Hindawi
Wireless Communications and Mobile Computing
Volume 2023, Article ID 4386621, 11 pages
https://doi.org/10.1155/2023/4386621

Research Article

A Network Key Node Identification Method Based on Improved Multiattribute Fusion

Bo Chen[1,2] **Rui Tong,**[1] **Yufeng Chen**[1] **Panling Jiang,**[1] **Xiue Gao,**[3] **and Hang Tao**[1]

[1]*School of Electrical and Information Engineering, Hubei University of Automotive Technology, Shiyan 442002, China*
[2]*School of Electronic and Electrical Engineering, Lingnan Normal University, Zhanjiang 524048, China*
[3]*School of Computer Science and Intelligence Education, Lingnan Normal University, Zhanjiang 524048, China*

Correspondence should be addressed to Yufeng Chen; chenyf_dy@huat.edu.cn

Received 24 May 2022; Revised 18 August 2022; Accepted 3 October 2022; Published 2 May 2023

Academic Editor: Lei Zhang

Considering the shortcomings of the existing network key node identification methods based on multiattribute fusion, which have single evaluation methods and low decision accuracy, combined with the advantages of the high accuracy of TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) algorithm and the applicability of grey relational analysis method for incomplete information evaluation, the concept of relative closeness is proposed, and nodes are ranked in importance based on the relative closeness; a key node identification method algorithm based on improved multiattribute fusion is designed. First, the identification problem of key nodes is transformed into multiattribute decision-making method, and the decision matrix is obtained. Second, the weighting matrix is obtained by weighting them in both subjective and objective dimensions, the relative closeness is calculated for the weighting matrix. Finally, sort the network nodes by relative closeness, and network performance simulation experiments are designed using various combinations of evaluation methods and key node identification methods. The simulation results show that this method is more adaptable and improves the identification accuracy of the network key nodes.

1. Introduction

Complex networks have attracted much attention from researchers owing to their scale-free, fragility, self-organization, and other characteristics. In real life, many systems, such as social networks, power networks, and transportation networks, can be represented using complex networks. The key nodes of various types of complex networks play an important role in the network structure and function, and knowing how to identify the key nodes is crucial for complex network reliability. Mining important nodes in social networks can help with decision-making in areas such as public opinion monitoring and advertising and marketing [1, 2]. In transportation networks, identifying key nodes of transportation hubs in advance can effectively prevent traffic congestion problems [3, 4]. In power networks, identifying key nodes of power networks in advance can implement protection and maintenance measures for key grid nodes [5]; as can be seen, discovering key nodes of various types of complex networks has high practical value.

Many network critical node identification methods have been proposed, such as degree centrality, betweenness centrality, K-shell, and structural holes. On this basis, many scholars have proposed improvements to these identification methods. Considering the characteristics of directed weighted networks, Zhao et al. [6] proposed JP-degree centrality in view of the shortage of traditional degree centrality that cannot be applied to directed weighted networks. The literature addressed the lack of degree centrality, which is difficult to directly apply to community networks, and proposed semilocal centrality algorithm that combined community structure with node degree [7]. Wang et al. [8] considered the form of vectors and proposed multiorder neighbor shell vector centrality. Wang et al. [9] introduced hierarchical flow betweenness to improve the structural hole method. Wang et al. [10] proposed and applied an improved efficiency centrality method to weighted networks. Hu et al. [11] proposed an importance identification method for network nodes based on neighborhood information entropy. Considering that the PageRank algorithm is only suitable for static networks, Xu and Wang [12] proposed an ALR algorithm that combines H-index and LeaderRank to adapt to changes in network topology. The aforementioned methods are single-index identification and their improvement, which describe the importance of nodes in a network from different perspectives; however, different networks have different structural characteristics, and even different parts of the same network have different structures. Therefore, a single metric identification and improving its performance in different networks can be difficult. For this reason, many scholars have applied multiattribute decision-making to key node identification.

The multiattribute decision method uses multiple key node identification methods as metrics for comprehensive evaluation of nodes, which no longer emphasizes the influence of a single factor one-sidedly and is often used for comprehensive evaluation of network key nodes. Yu et al. [13] and Liu et al. [14] used the subjective weighting method to determine the weights of evaluation metrics and applied it to network key node identification in combination with TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method to achieve better results; Yang et al. [15] used information on the decision matrix to objectively assign weights to each metric. Other studies introduced the SIR (Susceptible Infected Recovered) model to dynamically calculate the weights of each evaluation metric [16, 17]. A combined centrality to the gravitational law to comprehensively identify the influence of the network nodes was applied [18]. Some studies proposed further improvements to the multiattribute decision method in terms of weights [19, 20]. The above methods often use only one method, TOPSIS or Vikor, when calculating the evaluation results, and directly use the sample data for analysis; however, in real networks, it is difficult to ensure the integrity of information acquisition in the system, and the decision results will cause certain errors.

The grey relational analysis is a method for measuring the degree of association between factors based on the similarity or dissimilarity of their trends; that is, "grey relational degree" is a simple and reliable method in the analysis system that can solve this problem well. It is better suited to situations where the system information is incomplete. Therefore, this study proposes a key node identification method based on improved multiattribute fusion, which fully combines the advantages of the high accuracy of the TOPSIS algorithm and the grey relational analysis method for incomplete information evaluation and improves the identification accuracy of the network key nodes.

The main contributions of this study are in the following areas:

(1) An improved multiattribute fusion key node identification method combining TOPSIS and grey relational analysis is proposed

(2) The subjective and objective comprehensive weighting method is proposed, and the relative closeness is proposed to calculate the evaluation results

(3) Example algorithms were designed to analyze and compare the network performance of different combinations of node importance evaluations and different networks

This study is organized as follows: Section 2 introduces several typical key node identification methods. Section 3 elaborates the algorithm flow and specific steps of this study. Section 4 illustrates the effectiveness and applicability of the proposed method by designing different simulation experiments. Section 5 is the conclusion section, which summarizes the research and provides future directions.

2. Metrics for Evaluating the Importance

The typical key node identification method is used as an evaluation metric of node importance. The node importance metrics are as follows.

2.1. Degree Centrality (DC). Degree centrality is the most direct metric to characterize the centrality of a node in network analysis. The larger the node degree of a node, the higher the DC of the node, and the more important the node is in the network. The formula is as follows:

$$\mathrm{DC}_i = \frac{k_i}{N-1}, \tag{1}$$

where N is the number of nodes and k_i is the degree of the node i.

2.2. Structural Hole (SH). There is no direct or indirect connection between the two nodes in the network, so the vacancy between the nodes is a structural hole. Burt proposed to calculate the network constraint coefficient to measure the structural hole, and the formula is as follows:

$$\mathrm{SH}_i = \sum_j \left(P_{ij} + \sum_{q \neq i \neq j} P_{iq} P_{qj} \right)^2, \tag{2}$$

where P_{ij} is the ratio of the energy invested by node i to maintain the neighbor relationship with node j to the total energy and q is the indirect node between node i and node j. The smaller the constraint coefficient SH_i, the larger the SH and the more important the position of the node.

2.3. Closeness Centrality (CC). Closeness centrality reflects the proximity between a node and other nodes in the network. The formula is as follows:

$$\mathrm{CC}_i = \frac{N}{\sum_{j=1}^{N} d_{ij}}, \tag{3}$$

where N is the number of nodes and d_{ij} is the shortest distance between node i and node j. The higher the value of the CC of a node, the more important its position is.

2.4. Betweenness Centrality (BC). Betweenness centrality is a measure of graph centrality based on the shortest path. The centrality of a node is the number of shortest paths through that node. The formula is as follows:

$$\mathrm{BC}_i = \sum_{j \neq i \neq k \in V}^{N} \frac{g_{jk}(i)}{g_{jk}}, \quad (4)$$

where $g_{jk}(i)$ represents the number of shortest paths between nodes j and k through node i and g_{jk} represents the number of all shortest paths between nodes j and k. The larger the value of BC, the more important position the node assumes in the information flow of the network.

The degree centrality is simple and suitable for all kinds of basic networks, but not very accurate. Since the structural hole can calculate the dependence of nodes on other nodes in the network, and the regular network has a high clustering coefficient, clustering coefficient is a measure of how well a node's neighbors are connected to each other. Structural holes are suitable for regular networks and small-world networks with a high degree of clustering coefficient. Degree centrality and structural hole only utilizes the local features of the network, and it has certain limitations. Closeness centrality and betweenness centrality make use of the global features of the network, that is, the position of a node in the whole structure. The closeness centrality can avoid being affected by the distance extremes generated by individual isolated nodes. The betweenness centrality represents the degree of independence between nodes; they are suitable for random networks and scale-free networks. Most of the real networks cover all or part of the characteristics of the above-mentioned standard networks. For example, scale-free networks are universal, and social networks, biological networks, trade networks, and other types of networks have scale-free network characteristics. Therefore, this study integrate the locality and globality of several metrics, combines the advantages of each method, and applies these metrics to multi-indicator fusion.

3. The Specific Flowchart

The idea of the node importance identification method based on multiattribute decision-making is to regard the nodes in the complex network as a scheme, regard multiple basic evaluation metrics for evaluating the importance of nodes as attributes of each scheme, and then judge the importance of nodes through the decision results. The specific implementation method of the method is as follows.

3.1. Constructing the Decision Matrix. Let there be N nodes in the complex network, and then, the corresponding set of decision schemas can be denoted as $A = \{A_1, A_2, \cdots A_N\}$. If there are m metrics to evaluate the importance of each node, the corresponding set of schema attributes is denoted as $S = \{S_1, S_2, \cdots S_m\}$. The value of the jth metric of the ith node is denoted as $A_i(S_j)$, which constitutes the decision matrix.

$$X = \begin{pmatrix} A_1(S_1) & . & . & A_1(S_m) \\ . & . & . & . \\ . & . & . & . \\ A_N(S_1) & . & . & A_N(S_m) \end{pmatrix}. \quad (5)$$

Table 1: Comparison matrix of node importance metrics.

	DC	SH	CC	BC
DC	1	0	0	0
SH	2	1	1	0
CC	2	1	1	0
BC	2	2	2	1

Then, the metrics were regularized as follows:

$$r_{ij} = \frac{A_i(S_j)}{A_i(S_j)^{\max}}, \qquad r_{ij} = \frac{A_i(S_j)^{\min}}{A_i(S_j)}, \quad (6)$$

where

$$A_i(S_j)^{\max} = \max\left\{A_i(S_j), (1 \le i \le N)\right\} A_i(S_j)^{\min} = \min\left\{A_i(S_j), (1 \le i \le N)\right\}. \quad (7)$$

The standardized decision matrix is denoted as $R = (r_{ij})_{N*m}$.

3.2. Calculation of the Weight of each Metric

3.2.1. The AHP Method to Calculate Subjective Weights of Metrics. First, the three-scale method is used to build a comparison matrix for each metric after a two-by-two comparison of each metric. Table 1 lists the values in the comparison matrix B constructed according to the three-scale method in the following equation:

$$B = (b_{ij}) = \begin{cases} 2, & \text{Metric } i \text{ is more important than metric } j, \\ 1, & \text{Metric } i \text{ is as important as metric } j, \\ 0, & \text{Metric } j \text{ is more important than metric } i. \end{cases} \quad (8)$$

The comparison matrix is then used to construct a judgment matrix C using the difference method, and a consistency test is performed. Finally, the metrics' weights are obtained by the following method.

$$M_i = \prod_{j=1}^{4} c_{ij}, \qquad W_i = \sqrt[4]{M_i}, \quad (9)$$

where $C = (c_{ij})$. After normalizing W_i, the final weight can be obtained.

3.2.2. The Entropy Method for Calculating Objective Weights of Metrics. In information theory, entropy is used to determine the degree of dispersion of a metric. The greater the degree of dispersion of a metric, the greater its weight in the composite weight. This is a classical method for assigning weights. The entropy of the jth metric is calculated as follows:

$$e_j = -\frac{1}{\ln |N|}\sum_{i=1}^{|N|} p_{ij} \ln\left(p_{ij}\right), \quad j = 1, 2, \cdots m,$$
$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{N} r_{ij}}, \quad i = 1, 2, \cdots N, j = 1, 2, \cdots m, \tag{10}$$

where e_j is the entropy of the jth column of metrics and p_{ij} is the weight of the jth indicator of the ith node in that column of metrics. Finally, the weight of each is determined as follows:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m}\left(1 - e_j\right)}, \tag{11}$$

where $1 - e_j$ is the information entropy redundancy and w_j satisfies $\sum w_j = 1$.

3.2.3. Calculation of Composite Weights. This algorithm integrates the subjective and objective weights and reasonably allocates the subjective and objective weight coefficients, and the final combined weight is expressed as follows:

$$w_j = \alpha w_{j1} + \beta w_{j2}, \tag{12}$$

where w_{j1} is the subjective weight calculated using the AHP method and w_{j2} is the objective weight calculated using the entropy weight method. α and β are the weighting coefficients, solved as follows:

$$\alpha = \frac{\sum_{i=1}^{N}\sum_{j=1}^{m} w_{j1} r_{ij}}{\sqrt{\left(\sum_{i=1}^{N}\sum_{j=1}^{m} w_{j1} r_{ij}\right)^2 + \left(\sum_{i=1}^{N}\sum_{j=1}^{m} w_{j2} r_{ij}\right)^2}},$$
$$\beta = \frac{\sum_{i=1}^{N}\sum_{j=1}^{m} w_{j2} r_{ij}}{\sqrt{\left(\sum_{i=1}^{N}\sum_{j=1}^{m} w_{j1} r_{ij}\right)^2 + \left(\sum_{i=1}^{N}\sum_{j=1}^{m} w_{j2} r_{ij}\right)^2}}. \tag{13}$$

The coefficients obtained from the above equation are then normalized to give the final weight coefficients α and β.

3.3. Relative Closeness Calculation. First, we construct the weighting matrix Y as follows:

$$Y = \left(y_{ij}\right) = \left(w_j r_{ij}\right) = \begin{pmatrix} w_1 r_{11} & \cdots & w_m r_{1m} \\ . & \cdots & . \\ . & \cdots & . \\ w_1 r_{N1} & \cdots & w_m r_{Nm} \end{pmatrix}. \tag{14}$$

3.3.1. Calculate the Euclidean Distance. The positive and negative ideal decision schemas are determined from the matrix Y. The Euclidean distance between each option and the positive and negative ideal options is then calculated using the following equation:

$$D_i^+ = \left[\sum_{j=1}^{m}\left(y_{ij} - y_j^{\max}\right)^2\right]^{1/2},$$
$$D_i^- = \left[\sum_{j=1}^{m}\left(y_{ij} - y_j^{\min}\right)^2\right]^{1/2}. \tag{15}$$

3.3.2. Calculate the Grey Relational Degree. Calculate the grey relational coefficient between the ith sample and the positive ideal sample on the jth metric based on the weighted normalization matrix:

$$S_{ij}^+ = \frac{\min_i \min_j \Delta y_{ij} + \rho \max_i \max_j \Delta y_{ij}}{\Delta y_{ij} + \rho \max_i \max_j \Delta y_{ij}}, \tag{16}$$

where $\Delta y_{ij} = |y_j^+ - y_{ij}|$, $\min_i \min_j \Delta y_{ij}$ is the two-level minimum difference, $\max_i \max_j \Delta y_{ij}$ is the two-level maximum difference, and $\rho \in [0, 1]$ is the discrimination coefficient; the smaller the discrimination coefficient, the greater the difference between the correlation coefficients and the stronger the discrimination ability, usually taken as 0.5. Then, the grey relational coefficient matrix of each sample and the positive ideal sample is determined as follows:

$$W^+ = \begin{pmatrix} s_{11}^+ & \cdots & s_{1m}^+ \\ . & \cdots & . \\ . & \cdots & . \\ s_{N1}^+ & \cdots & s_{Nm}^+ \end{pmatrix}. \tag{17}$$

The grey relational of the ith sample with the positive ideal sample is expressed as follows:

$$W_i^+ = \frac{1}{m}\sum_{j=1}^{m} s_{ij}^+. \tag{18}$$

Similarly, replacing $\Delta y_{ij} = |y_j^- - y_{ij}|$ in Equation (16) with Δy_{ij}, the grey relational degree of each sample with the negative ideal sample can be obtained.

$$W_i^- = \frac{1}{m}\sum_{j=1}^{m} s_{ij}^-. \tag{19}$$

3.3.3. Calculate the Relative Closeness. First, the Euclidean distance and grey relational degree are made dimensionless separately as follows:

$$\varphi_i = \frac{\Phi_i}{\max_{1 \le i \le N}\left(\Phi_i\right)}, \tag{20}$$

where Φ_i represents the D_i^+, D_i^-, W_i^+, and W_i^- derived and is represented by d_i^+, d_i^-, w_i^+, and w_i^-, respectively, after it is made dimensionless. Combining the Euclidean distance

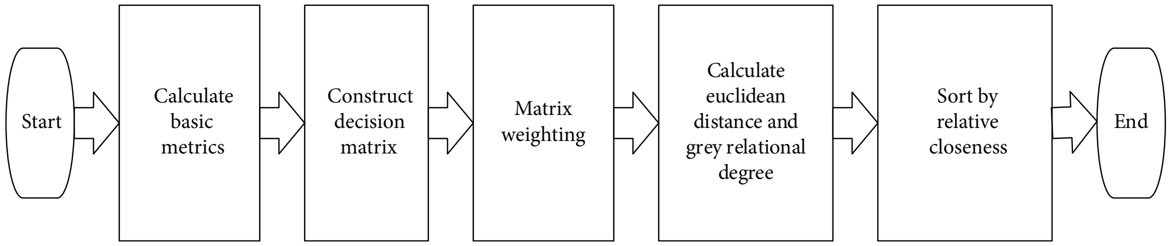

Figure 1: Flowchart of the algorithm.

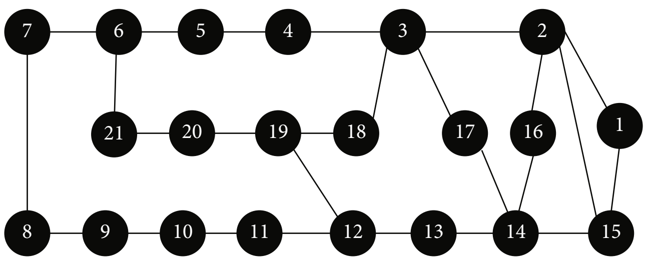

Figure 2: ARPA network topological structure.

and the grey relational degree, we obtain the following:

$$T_i^+ = e_1 d_i^- + e_2 w_i^+,$$
$$T_i^- = e_1 d_i^+ + e_2 w_i^-, \tag{21}$$

where $e_1 + e_2 = 1$. The values of e_1 and e_2 can be set according to preferences. This study takes $e_1 = e_2 = 0.5$. Finally, the relative closeness is calculated, and the final comprehensive evaluation result can be obtained using the following equation:

$$\delta_i = \frac{T_i^+}{T_i^+ + T_i^-}. \tag{22}$$

3.4. Steps of Algorithm. The steps of the key node identification algorithm based on improved multiattribute fusion are shown in Figure 1.

Step 1. Calculate basic evaluation metrics of the network, such DC and SH.

Step 2. Construct decision matrix and normalize it to form a multiattribute decision matrix.

Step 3. Substitute the weights of each metric obtained from the combination of subjective and objective methods into decision matrix to obtain the weighted matrix.

Step 4. Calculate Euclidean distance and grey relational degree by using weighted matrix.

Step 5. The relative closeness is calculated to get the comprehensive importance of the nodes, which is ranked from largest to smallest. The larger the closeness, the higher the importance of the node in the network.

Table 2: Ranking results of node importance evaluation on ARPA network.

Ranking	DC	SH	CC	BC	Proposed method
1	3 2 14	3	3	3	3
2	6 12 15 19	14	19	12	12
3	1 4 5 7 8 9 10 11 13 16 17 18 20 21	12 19	12	19	19
4		6	18	6	14
5		2	4 13 14	4	6
6		15	17	14	2
7		17	2 20	13	4
8		13 18	5 6	5	13
9		4	11	11	5
10		5 7 11	15	2	11

4. Algorithm Analysis

4.1. Evaluation Methodology. Different network models are deliberately attacked, and the key nodes identified by each algorithm are removed one by one. The impact of removing key nodes on the network is measured using three indexes: average network efficiency, network connectivity coefficient, and maximum-connected subgraph ratio, and then, the recognition accuracy of different algorithms is compared.

4.1.1. The Average Network Efficiency. This is defined as the average of the sum of the reciprocal of the distances between any two points in the network, which reflects the ability of information to flow in the network. The higher the average network efficiency, the better the integrity of the network when it is under attack. It is defined as follows:

$$\eta = \frac{1}{N \times (N-1)} \times \sum_{i \neq j} \frac{1}{d_{ij}}, \tag{23}$$

where d_{ij} denotes the distance between nodes i, j.

The accuracy of the algorithm's identification is determined using the average rate of decline in the network's efficiency. The faster the decline, the faster the network is down, and the more important the identified nodes are.

4.1.2. Network Connectivity Coefficient. This measures the relationship between the network invulnerability and the number of connected branches. It can analyze the partitioning

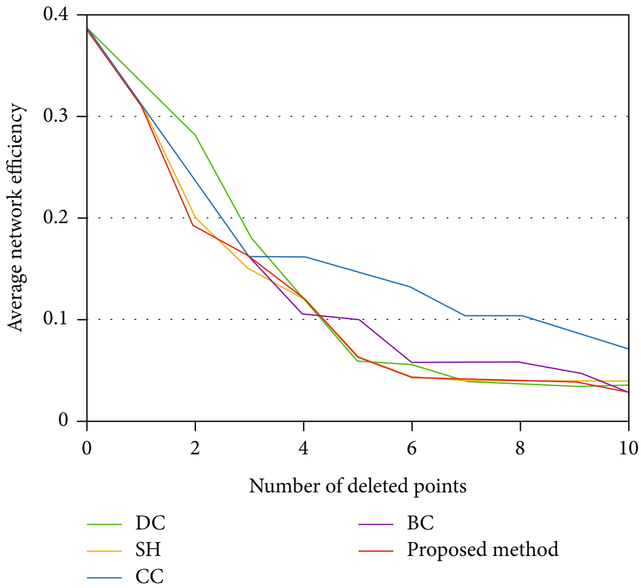

FIGURE 3: Comparison of average network efficiency of different methods.

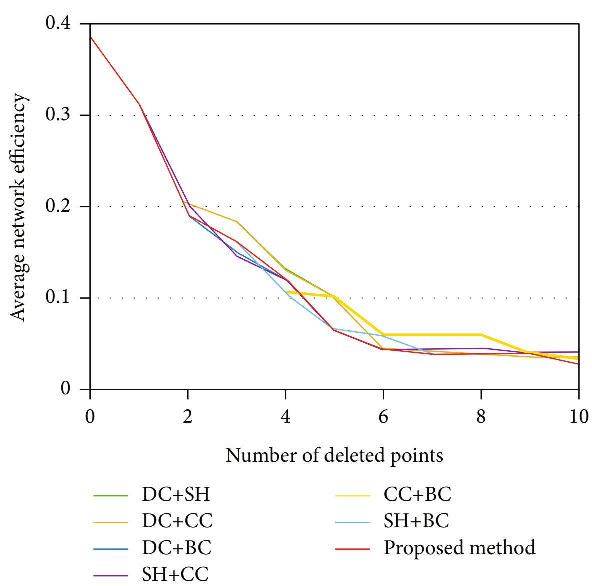

FIGURE 4: Comparison of different combinations of two metrics with the method in this study.

of the network after the deletion of nodes. The smaller the network connectivity coefficient, the more severely segmented the network is and the worse the invulnerability is, indicating that the deleted node is more important. The expression of network connectivity coefficient is expressed as follows:

$$\Phi = \frac{1}{\omega \sum_{i=1}^{\omega} (N_i/N) \times \xi_i}, \quad (24)$$

where ω is the number of connected subgraphs of the network, N_i is the number of nodes inside the ith connected subgraph,

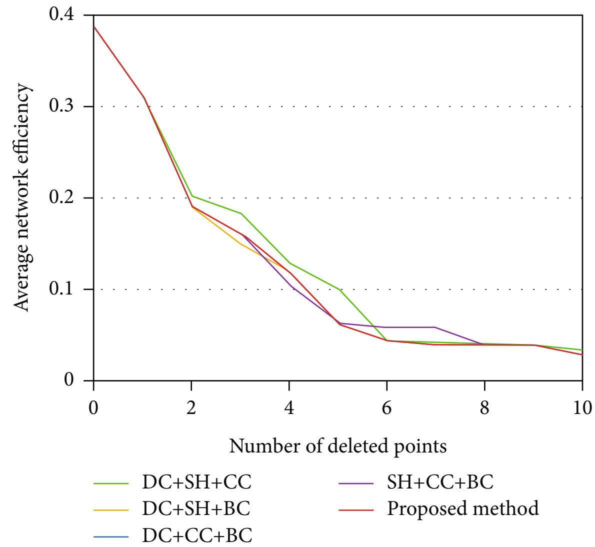

FIGURE 5: Comparison of different combinations of the three metrics with the method in this study.

and ξ_i and is the average distance inside the ith connected subgraph, expressed as follows:

$$\xi = \frac{1}{N \times (N-1)} \times \sum_{i=1}^{N} \sum_{j=i+1}^{N} d_{ij}. \quad (25)$$

4.1.3. The Maximum-Connected Subgraph Ratio. This is defined as the ratio of the number of nodes in the maximum-connected subgraph in the network to the total number of nodes in the network, expressed as follows:

$$S = \frac{E_m}{E}, \quad (26)$$

where E_m is the number of nodes in the maximum-connected subgraph and E is the total number of nodes in the initial network. The faster the maximum-connected subgraph ratio decreases, the more severely the network is segmented, indicating that the more removed points are important.

4.2. Algorithm Examples

4.2.1. Analysis of the Effectiveness. In order to illustrate the effectiveness of this method, ARPA network is used in this paper. Figure 2 shows the ARPA (Advanced Research Projects Agency) network topology, which consists of 21 nodes and 23 links.

Table 2 gives the results of the ranking of the node importance determined by the algorithm proposed in this study and DC, SH, CC, and BC on the ARPA network.

The method of this study and DC, SH, CC, and BC all have 10 identical nodes with different rankings, showing that the proposed method has certain feasibility. From the overall view of the sorting results, DC, SH, and CC all have different nodes in the same ranking, and it is obviously difficult to distinguish their importance; BC and the proposed method can perform better. From the point of view of a single node,

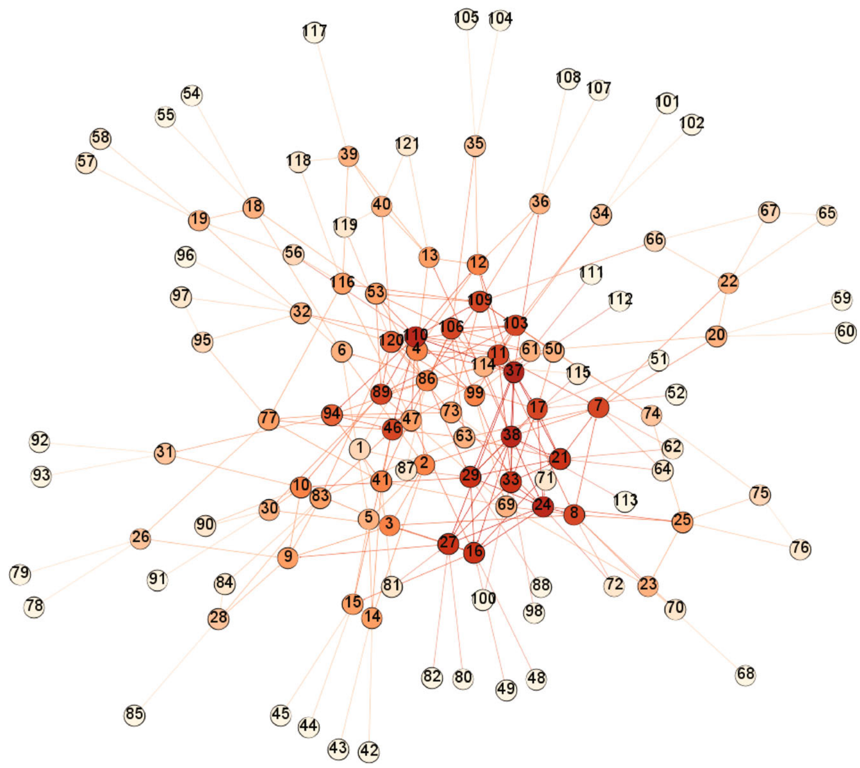

Figure 6: C2 network.

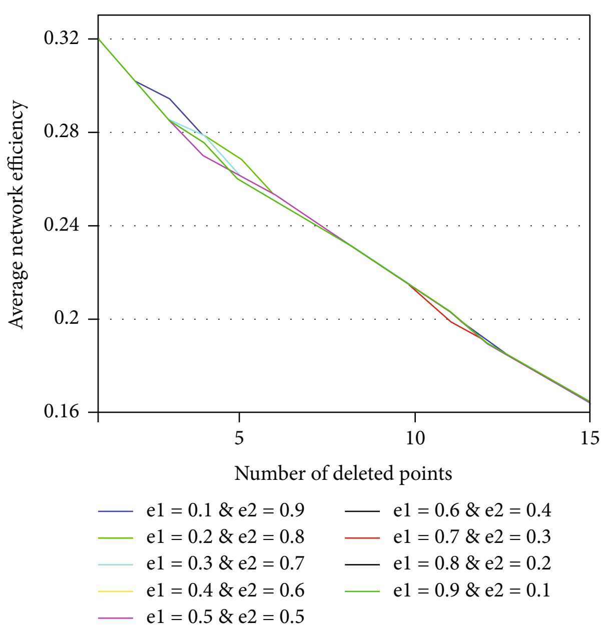

Figure 7: Comparison of different combinations of preference coefficient.

node 2 is more important than node 4 different from CC and BC. As shown in Figure 2, node 2 links with more nodes and plays an important role in information flow, which is obviously more important than node 4, similarly for the comparison between node 12 and node 14.

In order to further illustrate the effectiveness of the algorithm in this paper, the average network efficiency is used for comparative analysis; the importance of nodes is judged by the rate of decline of the average network efficiency after deleting nodes.

It can be seen from the Figure 3 that the average network efficiency of the algorithm in this paper decreases the fastest when the first 2 nodes are deleted, same as BC; explain that node 12 is more important. With the deletion of nodes, the average network efficiency of the algorithm in this paper decreases faster than these four methods, indicating that the above description of a single node is more precise; the algorithm in this study is more reasonable than other algorithms.

4.2.2. Analysis of Different Metric Combinations. To verify the effectiveness of the method itself in this study, the ARPA network was also used for the analysis to verify the effectiveness of the multiattribute fusion method by comparing it with different combinations of individual metric. The results are shown in Figures 4 and 5.

From Figures 4 and 5, the overall decline rate of the average network efficiency of this study's method is higher than the different combination methods of each metric.

When comparing two metric combination methods, this method performs significantly better in removing the first five key nodes and the first ten key nodes than other methods.

Similarly, when comparing three metric combination methods, this method outperforms the others. It is clear that the combination proposed in this study is reasonable and its performance is better than other combination methods.

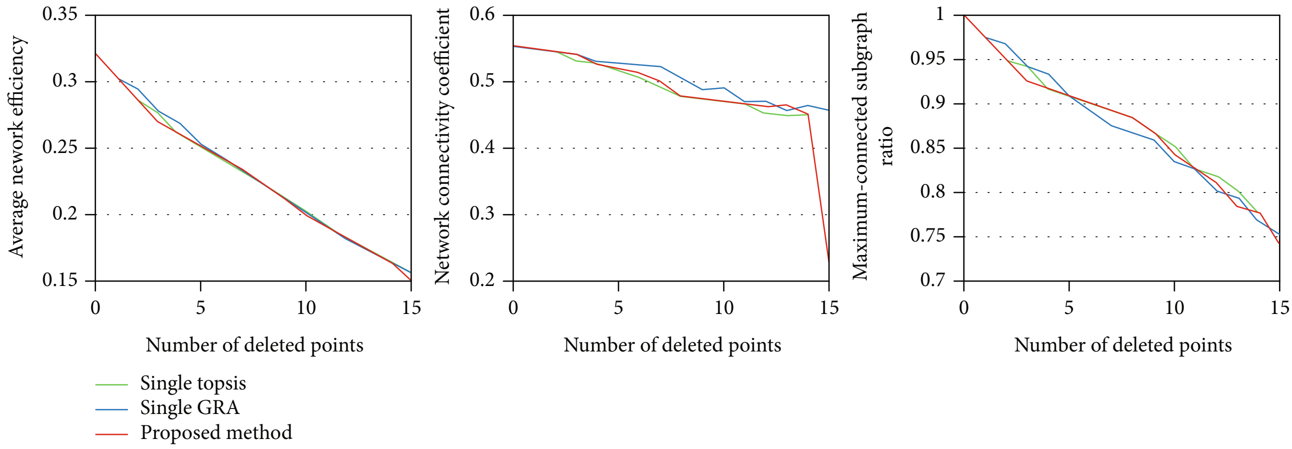

FIGURE 8: Comparison of different evaluation method.

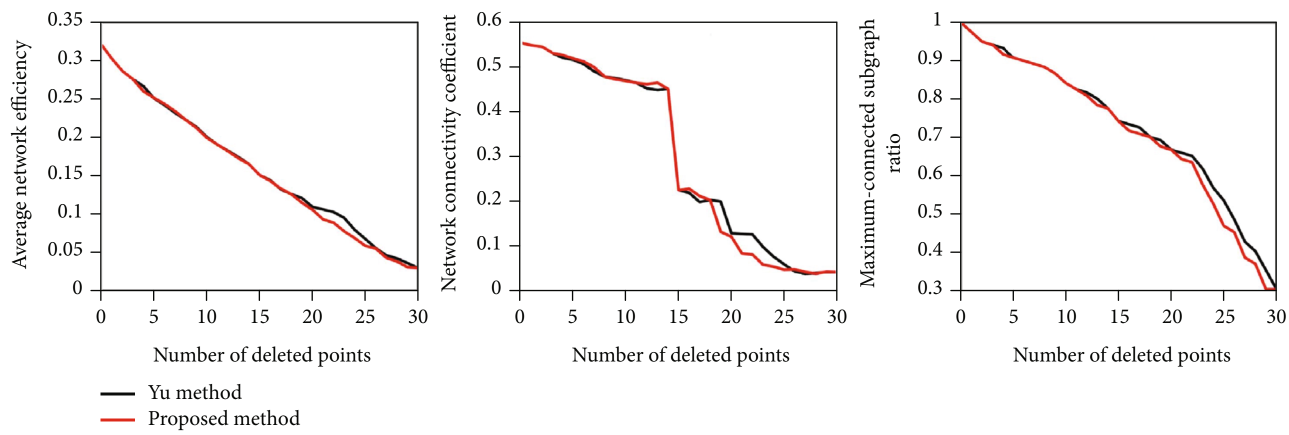

FIGURE 9: Comparison of different evaluation metrics under the C2 network.

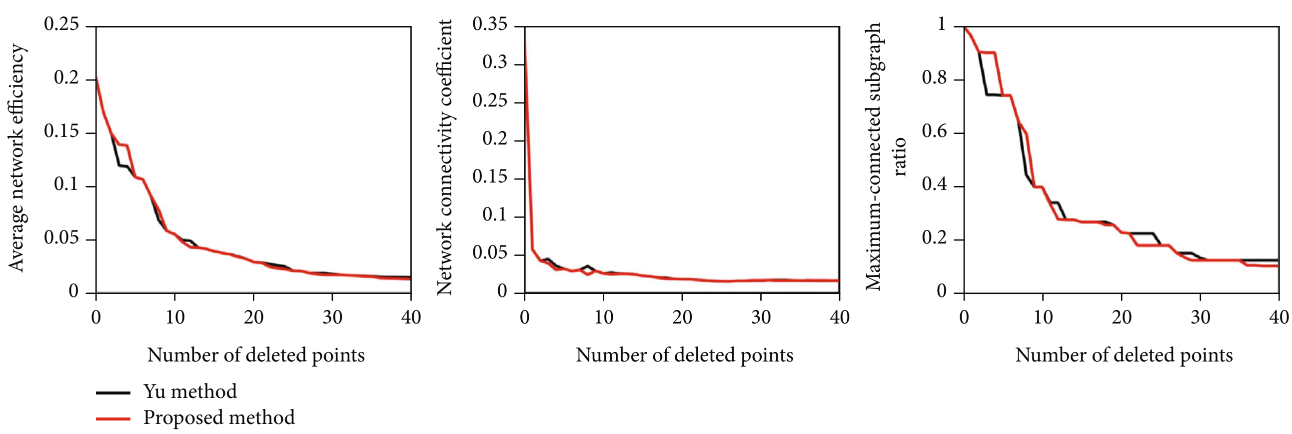

FIGURE 10: Comparison of different evaluation metrics under the Ca-netscience network.

4.2.3. Analysis of Different Preference Coefficient Combinations. For the setting of the preference coefficient, the influence of the preference coefficient (e_1, e_2) on the experimental results is verified by setting 9 pairs of different combinations. The method of this study is applied to the C2 (command and control) network with 121 nodes, which is a typical air defense command and control system network, and the network is constructed by modeling method. The network structure is shown in Figure 6. The average network efficiency is also used for comparative analysis. The experimental results are shown in Figure 7.

It can be seen from the Figure 7 that the different combinations of preference coefficient have little change in the performance of the network. $e_1 = e_2 = 0.5$ has slightly better

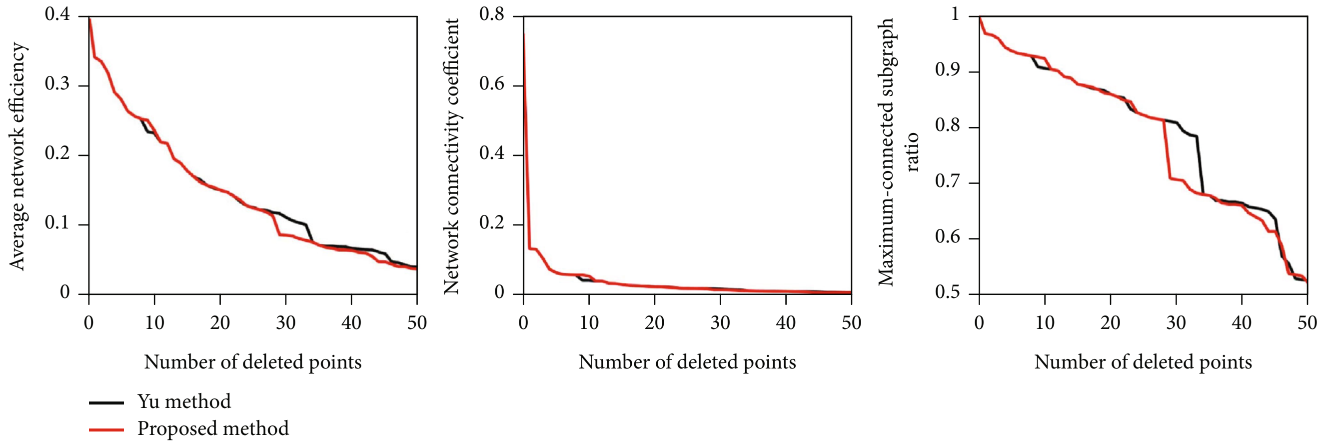

FIGURE 11: Comparison of different evaluation metrics under the biocelegans network.

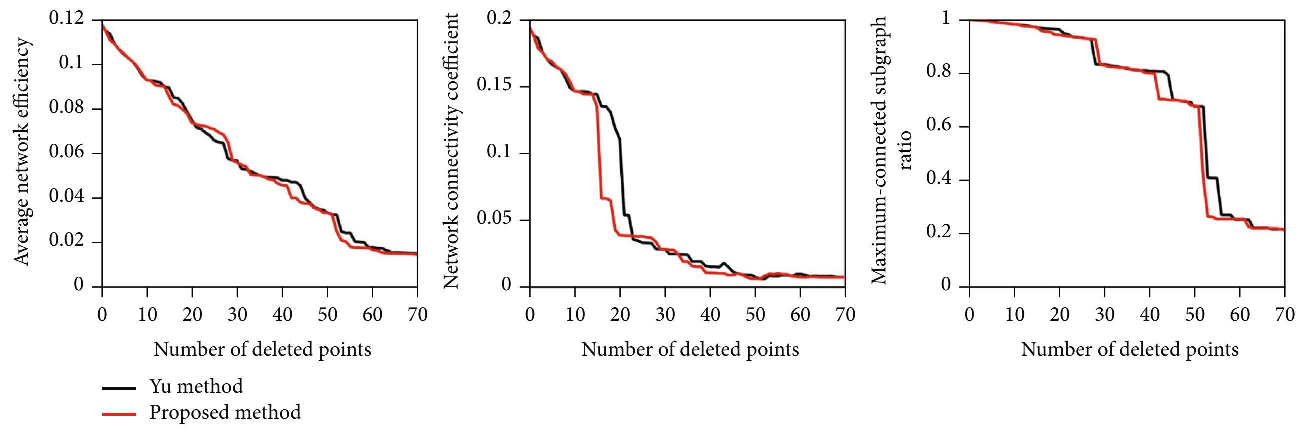

FIGURE 12: Comparison of different evaluation metrics under the power network.

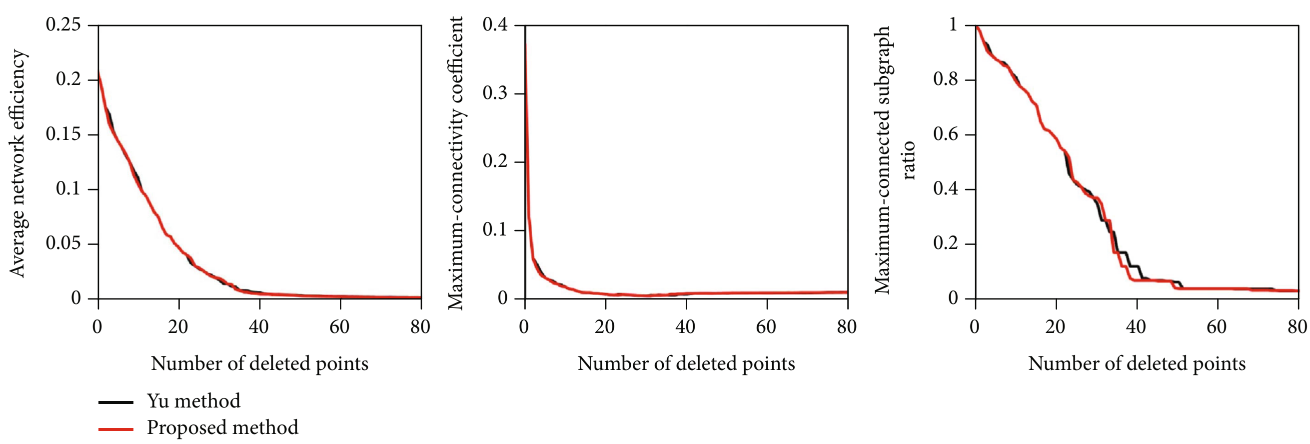

FIGURE 13: Comparison of different evaluation metrics under the retweet network.

performance and is taken in the subsequent simulations of this paper.

4.2.4. Performance Analysis of Different Evaluation Method. In order to prove the superiority of the evaluation method combining TOPSIS and GRA (grey relational analysis) in this paper, a comparison test between the single evaluation method and the combination method proposed in this paper is designed, and C2 network was used for experiments. The average network efficiency, network connectivity coefficient, and maximum connectivity subgraph ratio are used for comparative analysis. The experimental results are shown in Figure 8.

For the average network efficiency, the performance of the proposed method is slightly better than the single evaluation method. For the network connectivity coefficient, the

Table 3: Statistical characteristics of each network.

Network	Nodes number	Edges number	Attribute
C2	121	256	Air defense command and control system network; nodes are command entities, and edges are abstractions of relationships between entities
Ca-netscience	379	914	Scientific collaboration network in network theory and experiments; nodes are scientists, and edges are cooperative relationship
Biocelegans	453	4600	Metabolic network of celegans; nodes are substrates, edges are metabolic reactions
Power	662	906	Power networks; nodes are power lines, edges are substations
Retweet	761	1000	Retweet and mentions network from the UN conference held in Copenhagen; nodes are twitter users and edges are retweets.

proposed method is slightly inferior to the single TOPSIS, but significantly better than the single GRA, and for the maximum connectivity subgraph ratio, the performance is just the opposite, slightly inferior to a single GRA, but better than a single TOPSIS. In general. The combined method proposed in this paper is feasible, and because it can combine the advantages of the two methods, it performs better than the single evaluation method.

4.2.5. Performance Analysis of Different Networks. To further illustrate the applicability of this method, the method of this study is applied to other different networks including computer generated network C2 network and real-world networks including Ca-netscience network, biocelegans network, power network, and retweet network.

The method in this study is compared with Yu et al.'s method [13], and the evaluation methods used for analysis are network efficiency, network connectivity coefficient, and maximum connectivity subgraph ratio. Because removing 5%-10% of the important nodes in the network is enough to bring down the network, the top ranked nodes are removed in different network. The performance of each method is observed, and the simulation plots are shown in Figures 9–13.

In this paper, five real networks are selected as test networks, and the statistical characteristics of each network are shown in Table 3. Except C2 network constructed by modeling method, other networks are from https://networkrepository.com/

(1) C2 Network. The analysis results of C2 network are shown in Figure 9; for average network efficiency and maximum connectivity subgraph ratio, the performance is slightly better than Yu et al.'s method when the first 15 nodes were deleted. However, this method is significantly better than Yu et al.'s method after the 15th node is deleted. For network connectivity coefficient, the performance of this method is slightly inferior to the method in some periods, and the method in this paper is still improved in general.

(2) Ca-netscience Network. In Figure 10, for average network efficiency and maximum connectivity subgraph ratio, the performance is slightly inferior to Yu et al.'s method when the first 10 nodes were deleted, but the effect of this paper is obviously better than after the 10th node is deleted. For network connectivity coefficient, our method outperforms Yu et al.'s method in the whole process. On the whole, our method performs slightly better than Yu et al.'s method.

(3) Biocelegans Network. As shown in Figure 11, the performance of our method in this study is slightly inferior to Yu et al.'s method when the first 10 nodes were deleted, but after that, the effect of this method is obviously better in different evaluation methodology.

(4) Power Network. In Figure 12, for average network efficiency, the performance of our method in this paper is slightly worse than Yu et al.'s method when deleting 20th nodes to 30th nodes, and others period perform better. For network connectivity coefficient and maximum connectivity subgraph ratio, our method works significantly better.

(5) Retweet Network. As shown in Figure 13, for retweet network, the performance of the approach in this paper is almost identical to Yu et al.'s method. But for maximum connectivity subgraph ratio, the improvement effect of our method in this paper is more obvious.

We notice that the method in this paper is slightly worse in some periods; the reason for this phenomenon is related to the network structure of the network itself. The basic evaluation metrics selected in this study are not quite suitable for these networks, which leads to the difference in the evaluation performance. It is necessary to select more suitable metrics for the structure of the different network, which is one of the future research directions. But in general, our method is clearly more suitable for various networks and performs better in different evaluation methods.

In summary, this method shows better performance in different combinations of node importance evaluation and has good algorithmic applicability to be applied in different networks, which has some practical value.

5. Conclusions

In this study, a subjective and objective comprehensive weighting method is proposed to weight the decision matrix, and combined with the advantages of TOPSIS and grey relational analysis algorithm, the relative closeness is proposed and applied to the node importance identification of complex networks. Finally, different comparative experiments and evaluation methodology are designed to analyze the performance of the algorithm. For the effectiveness of the algorithm itself in this study, its performance outperforms the combined approach with different metrics. Furthermore, this algorithm outperforms Yu et al.'s method in terms of average network efficiency, network connectivity coefficient, and maximum connectivity subgraph ratio for different types of networks, which indicates that this scheme is more reasonable and the evaluation results of nodes are closer to the actual situation and achieve good results.

The paper also has potential limitations, such as the selection of indicators in different networks, AHP will cause rank inversion problems, and whether the algorithm is still applicable in dynamic network link prediction. As future research, look for new weight calculation methods, such as alpha-discounting method to solve the problem [21], and try to use LSTM [22, 23] to solve the link prediction problem.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work is supported by Natural Science Foundation of Guangdong Province (2022A1515010737) and China University Industry-University-Research Collaborative Innovation Fund (2021FNA04017).

References

[1] Q. C. Hu, Y. S. Yin, P. F. Ma, Y. Gao, Y. Zhang, and C. X. Xing, "A new approach to identify influential spreaders in complex networks," *Acta Physica Sinica*, vol. 62, no. 14, article 140101, 2013.

[2] B. L. Zhang, *Research on Information Diffusion and Influence Maximization in Social Networks*, Nanjing University, 2016.

[3] Y. S. Jiang, "Key node identification of navigation network based on structural centrality," *Computer and Modernization*, no. 7, pp. 108–113, 2018.

[4] K. Yan, L. Li, and Y. B. Qin, "Key node identification methods based on road traffic networks," *Computer Engineering & Science*, vol. 40, no. 11, pp. 1983–1990, 2018.

[5] P. Ren, C. Li, P. Tao, C. F. Wu, and H. Li, "Node vulnerability evaluation for power network based on weighted entropy TOPSIS method," *Journal of Electric Power Science and Technology*, vol. 34, no. 3, pp. 143–149, 2019.

[6] G. H. Zhao, P. Jia, and A. M. Zhou, "Improved degree centrality for directed-weighted network," *Journal of Computer Applications*, vol. 40, Supplement 1, pp. 141–145, 2020.

[7] M. M. Tulu, R. Hou, and T. Younas, "Identifying influential nodes based on community structure to speed up the dissemination of information in complex network," *IEEE Access*, vol. 6, pp. 7390–7401, 2018.

[8] K. L. Wang, C. X. Wu, J. Ai, Z. Su, and School of Optical-Electrical and Computer Engineering, University of Shanghai for Science and Technology, Shanghai 200093, China, "Complex network centrality method based on multi-order K-shell vector," *Acta Physica Sinica*, vol. 68, no. 19, article 196402, 2019.

[9] Y. M. Wang, Q. Y. Wang, C. S. Pan, and B. Chen, "Method for key nodes identification in command and control network by considering structural holes," *Fire Control & Command Control*, vol. 42, no. 3, pp. 59–63, 2017.

[10] Y. Wang, S. Wang, and Y. Deng, "A modified efficiency centrality to identify influential nodes in weighted networks," *Pramana*, vol. 92, no. 4, 2019.

[11] G. Hu, X. Xu, H. Gao, and X. C. Guo, "Node importance recognition algorithm based on adjacency information entropy in networks," *Systems Engineering-Theory & Practice*, vol. 40, no. 3, pp. 714–725, 2020.

[12] S. Xu and P. Wang, "Identifying important nodes by adaptive LeaderRank," *Physica A Statistical Mechanics & Its Applications*, vol. 469, pp. 654–664, 2017.

[13] H. Yu, Z. Liu, and Y. J. Li, "Key nodes in complex networks identified by multi-attribute decision-making method," *Acta Physica Sinica*, vol. 62, no. 2, article 020204, 2013.

[14] Z. Liu, C. Jiang, J. Wang, and H. Yu, "The node importance in actual complex networks based on a multi-attribute ranking method," *Knowledge-Based Systems*, vol. 84, pp. 56–66, 2015.

[15] Y. Z. Yang, L. Yu, X. Wang, S. Y. Chen, Y. Chen, and Y. P. Zhou, "A novel method to identify influential nodes in complex networks," *International Journal of Modern Physics C*, vol. 31, no. 2, p. 2050022, 2020.

[16] J. T. Hu, Y. X. Du, H. M. Mo, D. J. Wei, and Y. Deng, "A modified weighted TOPSIS to identify influential nodes in complex networks," *Physica A Statistical Mechanics & Its Applications*, vol. 444, pp. 73–85, 2016.

[17] P. L. Yang, X. Liu, and G. Q. Xu, "A dynamic weighted TOPSIS method for identifying influential nodes in complex networks," *Modern Physics Letters B*, vol. 32, no. 19, p. 1850216, 2018.

[18] X. L. Yan, Y. P. Cui, and S. J. Ni, "Identifying influential spreaders in complex networks based on entropy weight method and gravity law," *Chinese Physics B*, vol. 29, no. 4, article 048902, 2020.

[19] X. Liu, G. Q. Xu, and P. L. Yang, "Node importance evaluating of network based on combination weighting VIKOR method," *Application Research of Computers*, vol. 36, no. 8, pp. 2368–2371, 2019.

[20] T. Bian and Y. Deng, "A new evidential methodology of identifying influential nodes in complex networks," *Chaos Solitons & Fractals*, vol. 103, pp. 101–110, 2017.

[21] F. Smarandache, "Three non-linear a-discounting MCDM-method examples," in *Proceedings of The 2013 International Conference on Advanced Mechatronic Systems (ICAMechS 2013)*, pp. 174–176, Luoyang, China, 2013.

[22] L. Zhang, Z. Huang, W. Liu, Z. Guo, and Z. Zhang, "Weather radar echo prediction method based on convolution neural network and long short-term memory networks for sustainable e-agriculture," *Journal of Cleaner Production*, vol. 298, article 126776, 2021.

[23] L. Zhang, C. Xu, Y. Gao, Y. Han, X. du, and Z. Tian, "Improved Dota2 lineup recommendation model based on a bidirectional LSTM," *Tsinghua Science and Technology*, vol. 25, no. 6, pp. 712–720, 2020.