprehensively by taking four parameters, i.e., degree centrality, betweenness centrality, closeness centrality, and subgraph centrality, as attributes of the Multiple Attribute Decision Making scheme, to determine the degree of importance of a single node in the network. To characterize the collaborative network of traditional manufacturing enterprises, this paper gives the following definitions for the identified node importance indexes.

Definition 1. Degree Centrality is the ratio of the number of edges connected to a node to the maximum number of edges possible for that node, and its larger value means that it is more important in the network. The degree centrality of node v_i is denoted as:

$$C_D(v_i) = \frac{k_i}{n-1} \tag{1}$$

Where k_i is the node degree, which indicates the number of nodes or edges in the network that are directly connected to node v_i.

Definition 2. Betweenness Centrality is the number of shortest paths through a node in a network, and the larger the value, the more influence it has in the network. The betweenness centrality of node v_i is denoted as:

$$C_B(v_i) = \sum_{t \neq i \neq s \in V} \frac{g_{ts}(v_i)}{g_{ts}} \tag{2}$$

Where $g_{ts}(v_i)$ denotes the number of paths between nodes v_t and v_s where the shortest path crosses node v_i, and g_{ts} denotes the total number of all the shortest paths that exist from node v_t to node v_s.

Definition 3. Closeness Centrality is the reciprocal of the average distance from a node to all the other nodes in the network, reflecting the "centrality" of the node in the entire network, and the larger its value, the closer it is to the center of the network. The closeness centrality of node v_i is denoted as:

$$C_C(v_i) = (n-1)/\sum_{j \neq i}^{n} d_{ij} \tag{3}$$

Where d_{ij} denotes the number of edges contained in the shortest path from node v_i to node v_j.

Definition 4. Subgraph Centrality is the number of closed pathways that start and end at a node in the network, and a closed pathway represents a connected subgraph in the network. The subgraph centrality of node v_i is denoted as:

$$C_S(v_i) = \sum_{m=0}^{\infty} \frac{\mu_m(v_i)}{m!} \tag{4}$$

where $\mu_m(v_i)$ is the number of loops starting at node v_i and returning to node v_i via m connected edges, and the contribution of each loop to the subgraph centrality of a node decreases with increasing length.

4. Comprehensive evaluation of node importance based on Multiple Attribute Decision Making

In the previous paper, multiple indexes for evaluating the importance of nodes were given, and corresponding definitions were given for each index, but different index explored the importance of nodes in complex networks from different perspectives, and there is a great one-sidedness in judging the importance of a node in a network by relying on a single index only. Therefore, this paper selects four indicators, i.e., degree centrality, betweenness centrality, closeness centrality, and subgraph centrality, to comprehensively evaluate the importance of network nodes.

Currently, scholars use several methods, including MEREC (Method Based on The Removal Effects of Criteria) [33], MABAC (Multi-Attributive Border Approximation Area Comparison) [34], MAIRCA (Multi-Attribute Ideal Real Comparative Analysis) [35], VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenie) [36]**Error! Reference source not found.**, MARCOS (Measurement of Alternatives and Ranking According to The Compromise Solution) [37], and TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) [38], to analyze problems with multiple attributes decision making. Compared to other methods, TOPSIS method can be flexibly applied to any indicator and in various problem domains, and the normalization of indicator criteria reduces interference from outliers. Furthermore, the TOPSIS method uses the concept of positive and negative ideal solutions to reflect the interdependence between indicators, resulting in a more accurate evaluation of the importance of network nodes in traditional collaborative networks of manufacturing companies.

In addition, current scholars comprehensively evaluate the importance of network nodes from hierarchical analysis [39-41], principal component analysis [42, 43], and coefficient of variation [44] combined with Multiple Attribute Decision Making methods, respectively. Hierarchical analysis is mainly based on the experience of experimental personnel to judge the degree of importance between the indexes, which is more subjective; principal component analysis is suitable for the situation when the number of indexes is large, and select the indexes in which the number of information accounts for a larger proportion of the indexes as the principal component, which may lead to the lack of part of the data while reducing the workload; and coefficient of variation directly utilizes the full information contained in the indexes to calculate the weight, which is an objective weighting method.

Therefore, this paper adopts the Coefficient of Variation Method (CVM) to determine the calculation weight of each importance evaluation index, in order to obtain the comprehensive value of the importance of each node; secondly, the importance of the nodes is comprehensively evaluated and the key nodes are found through the Multiple Attribute Decision Making method based on the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS).

Assume that there are n collaborative enterprise nodes to be evaluated in the traditional manufacturing enterprise collaborative network, the corresponding decision scheme is $A = \{A_1, A_2, A_3, \cdots, A_n\}$, the importance evaluation index is k, $k = 4$, in this paper, the attribute of the scheme is $f_k(k = 1,2,3,4)$, and the initial decision matrix X is constructed:

$$X = \begin{bmatrix} A_1(f_1) & A_1(f_2) & A_1(f_3) & A_1(f_4) \\ A_2(f_1) & A_2(f_2) & A_2(f_3) & A_2(f_4) \\ \vdots & \vdots & \vdots & \vdots \\ A_n(f_1) & A_n(f_2) & A_n(f_3) & A_n(f_4) \end{bmatrix} \tag{5}$$

where $A_i(f_j)(i = 1,2,3, \cdots, n; j = 1,2,3,4)$ is denoted as the value of the jth index for the ith node.

The equations for determining the weight of each index $w_j(j = 1,2,3,4)$ based on the coefficient of variation method is as follows:

$$w_j = \frac{V_j}{\sum V_j} \tag{6}$$

where V_j is the coefficient of variation of the jth index, and

$$V_j = \frac{\sigma_j}{\bar{x}_j} \tag{7}$$

where σ_j is the standard deviation of the jth index in the subsequently derived normalized decision matrix Y and $\bar{x}_j$ is the mean of the jth index.

The steps of the TOPSIS-based Multiple Attribute Decision Making method for comprehensive evaluation of node importance algorithm are as follows.

Step 1: Normalize the initial decision matrix to obtain the normalized decision matrix Y.

$$y_{ij} = \frac{A_i(f_j)}{\sqrt{\sum_{i=1}^{n}[A_i(f_j)]^2}} \tag{8}$$

$$Y = \begin{bmatrix} y_{11} & y_{12} & y_{13} & y_{14} \\ y_{21} & y_{22} & y_{23} & y_{24} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & y_{n3} \cdots & y_{n4} \end{bmatrix} \tag{9}$$

Step 2: Determine the weights $w_j\left(j = 1,2,3,4; \sum w_j = 1\right)$ of each index, and generate a weighted normalized decision matrix Z with the normalized decision matrix.

$$Z = \left(z_{ij}\right) = \left(w_j y_{ij}\right) = \begin{bmatrix} w_1 y_{11} & w_2 y_{12} & w_3 y_{13} & w_4 y_{14} \\ w_1 y_{21} & w_2 y_{22} & w_3 y_{23} & w_4 y_{24} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 y_{n1} & w_2 y_{n2} & w_3 y_{n3} \cdots & w_4 y_{n4} \end{bmatrix} \tag{10}$$

Step 3: Determine the positive and negative ideal decision schemes for the index, respectively:

$$A^+ = \left\{\max_{i\in N}(z_{i1}, z_{i2}, \cdots, z_{i4})\right\} = \{z_1{}^{max}, z_2{}^{max}, \cdots z_4{}^{max}\} \tag{11}$$

$$A^- = \left\{\min_{i\in N}(z_{i1}, z_{i2}, \cdots, z_{i4})\right\} = \left\{z_1{}^{min}, z_2{}^{min}, \cdots z_4{}^{min}\right\} \tag{12}$$

where $N = \{1,2,\cdots,n\}$.

Step 4: Calculate the Euclidean distance from each node index to the positive ideal decision scheme A^+ and the negative ideal decision scheme A^-, respectively:

$$D_i{}^+ = \sqrt{\sum_{j=1}^{4}\left(z_{ij} - z_j{}^{max}\right)^2} \tag{13}$$

$$D_i{}^- = \sqrt{\sum_{j=1}^{4}\left(z_{ij} - z_j{}^{min}\right)^2} \tag{14}$$

Step 5: Calculate the closeness Q_i of each node index to the ideal decision in conjunction with the Euclidean distance:

$$Q_i = \frac{D_i{}^-}{D_i{}^+ + D_i{}^-} \tag{15}$$

According to the closeness, the importance of the nodes is ranked in a descending order. A larger closeness indicates that the node is more important in the network. As a result, obtain the evaluation results of the nodes in the network are attained, and thus the key nodes (key collaborative subjects) are determined.

5. Case Study

5.1 Case Background

Table 1
List of enterprises for production numbers

Number	Collaborative enterprise	Number	Collaborative enterprise	Number	Collaborative enterprise	Number	Collaborative enterprise
v_1	Motorcycle Steel Supply	v_9	engine supply	v_{17}	Vehicle sensor supply	v_{25}	Customer Relationship Management Supply
v_2	Motorcycle Aluminum Supply	v_{10}	Assembly service supply	v_{18}	Transmission supply	v_{26}	Advertiser supply
v_3	Cloud platform construction program supply	v_{11}	Welding equipment supply	v_{19}	Logistics and Distribution Supply	v_{27}	Vehicle after-sales service provision
v_4	Supply of motorcycle powertrain components	v_{12}	Paint line supply	v_{20}	Vehicle horn supply	v_{28}	Tire rubber supply
v_5	Battery supply	v_{13}	Vehicle R&D technology supply	v_{21}	Logistics and Warehousing Supply	v_{29}	Motorcycle recycling collaboration
v_6	Assembly line supply	v_{14}	Logistics and Warehousing Supply	v_{22}	Logistics Management Supply	v_{30}	Motorcycle Tuning Collaboration
v_7	Industry Analytics Data Supply	v_{15}	Motorcycle Balancer Supply	v_{23}	Supply of vehicle design solutions	v_{31}	Personalized Customized Service Collaboration
v_8	Clutch debugger supply	v_{16}	Supply of ancillary parts	v_{24}	Collaboration on technology licensing	v_{32}	Digital Marketing Supply

This paper takes traditional manufacturing enterprise A as an example to verify the feasibility and effectiveness of the proposed method. Enterprise A is a motor vehicle manufacturing enterprise, mainly engaged in the research and development, design, and production of motorcycles and their engines, spare parts, agricultural machinery, electric batteries, etc. Affected by its resource constraints and lack of innovation ability, Enterprise A can no longer adapt to the increasingly diverse consumer demands, the rapidly changing technological development, and the complex and diverse market environments, and can-not afford the high cost of independent innovation, so it decided to build a collaborative network to realize its innovation and development in the way of multi-subject collaboration. This collaborative network contains a total of 32 collaborative enterprises with motorcycle production as the leader, forming a cooperative production network system of enterprises with comprehensive support for the upper, middle, and lower product chains, and the services provided by each collaborative enterprise to Enterprise A are shown in Table 1.

5.2 Network Model Construction

Table 2
Traditional manufacturing enterprise a collaborative network affiliation

Number	v_0	v_1	v_2	v_3	v_4	v_5	v_6	⋯	v_{32}
v_0	0	1	1	1	1	1	0	⋯	1
v_1	1	0	0	0	0	1	1	⋯	0
v_2	1	0	0	0	1	0	0	⋯	0
v_3	1	0	0	0	0	0	1	⋯	1
v_4	1	0	1	0	0	1	0	⋯	0
v_5	1	1	0	0	1	0	1	⋯	0
v_6	0	1	0	1	0	1	0	⋯	0
⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯
v_{32}	1	0	0	1	0	0	0	⋯	0

Note: v_0 is traditional manufacturing enterprise A itself, with 1 representing an affiliation and 0 representing no affiliation.

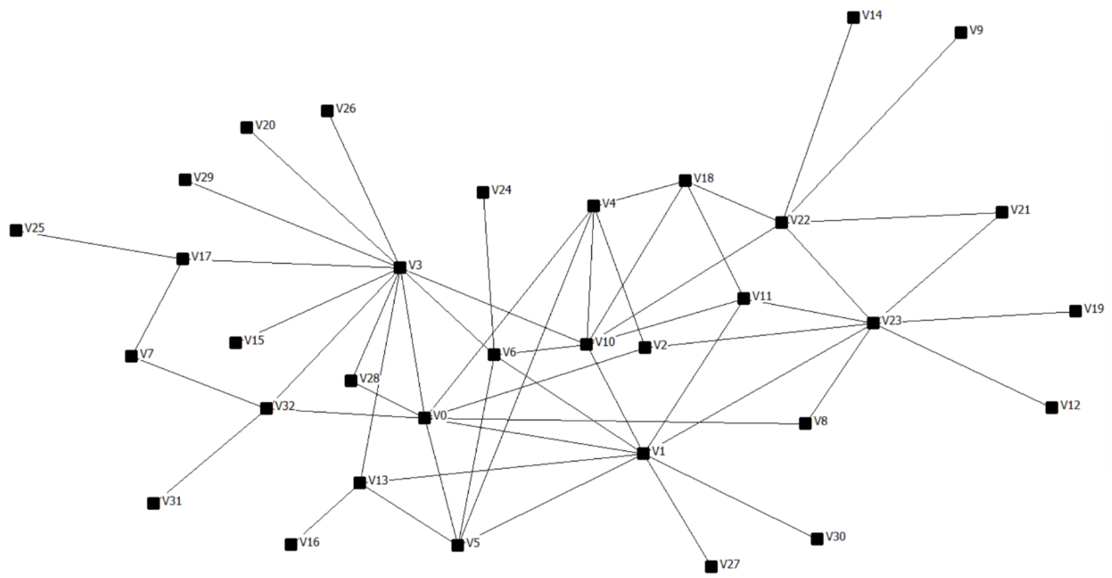


Fig. 2. Collaborative Network Topology of Traditional Manufacturing Enterprise A

According to the above network construction idea, the collaborative enterprises are regarded as network nodes, and the collaborative network model for traditional manufacturing enterprise A is constructed through the association relationship between each enterprise. The association relationship between each enterprise is analyzed as shown in Table 2, and the topology schematic of traditional manufacturing enterprise A collaborative network is shown in Figure 2. Where $v_i(i = 1,2,3,\cdots,32)$ is a network node.

5.3 Node Importance Analysis

The nodes in the collaborative network of traditional manufacturing enterprises are calculated based on degree centrality, betweenness centrality, closeness centrality, and subgraph centrality, respectively, and the results are shown in Table 3, where only the top 10 nodes with higher rankings are listed.

Table 3
Topology index calculation results (Top 10)

Ranking	C_D		C_B		C_C		C_S	
	Node	Importance value	Node	Importance value	Node	Importance value	Node	Importance value
1	v_3	0.333	v_3	213.979	v_3	0.508	v_{10}	0.761
2	v_1	0.273	v_{10}	119.807	v_{10}	0.500	v_1	0.636
3	v_{23}	0.242	v_1	105.861	v_1	0.485	v_3	0.598
4	v_{10}	0.212	v_{23}	98.969	v_6	0.457	v_{23}	0.549
5	v_{22}	0.182	v_{22}	78.442	v_{13}	0.427	v_6	0.535
6	v_4	0.152	v_6	51.300	v_5	0.421	v_5	0.513
7	v_5	0.152	v_{32}	42.142	v_4	0.416	v_{13}	0.505
8	v_6	0.152	v_{13}	41.208	v_{11}	0.416	v_4	0.503
9	v_{11}	0.121	v_{17}	38.700	v_{23}	0.410	v_{11}	0.497
10	v_{13}	0.121	v_2	12.670	v_{22}	0.405	v_{32}	0.492

5.4 Multiple Attribute Decision Making Critical Node Identification

Step 1: The initial decision matrix X is obtained from Table 3, and the normalized decision matrix Y is obtained by normalizing the initial decision matrix X.

$$Y = \begin{bmatrix} 0.388 & 0.388 & \dots & 0.242 \\ 0.129 & 0.041 & \dots & 0.180 \\ \vdots & \vdots & \ddots & \vdots \\ 0.172 & 0.166 & \dots & 0.187 \end{bmatrix}$$

Step 2: According to the Coefficient of Variation Method (CVM), the weights of the indexes were determined as $w_{C_D} = 0.220$, $w_{C_B} = 0.467$, $w_{C_C} = 0.046$, and $w_{C_S} = 0.267$, respectively, and were used together with the normalized decision matrix to generate a weighted normalized decision matrix Z. Specific data for each index are shown in Table 4.

Table 4
Results of the weights of indexes based on the coefficient of variation method

Index	$\bar{x}_j$	$\bar{x}_j$	v_j	w_j
C_D	0.135	0.116	0.865	0.220
C_B	0.086	0.157	1.833	0.467
C_C	0.174	0.031	0.179	0.046
C_S	0.123	0.129	1.047	0.267

$$Z = \begin{bmatrix} 0.086 & 0.181 & \dots & 0.081 \\ 0.029 & 0.019 & \dots & 0.060 \\ \vdots & \vdots & \ddots & \vdots \\ 0.038 & 0.078 & \dots & 0.063 \end{bmatrix}$$

Step 3: The positive ideal decision scheme can be obtained from the matrix Z:

$$A^{+} = \{{z_1}^{max}, {z_2}^{max}, \cdots {z_4}^{max}\} = \{0.104, 0.324, 0.011, 0.097\}$$

The negative ideal decision scheme is

$$A^{-} = \left\{{z_1}^{min}, {z_2}^{min}, \cdots {z_4}^{min}\right\} = \{0.009, 0, 0.006, 0\}$$

Step 4: From Eqs. (13)-(14), the Euclidean distance from each scheme to A^+ and A^- is $D_i^+$and D_i^- respectively.

$$D_i^+ = \sqrt{(z_{i1} - 0.104)^2 + (z_{i2} - 0.324)^2 + (z_{i3} - 0.011)^2 + (z_{i4} - 0.097)^2}$$

$$D_i^- = \sqrt{(z_{i1} - 0.009)^2 + (z_{i2} - 0)^2 + (z_{i3} - 0.006)^2 + (z_{i4} - 0)^2}$$

Step 5: From Eq. (15), the closeness Q_i of each node index to the ideal decision is obtained, as shown in Table 5, in which only the top 10 nodes with higher ordering rankings are listed.

Table 5
Evaluation Results of MADM Based on CVN-TOPSIS (Top 10)

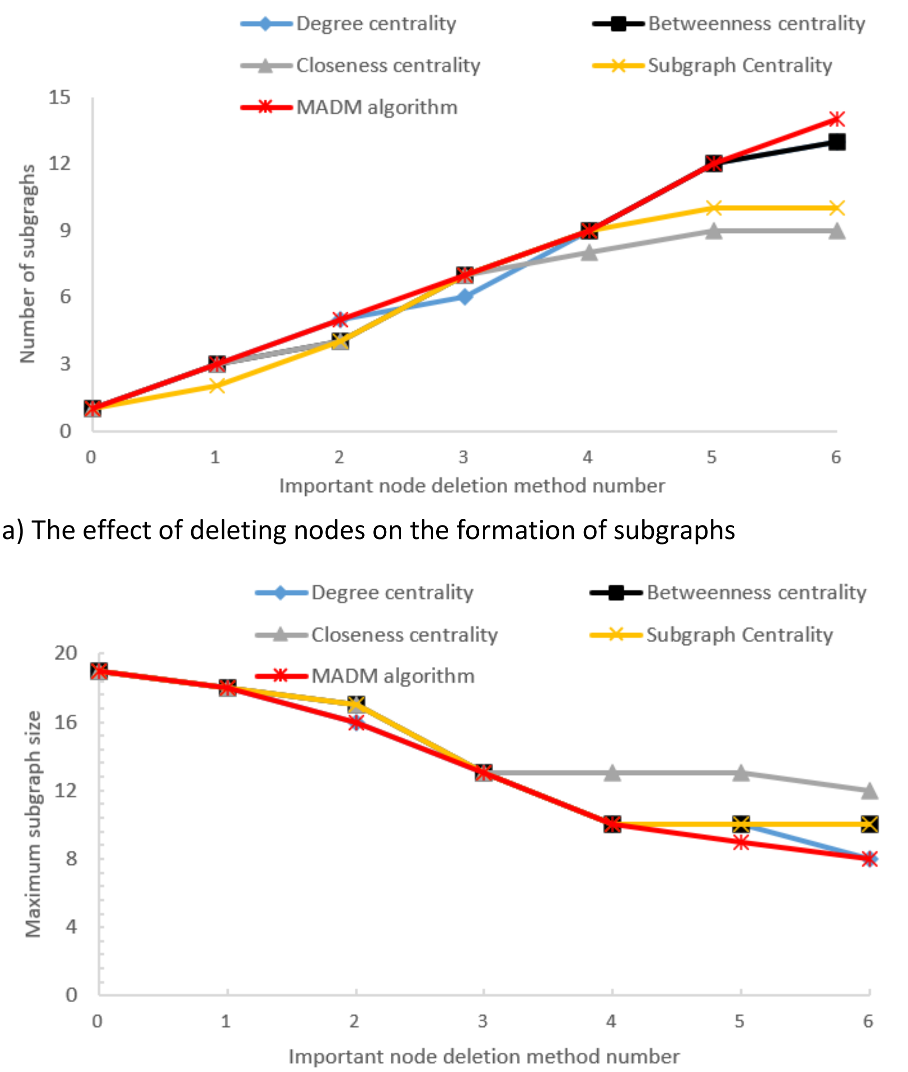
Ranking	Node	D_i^+	D_i^-	Q_i
1	v_3	0.021	0.346	0.943
2	v_1	0.145	0.213	0.596
3	v_{10}	0.168	0.196	0.539
4	v_{23}	0.178	0.178	0.500
5	v_{22}	0.232	0.128	0.355
6	v_{32}	0.257	0.104	0.288
7	v_6	0.268	0.101	0.274
8	v_{13}	0.272	0.094	0.258
9	v_{17}	0.279	0.084	0.231
10	v_5	0.316	0.077	0.197

From Table 3, we can learn the rankings of degree centrality, betweenness centrality, closeness centrality, and subgraph centrality, and from Table 5, we can learn the ranking of the closeness Q_i. The closeness of the nodes ranked in the top 6 of the node closeness ranking is much higher than that of the other nodes, and due to the large number of nodes, we only analyze the nodes ranked in the top 6 of the closeness ranking here, as shown in Table 6.

Table 6
Top 6 Important Nodes of Traditional Manufacturing Company A Collaborative Network

Ranking	C_D	C_B	C_C	C_S	Q_i
1	v_3	v_3	v_3	v_{10}	v_3
2	v_1	v_{10}	v_{10}	v_1	v_1
3	v_{23}	v_1	v_1	v_3	v_{10}
4	v_{10}	v_{23}	v_6	v_{23}	v_{23}
5	v_{22}	v_{22}	v_{13}	v_6	v_{22}
6	v_4	v_6	v_5	v_5	v_{32}

5.5 Critical Node Importance Evaluation and Validation



(a) The effect of deleting nodes on the formation of subgraphs

(b) The effect of deleting nodes on forming the maximum size of a subgraph

Fig.3. Impact of deleting critical nodes on the network

As shown in Table 5, the top 6 important nodes of the collaborative network of traditional manufacturing enterprise A obtained by different algorithms are inconsistent. To verify the reasonableness and accuracy of the important nodes identified by the Multiple Attribute Decision Making method based on CVM-TOPSIS in the referential network, the top 6 important nodes are defined as $v_{c,i}(i = 1,2,3,4,5,6)$, and which are sequentially ranked in terms of their importance as $v_{c,1}$, $v_{c,2}$, $v_{c,3}$, $v_{c,4}$, $v_{c,5}$, $v_{c,6}$. By analyzing the impact of the failure of the important nodes identified by degree centrality, betweenness centrality, closeness centrality, subgraph centrality and closeness on the performance of the network, the situation where a node that suffers from damage causes irreparable damage to the network is investigated.

To analyze the impact of the failure of important nodes on the network performance, it is necessary to compare the different algorithms on the ranking of network nodes, the network nodes are sequentially deleted according to importance, in order to compare the impact on the network connectivity after the deletion of the identified important nodes. The specific deletion method is as follows: (i) delete $v_{c,1}$, recorded as mode 1; (ii) delete $v_{c,1}$, $v_{c,2}$, recorded as Mode 2; (iii) delete $v_{c,1}$,

$v_{c,2}$, $v_{c,3}$, recorded as Mode 3; (iv) delete$v_{c,1}$, $v_{c,2}$, $v_{c,3}$, $v_{c,4}$, recorded as Mode 4; (v) delete $v_{c,1}$, $v_{c,2}$, $v_{c,3}$, $v_{c,4}$, $v_{c,5}$, recorded as Mode 5; (vi) delete $v_{c,1}$, $v_{c,2}$, $v_{c,3}$, $v_{c,4}$, $v_{c,5}$, $v_{c,6}$, recorded as Mode 6. In addition, if no critical node is deleted, i.e., it is recorded as mode 0. To evaluate the effect of node set deletion on network connectivity, the performance difference of different algorithms on network important node identification is compared by counting the number and size of sub-networks formed by deleting nodes according to the above ways. When the number of subgraphs formed by deleting nodes is higher and the maximum size of subgraphs is smaller, it means the accuracy of the node identification algorithm is higher. The number of subgraphs generated and the maximum size of subgraphs are shown in Figure 3.

The network connectivity information of the traditional manufacturing enterprise A collaborative network after deleting the corresponding important nodes is presented in Figure 3a shows that after sequential deletion, the important nodes identified by the CVM-TOPSIS-based Multiple Attribute Decision Making method have a higher number of subgraphs than the important nodes identified by the other four parameters, which indicates a higher degree of discretization among these nodes. In this case, taking v_{32} as an example, v_{32} causes the network relationship interruption due to a failure or a network attack, which in turn causes the failure of nodes v_7 and v_{31}. In reality, this collaborative enterprise provides digital marketing services. With the profound evolution of Big data, Cloud computing, Artificial intelligence, Blockchain, and other new generations of digital technologies, the booming intelligence industry, and digital economy is booming, and the deep promotion of the In the era of the deep integration between information technology and traditional manufacturing industry, this enterprise failure will lead to the scenario where the critical core resources of traditional manufacturing enterprise A cannot be accessed, thereby causing to the failure of the entire collaborative network.

Figure 3b shows that the important nodes identified by the CVM-TOPSIS-based Multiple Attribute Decision Making method after sequential deletion correspond to smaller subgraph maximum sizes than the important nodes identified by the other four parameters, indicating that these nodes lead to more damages to network connectivity. In this case, taking v_{22} as an example, v_{22} causes the network relationship interruption due to a failure or a network attack, which in turn causes nodes v_9, v_{14}, and v_{21} to fail. In reality, this collaborative enterprise provides logistics supply management services, and if this enterprise failure leads to logistics paralysis of traditional manufacturing enterprise A, then the normal operation of this enterprise should be ensured in the actual collaborative development process.

In summary, after the top six important nodes are deleted, the number of subgraphs corresponding to the important nodes identified by the CVM-TOPSIS-based Multiple Attribute Decision Making method after deleting two nodes is greater than the degree centrality C_D, betweenness centrality C_B, closeness centrality C_C, subgraph centrality C_S, and the maximum size of the corresponding subgraphs is smaller than that of other algorithms, so that the Multiple Attribute Decision Making method proposed in this paper, which is based on CVM-TOPSIS, has a better performance of identification and a high level of accuracy in the referral network.

5. Conclusions

The construction and operation of a collaborative production network based on multi-subject collaboration is an important path and means for enterprises to cope with personalized, diversified, and differentiated market demands, and has an important impact on traditional manufacturing enterprises to achieve innovative development. In this paper, for the problem of identifying key collaborative subjects in the collaborative network of traditional manufacturing enterprises, a method of identifying and evaluating the importance of nodes in the collaborative network of traditional manufacturing enterprises based on Multiple Attribute Decision Making is proposed. The contributions and conclusions of this paper are as follows.

Firstly, based on the complex network theory, we constructed the collaborative network model of traditional manufacturing enterprises, and the analytical method was determined on the basis of the weights of evaluation indexes of the coefficient of variation method (CVM), which reduces the subjectivity and uncertainty in the decision-making process of evaluation indexes' weights. Secondly, the four parameters of degree centrality, betweenness centrality, closeness centrality, and subgraph centrality are fully considered to explore the importance of nodes in complex networks from different perspectives, so as to make the determination of the weights of evaluation indexes more reasonable. Lastly, Multiple Attribute Decision Making method based on the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is proposed to comprehensively evaluate the importance of nodes and find the key collaborative subjects in the collaborative network. The results of this paper have proven that the Multiple Attribute Decision Making method is effective in identifying the key collaborative subjects in the collaborative network of traditional manufacturing enterprises. Compared with the traditional approach that the importance of a particular node in the network, the failure of the important node identified by the algorithm proposed in this paper brings more damage to network connectivity. It helps traditional manufacturing enterprises focus on the protection and maintenance of the key collaborative subjects when coping with competitive external market environment, and provides a substantial reference to the normal operation of collaborative network organizations.

There are still some shortcomings in this study. Firstly, the model in this paper has simplified the actual situation to some extent, such as ignoring the correlation between different indicators in the network and not considering the task background in the process of network operation. In addition, the composition of the indicators is mainly from the perspective of network topology, without fully considering the characteristics of traditional manufacturing enterprises collaborative network. The next research work will address the above problems, analyze the network from multiple evaluation perspectives. The study will integrate a combination of subjective and objective empowering method, and introduce vulnerability analysis methods in the areas such as collaborative innovation production design, system robustness control, etc. to carry out more in-depth research.

Author Contributions

Conceptualization, T. Yang and Y.H. Ding; methodology, T. Yang and Y.H. Ding; software, T. Yang; validation, T. Yang, Y.H. Ding and F. Jiang; formal analysis, Y.H. Ding; investigation, Y.H. Ding; resources, Y.H. Ding; data curation, F. Jiang; writing-original draft preparation, Y.H. Ding; writing-review and editing, T. Yang; visualization, Y.H. Ding; supervision, T. Yang; project administration, T. Yang; funding acquisition, T. Yang. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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