Influential node identification method of assembly system based on TOPSIS and Topology

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Abstract. In order to find the influential manufacturing resources in a complex assembly system, a topology model of a complex assembly system was constructed based on the complex network theory. Complex network evaluation indicators with different attributes were used to evaluate the network, and AHP subjective weight method was used to determine the subjective weights between different evaluation indicators. Then the CRITIC weighting method was used to give the objective weights of each evaluation index, and perform subjective evaluation. The combination was modified to obtain the final combination weight, and the importance of key manufacturing resources was ranked by the TOPSIS comprehensive decision method. Based on the simulation calculation of the automobile assembly line network, the analysis and comparison of the ranking results were performed. The analysis results show that the comprehensive evaluation and comparison method has the comparative advantage of identifying key resources.

1. Introduction

With the advancement of science and the continuous development of society, more and more factors need to be considered in the manufacturing process of complex products, more and more parts are required in the production process of products, and the mixed flow characteristics of products are more and more complicated. Taking the production of a car as an example, more than 300 parts are required during the assembly process, and 3-4 types of cars are produced simultaneously on the same production line. Any problems with parts, personnel, technology, equipment, etc. involved in the production of the car will affect the assembly process. Therefore, for complex assembly systems, it is necessary to identify key manufacturing resources, find weak links in the manufacturing process, and analyze the ability to resist risks throughout the production process. With the rise of the complex network theory, many scholars have linked the complex network theory with the manufacturing system. The complex network theory is very useful for analyzing the structural vulnerability of the system and identifying key elements and weak links. For example, Guibing Gao [¹] used complex network theory in engine assembly systems, and from the perspective of structural and functional fragility, established a comprehensive evaluation model of the system's overall vulnerability; Hua Li [²] used the complex network method in the production line to analyze and optimize the fragility of the
production system due to the uneven distribution of the process; Ting Yang [3] established a directed weighted network model for the mixed production line to optimize the network's topological performance. Based on the above literature analysis, for the identification of key resources in complex manufacturing systems, complex network related theories provide relevant tools that are worthy of further research. However, many literatures deal with different evaluation indicators, which are more related to manufacturing systems, but the correlation and specific utility of different indicators are rarely involved. At the same time, some scholars have used multiple attribute evaluation methods to evaluate the importance of nodes in complex networks in other fields. For example, Hui Yu [4] used TOPSIS comprehensive decision-making methods and multi-attribute evaluation indicators to obtain an evaluation of complex network nodes. Li Qin [5] combined the improved principal component analysis method and TOPSIS method to comprehensively evaluate the importance of nodes in complex networks. There is less research on the use of integrated methods to identify key resources during the manufacturing process. Therefore, the use of integrated methods to identify key manufacturing resources in the assembly system is the content of this article.

This article takes the automobile assembly line as the research object. Firstly the related characteristics were analyzed, and the assembly system was modeled according to its characteristics, objects and the final research problems, and a network with parts was constructed as the research object. Then the classic network evaluation indicators such as the centrality of the median and k-shell were used to calculate and evaluate the network respectively. According to the combination of the focus of the evaluation index and the actual production, the importance of different indicators was subjectively evaluated and the weight was given by using the analytic hierarchy process [6], and the objective evaluation weight of each single indicator was evaluated by the CRITIC assignment method [7]. An objective correction was given to the AHP weights to ensure the objectivity of the evaluation indicators in the information evaluation. Finally, the TOPSIS comprehensive decision-making method [8] was used to perform comprehensive calculations using the combined weights to obtain the final index. This paper combines the actual case of an automobile assembly line, establishes a complex assembly system network and performs calculations, and compares and analyzes with other different schemes.

2. Assembly line network construction

2.1 Assembly line feature analysis
Feature one: During the assembly process, various parts are combined together, only spatial changes occur, no physical and chemical changes occur.
Feature two: The organizational form is pipelined, and different parts are installed at different stations in sequence.

2.2 Part assembly process transformation

As in Figure 1, the parts required for each station are obtained according to the actual production situation, and the assembly sequence of the parts in the station and the parallel and continuous relationship between the stations are obtained. In order to use the subsequent evaluation indicators
more flexibly, and at the same time, due to the limitation of the topology characteristics of the assembly network, this paper uses an undirected and unauthorized network model for research.

2.3 Network topology model construction

According to the above analysis, this article uses the parts in the assembly line as the basic elements, and uses the assembly relationship between the parts as the association between the elements, that is, the parts as nodes and the assembly relationship as edges to construct an unauthorized and undirected network $G = (V, E)$. Where $V = \{v_i|i \in K\}$ is a set of all nodes in the network, representing all parts in the assembly process, and $E = \{e_{ij} = (v_i, v_j)|i, j \in K\} \subseteq V \times V$ is a set of connecting edges between nodes, representing the process assembly relationship between parts, $N$ is the number of nodes, then the adjacency matrix of the network $A_{n \times n} = (a_{ij})_{n \times n}$ can be defined as,

$$a_{ij} = \begin{cases} 1, & (v_i, v_j) \in E \\ 0, & (v_i, v_j) \notin E \end{cases}$$  \hspace{1cm} (1)

3. Selection of evaluation indicators

3.1 Node Importance Evaluation Method based on Local Features

Node Importance Evaluation Method based on Local Features \cite{9}(NIL) is used as an index to evaluate local attributes.

$$NIL(i) = \frac{\sum_{j \in J} k_i \times k_j}{\sum_{i \in K} \sum_{j \in J} k_i \times k_j}$$  \hspace{1cm} (2)

Where $k$ is the degree of a node and $J$ is the set of neighbor nodes of node $v_i$. NIL reflects the direct influence of the part on surrounding connected parts.

3.2 Mixed Degree Decomposition Method

Mixed Degree Decomposition Method \cite{10} (MDD) is an improved K-shell decomposition method, it considers the impact of the removed shell.

$$MDD(i) = k(i)_r + \rho k(i)_e$$

Where $MDD(i)$ represents the K-shell value of the decomposed node, and $k(i)_e$ represents the degree of influence given to the node being striped by the removed node after Ks decomposition (that is the removed node's degree), $k(i)_r$ represents the K-shell value of the current node, and $\rho$ represents the degree of influence coefficient.

MDD method reflects the node location attributes, decomposes the network layer by layer, and finds the core nodes. It reflects the centrality of parts in complex assembly process. For a large assembly line, the closer it is to the core, the greater the impact on upstream and downstream, but it is easy to ignore the role of connecting nodes connecting different assemblies.

3.3 Betweenness Centrality

Betweenness centrality (BC) indicates the role of a node as a "bridge" on the way between other node pairs in the network,

$$BC(i) = \sum_{j \neq i \neq k \in K} \frac{g_{jk}(i)}{g_{jk}}$$  \hspace{1cm} (2)

Where $g_{jk}(i)$ represents the number of shortest paths between nodes $v_j$ and $v_k$ through node $v_i$. $g_{jk}$ are the total number of all shortest paths from node $v_j$ to node $v_k$. BC reflects the importance of the node to the overall situation. The more important the part, the more important it is to carry on and off, but there is a lack of analysis of local areas.
3.4 Indicators based on SIR virus transmission model
Assuming an infected node randomly infects its neighbor nodes with probability $\beta$ (all uninfected nodes in the network are susceptible), each infected node was set to a removed state at a fixed length rate $\gamma$. In the removal state, the node was considered dead, that is, the function that the node has failed.

The initial infection mode was set to single source. Reference [11] was used for experiments. Each node was used as the initial source of infection. In order to make the results more accurate, each source of infection was subjected to 100 independent experiments and the arithmetic average was taken as the final index value. This article takes the removal rate $\gamma = 0.2$ and the infection rate coefficient $\beta = 0.7$.

Jiabei Wu used the virus propagation model in Reference [12] to study the core resources in the manufacturing process. This method initially reflects the impact of equipment failure on the overall process, and also reflects the node's overall impact. This method mainly studies the dynamic characteristics of the network and lacks the analysis of the static characteristics of the network.

Based on the comprehensive analysis of multiple existing literatures and methods, the advantages and disadvantages of different evaluation methods and the applicable scenarios are analyzed.

4. Comprehensive weight evaluation

4.1 Combing of comprehensive sorting methods
1. Normalize the results obtained from different evaluation indicators;
2. Assign weights to different evaluation indicators. Depending on the analysis of the characteristics of the assembly line, subjective weighting method was used to assign weights;
3. Compare the similarity of different methods to obtain objective weights;
4. Consider the subjective and objective requirements at the same time, the combination weights with subjective and objective corrections are calculated;
5. Use the obtained evaluation results and the combined weights to make a comprehensive decision and get the final ranking results.

4.2 Evaluation results preprocessing
The extreme value normalization of the values of each indicators was calculated from Section 3,

$$x_{im} = \frac{l_{im} - l_{m min}}{l_{m max} - l_{m min}}$$

(3)

Where $i \in K$ represents the number of evaluation indexes and $m \in \{1,2,\ldots,M\}$, here $M = 4$. $l_{m max} = \max \{l_{1m}, \ldots, l_{nm}\} , l_{m min} = \min \{l_{1m}, \ldots, l_{nm}\}$. $x_{im}$ represents the value obtained by normalizing the m-th index value of node $v_i$, then the processed index matrix can be expressed as

$$X_{DM} = [X_{NIL}, X_{MDD}, X_{BC}, X_{SIR}] = [x_{im}]_{N \times M}$$

(4)

4.3 Determination of subjective weights
The AHP method was used to add subjective decision-making to the emphasis of each evaluation indicator. According to the method of Reference [6], the subjective weight of each indicator $\omega_m^A$ was obtained by constructing a comparison matrix, establishing a judgment matrix, and performing a consistency check.

4.4 Determination of objective weights
The CRITIC method is an objective weighting method suitable for determining attribute weights in multi-attribute decision problems. In this paper, the method of Reference [7] was used. The calculation process of this method is here,

(1) Calculate the Gini index to reflect the degree of dispersion in the information.
\[ \mu_m = \frac{\sum_{i=1}^{N} \sum_{k=1}^{N} |x_{im} - x_{km}|}{2 \sum_{i=1}^{N} \sum_{k=1}^{N} x_{km}} = \frac{\sum_{i=1}^{N} \sum_{k=1}^{N} |x_{im} - x_{km}|}{2N \sum_{i=1}^{N} x_{im}} \quad (5) \]

(2) Calculate the Kendall coefficient and measure the correlation between different evaluation indicators.

\[ \lambda_{st} = \frac{SC - DC}{\sqrt{(D - \sum_{i=1}^{N} SN_i^e (SN_i^e - 1)/2)(D - \sum_{i=1}^{N} SN_i^t (SN_i^t - 1)/2)}} \quad (6) \]

Where \( D = N(N-1)/2 \); \( SC \) represents the number of variable pairs in which the index values are consistent in any two index columns \( X_s \) and \( X_t \), and \( DC \) represents the number of variable pairs in which the index values are inconsistent in order; \( SN_s \) and \( SN_t \) indicate the numbers of the same index values in the index columns \( X_s \) and \( X_t \) respectively. Therefore, the overall Kendall correlation coefficient between the \( s \)-th indicator and other indicators can be defined as

\[ \lambda_s = \frac{1}{M} \sum_{t=1}^{M} \lambda_{st} \quad (7) \]

(3) The Gini coefficient and Kendall coefficient are combined to determine the objective weights of each indicator, that is, the objective weight \( \omega_m^C \) of the indicator \( m \) can be expressed as

\[ \omega_m^C = \mu_m (1 - \lambda_m) \sum_{t=1}^{M} (\mu_t (1 - \lambda_t)) \quad (8) \]

4.5 Determination of combination weights

The weights were modified by combination weighting method from Reference [13], by adding objective data information to avoid unbalanced subjective weights caused by unfamiliar evaluation indicators. Because the objective weight reflects the degree of differentiation of the index when making decisions, subjective weight was used as the main value and objective weight was used as the reference value in the weight evaluation.

Objective function: The deviation between the combination weight and the objective weight is the smallest, see formula (13.a).

Constraint 1: The ranking information of the combined weights is consistent with the ranking information of the subjective weights, see formula (13.b).

Constraint 2: The combination weight falls within a reasonable interval to ensure that the combination weight value of the \( m \)-th index falls within a reasonable value interval \([\alpha_m^-, \alpha_m^+]\), see formula (13.c).

\[ \alpha_m^- = \min \{ \omega_m^C, \omega_m^A \} \quad (9) \]

\[ \alpha_m^+ = \max \{ \omega_m^C, \omega_m^A \} \quad (10) \]

\[ \min \sum_{m=1}^{M} (W_m - \omega_m^C)^2 \quad (13. a) \]

\[ \begin{cases} W_m \leq W_n, \text{ when } \omega_m^A \leq \omega_n^A \quad (13. b) \\ \alpha_m^- \leq W_m \leq \alpha_m^+ \quad (13. c) \end{cases} \]

s.t. \[ \sum_{m=1}^{M} W_m = 1 \quad (13. d) \]

Where \( W_m \) represents the combined weight of the \( m \)-th index after correction, \( m, n \in \{1, 2, ..., M\} \).
4.6 TOPSIS Comprehensive Sort

The TOPSIS comprehensive decision-making method ranked according to the degree of approximation of the evaluated object and the idealized target, regarded the evaluation value of each node as a scheme, found the gap between each scheme and the ideal scheme through the comprehensive decision-making method, and sorted according to the gap.

The evaluation index matrix

\[
X_{DM} = [X_{NIL}, X_{MDD}, X_{BC}, X_{SIR}] = [x_{im}]_{N \times M}
\]

constructed by formula (6) according to 4.2. The main steps of the TOPSIS decision method are:

1) Normalize the matrix,

\[
Y = [y_{im}]_{N \times M} = \frac{x_{im}}{\sum_{k=1}^{N} x_{km}^2}
\] (12)

2) Generate a weighted network node importance matrix according to the index weights obtained in Section 4.5,

\[
Z = [z_{im}]_{N \times M} = [W_m \times y_{im}]_{N \times M}
\] (13)

3) Determine the positive ideal decision scheme \(P^+\) and the negative ideal decision scheme \(P^-\) according to the matrix \(Z\),

\[
P^+ = \{\max_{i \in N}(z_{i1}, ..., z_{im})\} = \{z_{i1}^\text{max}, ..., z_{im}^\text{max}\}
\]

\[
P^- = \{\min_{i \in N}(z_{i1}, ..., z_{im})\} = \{z_{i1}^\text{min}, ..., z_{im}^\text{min}\}
\] (14) (15)

Where \(z_{im}^\text{max}\) represents the ideal solution of the m-th index, and the index value of this node is better than that of other nodes; \(z_{im}^\text{min}\) represents the anti-ideal solution of the m-th index, and the index value of this node is the worst.

4) Calculate the Euclidean distance between each node of the network and the ideal solution and the anti-ideal solution,

\[
ED^+_i = \sqrt{\sum_{m=1}^{M} (z_{im} - z_{i1}^\text{max})^2}, ED^-_i = \sqrt{\sum_{m=1}^{M} (z_{im} - z_{i1}^\text{min})^2},
\] (16)

5) Calculate the relative approximation of each node in the network to the ideal solution,

\[
C_i = \frac{ED^-_i}{ED^+_i + ED^-_i}, i \in K
\] (17)

\(C_i \in [0,1]\). The closer the value is to 1, the more important the node is; the closer the value is to 0, the less important the node is.

6) Sort the importance of the nodes in the network according to the relative approximation of each node to the ideal solution.

4.7 Selection of verification method

In order to verify the validity of the method, this paper used three indicators of Reference [14] as a tool to measure the final result. These three indicators all reflect the importance of the nodes by removing the corresponding nodes in turn, which is, the vulnerability of the network [15].

1. Giant component scale. That is, the size of the subgraph with the largest number of nodes in the remaining connected subgraphs after removing the nodes. The smaller this value is, the greater the degree of network fragmentation, and the more important the corresponding removed nodes are.

2. Number of connected subgraphs. That is, after removing the nodes, the number of remaining connected subgraphs. The larger the value, the greater the degree of network fragmentation and the more important the corresponding nodes are.

3. Overall network efficiency. Network efficiency reflects the speed at which network information travels throughout the network. When a node is removed, the more the overall network efficiency decreases, the more important this node is.
5. Case analysis

5.1 Network Model of Assembly System

The case used in this article is the No.1 assembly line of an automobile assembly line in a certain automobile production base, involving a total of 198 parts and 24 stations, as shown in Figure 2.

According to the section 2, the parts and assembly relationships in the assembly line were abstracted to obtain the unauthorized and undirected network $G$, as shown in Figure 3.

5.2 Weight analysis and calculation

5.2.1 Subjective weight distribution. For a large assembly system such as an automobile assembly line, the position attribute of MDD reflects the core degree of manufacturing resources globally and can be regarded as the most important; while the NIL method reflects the local attributes and can be regarded as the weakest; SIR and BC indicators one reflects the impact of equipment failure, and one reflects the acceptance of the process. To a certain extent, it can also reflect the mutual relationship of parts. From the serious situation of the results, SIR is considered to be more important than the BC method. This article considers this scheme as the ideal scheme.

The subjective weights were determined through Section 4.3, and two comparison schemes of unfamiliar index methods were given here.

| Ideal subjective weight | NIL  | BC   | MDD  | SIR  |
|-------------------------|------|------|------|------|
| Subjective scheme 1     | 0.1040 | 0.1695 | 0.4501 | 0.2762 |
| Subjective scheme 2     | 0.1040 | 0.2762 | 0.1695 | 0.4501 |

5.2.2 Objective weight distribution. The objective weights calculated according to formula (7) - (10) were shown in Table 2.

| Objective weight | NIL  | BC   | MDD  | SIR  |
|------------------|------|------|------|------|
| Ideal objective weight | 0.2314 | 0.4968 | 0.1507 | 0.1211 |

5.2.3 Subjective and objective combination weights. In order to make the evaluation results more persuasive, this article modified the subjective weights through the combination weights method, and
used the methods in Section 4.5 to combine the subjective and objective weights to obtain the combined weights.

Table 3. Table of combined weight

| Indicator | Subjective weights | Objective weights | Reasonable value interval | Combination weights |
|-----------|--------------------|-------------------|---------------------------|---------------------|
|           | Weights | Order | Weights | Order | Weights | Order | Weights | Order |
| NIL       | 0.1040  | 4     | 0.2314  | 2     | [0.1040, 0.2314] | 0.2314 | 4     |
| BC        | 0.1695  | 3     | 0.4868  | 1     | [0.1695, 0.4868] | 0.2562 | 1     |
| MDD       | 0.4501  | 1     | 0.1507  | 3     | [0.1507, 0.4501] | 0.2562 | 1     |
| SIR       | 0.2762  | 2     | 0.1211  | 4     | [0.1211, 0.2762] | 0.2562 | 1     |

In this table, based on the order of importance of subjective weights, the influence of objective weights is fully considered as far as possible, so that the weight results are more reasonable within the value range.

5.3 Sorting results comparison

5.3.1 Sorting results. In order to compare the accuracy of the selection indicator, the method in Reference [16] was used as a comparison. Reference [16] took the node degree centrality, closeness centrality, betweenness centrality, and improved k-shell method as indicators, using the subjective weight method combined with TOPSIS comprehensive decision-making method to sort the importance of network nodes.

Table 4. Top 20 sorting results of different schemes

| Rank | Scheme | Scheme |
|------|--------|--------|
|      | Combination | Literature | Ideal subjective | Objective | Rank | Combination | Literature | Ideal subjective | Objective |
| 1    | 140     | 140     | 140     | 90      | 11    | 150     | 151     | 165     | 151     |
| 2    | 90      | 90      | 90      | 140     | 12    | 165     | 36      | 172     | 149     |
| 3    | 93      | 93      | 105     | 93      | 13    | 172     | 41      | 167     | 150     |
| 4    | 105     | 105     | 106     | 105     | 14    | 167     | 183     | 171     | 165     |
| 5    | 106     | 106     | 93      | 106     | 15    | 171     | 187     | 173     | 172     |
| 6    | 49      | 48      | 49      | 26      | 16    | 173     | 14      | 26      | 167     |
| 7    | 48      | 49      | 48      | 49      | 17    | 41      | 65      | 104     | 171     |
| 8    | 26      | 26      | 151     | 48      | 18    | 36      | 70      | 103     | 173     |
| 9    | 151     | 149     | 149     | 41      | 19    | 80      | 71      | 134     | 14      |
| 10   | 149     | 150     | 150     | 36      | 20    | 73      | 73      | 152     | 80      |

The three weighting schemes obtained according to Table 3 were all brought into the TOPSIS method for ranking, and the results were compared with the ranking scheme in Reference [16]. In Table 4, the rankings of the top 7 of all the schemes are basically the same, indicating that these part nodes are very important. Although the ranking results of the top 8-20 are different, the top 20 parts appear basically the same, especially the 149, 150, and 151 node all appear, only the order of the different solutions is different.

5.3.2 Verify the validity of the indicator selection. The ideal subjective weights obtained from the analysis and the subjective weighting schemes 1 and 2 as comparison were used as different schemes
respectively. The TOPSIS method was used to rank the importance of the nodes, which was compared with the scheme in Reference [16]. These four schemes are all subjective weight decision schemes. The difference is that the selected indicators of the three schemes in this paper are different from those in the Reference [16].

![Figure 4. Giant component scale change curve of subjective scheme](image)

In the giant component scale change curve, it needs to notice the downward trend of the curve. The earlier the curve decreases, the earlier the key nodes are deleted. In Figure 4, the curve of the ideal subjective scheme and the subjective scheme 1 is significantly lower than the curve of the literature scheme in Reference [16], and the subjective scheme 2 and the objective scheme are not much different from the literature scheme before deleting 40 nodes, but after 40, it is significantly lower. The curve of the literature scheme shows that the ranking results are ideal.

![Figure 5. Changing curve of number of connected subgraphs of subjective schemes](image)

In the curve of the number of connected subgraphs, it needs to notice the upward trend of the curve in the early stage. The larger the upward trend in the previous stage, the faster the network is broken, that is, the more important nodes are deleted earlier. In Figure 5, the curves of the three schemes used in this paper in the previous period are higher than the curves about the literature scheme in Reference [16], indicating that the ranking results are ideal.
Figure 6. Subjective Scheme Overall Network Efficiency Change Curve

The overall network efficiency curve needs to notice the previous downward trend. The more obvious the downward trend is, the more important nodes are deleted in advance. By enlarging the previous curve in Figure 6, before the 80th node is deleted, the downward trend of the four schemes in this paper is significantly larger than that the literature scheme curve, indicating that the ranking results are ideal.

The comparison of the above three methods shows that the four indicators used in this paper have a relative advantage in identifying key resources of the assembly system compared to Reference [16].

5.3.3 Verify the accuracy of subjective weight allocation. As shown in Figure 7, by comparing the ideal subjective weights obtained from the analysis with the comparison subjective schemes 1 and 2, the ideal scheme performs better in the three types of curves than the other two schemes, indicating that the subjective weights obtained in this analysis have a certain accuracy.

Figure 7. Comparison schemes change curve

5.3.4 Verify the validity of objective weights. When subjective weights were used to assign weights to evaluation indicators, if they are not completely familiar with the indicators, they will often affect the reasonable allocation of weights.
Figure 8. Change curve of comparison subjective scheme 1 and its combination scheme

As shown in Figure 8, the subjective scheme 1 and the objective scheme have basically the same curve change in the previous period, but since the 67th node, the change curve of the subjective scheme has been falling, indicating that the degree of network fragmentation has become smaller, reflecting the problem of node ranking at this time. In contrast, the curve of the objective scheme has been rising relative to the subjective scheme 1, indicating that the degree of fragmentation of the network continues to increase. When using the combined weighting scheme in section 4.5 and using objective weights to modify the weighting in subjective scheme 1, the curve of the revised scheme 1 lies between the first two, indicating that the node ranking is relatively good at this time. When the subjective weight assignor is not completely familiar with the evaluation index, the objective weight can be used to modify the subjective weight to a certain extent.

6. Summary
This article analyzed the characteristics of the assembly system, abstracted the assembly system into a network model, treated manufacturing resources as nodes, and used the relevant theories of complex networks and comprehensive decision-making to rank the importance of nodes in the network and uses existing evaluations. The indicators were compared and analyzed. By constructing a network model and identifying key parts, it not only has reference significance for the identification of other key production resources, but also can do a good job of key management of key production resources to maintain the stability of the production process.

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