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Gray Correlation Entropy-Based Influential Nodes Identification and Destruction Resistance of Rail-Water Intermodal Coal Transportation Network

Jiaxin Zhang, Junxi Chen, Yue Ma and Zhenlin Wei *

School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China; 21114104@bjtu.edu.cn (J.Z.); 22110250@bjtu.edu.cn (J.C.); 22125831@bjtu.edu.cn (Y.M.)
* Correspondence: zhlwei@bjtu.edu.cn

Abstract: Evaluating the importance of nodes in coal transportation networks and identifying influential nodes is a crucial study in the field of network science, vital for ensuring the stable operation of such complex networks. However, most existing studies focus on the performance analysis of single-medium networks, lacking research on combined transportation, which is not applicable to China's coal transportation model. To address this issue, this paper first establishes a static topological structure of China's coal-iron-water combined transportation network based on complex network theory, constructing a node importance evaluation index system through four centrality indicators. Subsequently, an enhanced TOPSIS method (GRE-TOPSIS) is proposed based on the Grey Relational Entropy Weight (GRE) to identify key nodes in the complex network from local and positional information dimensions. Compared to previous studies, this research emphasizes composite networks, breaking through the limitations of single-medium network research, and combines gray relational analysis with entropy weighting, enhancing the objectivity of the TOPSIS method. In the simulation section of this paper, we establish the model of China's coal-iron-water combined transportation network and use the algorithm to comprehensively rank and identify key nodes in 84 nodes, verifying its performance. Network efficiency and three other parameters are used as measures of network performance. Through simulated deliberate and random attacks on the network, the changing trends in network performance are analyzed. The results show that in random attacks, the performance drops to around 50% after damaging nearly 40 ordinary nodes. In contrast, targeting close to 16 key nodes in deliberate attacks achieves a similar effect. Once key nodes are well protected, the network exhibits a certain resistance to damage.

Keywords: logistics engineering; rail-water intermodal transport; complex network; influential nodes identification; network performance

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1. Introduction

How to evaluate and identify influential nodes in complex systems is a crucial study in network science, especially vital for ensuring the stable operation of complex networks. Different complex networks closely related to our lives, such as transportation networks, social networks, and so on [1–4], have been given significant exploration, for example, faster dissemination of information [5] and spread prevention of rumors and/or diseases [6]. Over the past few decades, key node identification has had a pronounced impact on the structure and correlation reactions of complex networks and has been widely studied and applied in many fields. For instance, the protection of essential stations and ports in transportation networks ensures the network's stability and efficient operation; identifying super-spreaders in viral transmission networks can substantially reduce the speed and scope of virus spread. Controlling the statements of influential figures in social networks can effectively promote or suppress information dissemination. Therefore, determining key nodes in complex networks is imperative.

Under the combined influence of coal supply and demand patterns, coal transportation patterns, economic layout, geographical environment, etc., China has formed a complex coal transportation network consisting of various transportation modes such as railways, highways, and waterways [7]. With the development of the national economy, the supply and demand of coal have grown rapidly, the size of the Coal Transportation Network (CTN) continues to expand, and the risks and uncertainties the network faces increase with its structural complexity and growing scale. In practical applications, the coal transportation supply chain, a complex network system comprising numerous routes, aims to meet coal demand. Its regular operation can be affected by various uncertainties. Hence, investigating supply chain vulnerability is of great theoretical significance and practical value to ensure the efficient operation of the supply chain and enhance its overall resilience [8]. Essentially, Rail-Water combined Coal Transportation Networks (RWCTN) belong to transportation networks. Complex network theory as an efficient tool has been used to study the importance evaluation of nodes in transportation networks of different modes. KOPSIDAS et al. [9] built a new index based on betweenness centrality, closeness centrality, and weighted node degree to evaluate the importance of nodes in Rail Transportation Networks (RTN). However, current research lacks comprehensive consideration of key node identification combining waterway and land transportation networks and mainly focuses on the impact of road network node units on the entire network in emergencies or vulnerability analysis of nodes in coal-iron-water combined transportation networks.

Therefore, most of the centrality-based methods for ranking influential nodes are proposed from a certain point of view, which more or less have restrictions and merely can be carried out on some specific networks [5]. Degree Centrality (DC) [10], Betweenness Centrality (BC) [11], and Closeness Centrality (CC) [12] are some of these classical centrality methods. WU et al. [10] proposed a node occupancy rate index based on node degree to evaluate the utilization level of rail transit nodes, identifying key nodes in six rail transit networks, namely Beijing, Hong Kong, Tokyo, Paris, London, and New York. MENG et al. [11] selected four indicators: DC, BC, CC, and Eigenvector Centrality (EC). They used principal component analysis to determine the weights of each indicator and then used factor analysis to identify key nodes in Shenzhen's rail transit. They also compared the topological complexity differences between the Space L model and the Space P model. KOPSIDAS et al. [9] proposed a new index based on betweenness centrality, closeness centrality, and weighted node degree to identify the importance of nodes in RTN. Meanwhile, researchers in [13] proposed community-aware centralities that classify nodes by taking into account local and global information based on intra-community and inter-community ties. A modularity vitality centrality measure was proposed in [14], which generalizes overlapping communities based on the community identification method. In [15], an incremental detection method is developed to explore critical nodes in the neighborhood and simulate the dynamics through snapshots. Two round-trip centralities are proposed to reinforce dense networks in [16,17]. A number of approaches to dealing with static social networks have been proposed to determine the best solution for partitioning the network into k communities [18]. A key node is generally a topological location that has a significant influence on the network. [19]. The influence maximization problem was investigated in static social networks [20]. Literature [21] confirms that weak ties play a crucial role in the propagation process and that nodes with high clustering coefficients are generally not critical nodes. Literature [22] proposes a TI-SC algorithm to identify influential nodes by exploring the relationship between key nodes and the scoring ability of other nodes.

The structure of transportation networks significantly influences their functions and performance. With in-depth research, scholars have conducted extensive studies on railway networks using complex theory methods. For example, Lyu Min et al. [23] considered both node network topology features and transportation service attributes, using entropy-TOPSIS to rank transportation network nodes and constructing a clustering node risk identification model to classify transportation risk nodes, though they didn't consider the actual spatial distance of nodes when building their network. WANG et al. [24] proposed a node importance evaluation method based on the TOPSIS method by combining the topology, industry characteristics, and directionality of the air cargo network. Du et al. [25] first proposed a TOPSIS-based method to rank critical nodes in complex networks that simultaneously identifies alternatives that satisfy the worst aspect with the farthest distance and the optimal aspect with the shortest distance. Yang et al. [26] proposed an improved weighted TOPSIS algorithm with the weights of evaluation indexes determined by the gray correlation analysis, which can identify the most important nodes in complex networks. Liu et al. [27] evaluated the propagation ability of nodes by embedding relative entropy in the TOPSIS method and applied it to several practical complex networks. Yang et al. [28] developed a comprehensive measure to identify important nodes in complex networks that combines the VIKOR method and the entropy weight method.

In summary, there has been a great deal of research on the importance of nodes in transport networks, but there is less research on RWCTN. Most node importance evaluation studies qualitatively analyze the evaluation results, lacking verification of method effectiveness, highlighting the need for a more scientific evaluation method. Based on gray correlation and entropy weighting, this paper proposes an improved GRE-TOPSIS. It calculates the correlation between each pair of nodes through grey correlation and entropy weighting and constructs a weighted adjacency matrix of the network. Finally, we use the weighted TOPSIS method to comprehensively assess the importance of nodes and identify key nodes in complex networks in terms of local and location information dimensions. Compared to previous research, this study breaks through the limitations of single-medium network research and combines gray correlation with entropy weighting, enhancing the objectivity of the TOPSIS method's calculations. In the simulation part of this paper, we establish the model of China's coal-iron-water combined transportation network and apply this algorithm to comprehensively rank 84 nodes, verifying the algorithm's performance. Using network efficiency and three other parameters as measures of network performance, we analyze the changing trends in network performance through simulated deliberate and random attacks.

The remainder of this paper is organized as follows: Section 2 completes the modeling of the coal-iron-water combined transportation network. Section 3 introduces the GRE-TOPSIS algorithm, providing a comprehensive evaluation method for node importance. Section 4 presents the experimental setup, including network model construction, node importance evaluation index system construction, comprehensive importance evaluation value calculation, and node importance analysis. Moreover, we further complete the simulated attacks and performance analysis in this section. Finally, conclusions and insights are drawn in Section 5.

2. Coal Iron-Water Combined Transportation Network Modeling

Based on the analysis of coal transfer and reserves in various provinces of China, it can be observed that the southeastern coastal economically developed regions of China have limited coal production, yet the demand is robust. In contrast, the northern regions, although economically less developed, possess abundant coal reserves. Therefore, to achieve a market supply-demand balance, it is necessary to transport coal from areas rich in production to areas with high demand. China's coal transportation mainly relies on railways, highways, and coastal and inland water transport. It has preliminarily formed a relatively complete iron-water combined coal transportation system, which is a railway transportation network that connects the north to the south, spans east to west, combines main and branch lines, and possesses a considerable scale [29].

Currently, the national railway coal transportation channels mainly consist of the "three western" coal export channels, channels entering the eastern regions, and channels entering and exiting the customs area. Waterway coal transportation includes maritime and inland waterway transportation. The major seaports in the north include Qinhuangdao Port, Jingtang Port, Qingdao Port, Tianjin Port, Rizhao Port, Huanghua Port, and Lianyungang Port. The primary receiving ports include Shanghai Port, Fuzhou Port, Ningbo Port, Shenzhen Port, Guangzhou Port, and so on. For inland transportation, the primary downstream ports include the Yangtze River's Wuhan Port, Pukou Port, Zhicheng Port, Jiujiang Port, Wuhu Port, and the Grand Canal's Xuzhou Port, Huaiyin Port, and Yangzhou Port, as well as the Pearl River system's Guigang Port. Major inland coal-receiving ports include Nantong Port, Zhenjiang Port, and Hangzhou Port.

The coal-iron-water combined transportation supply network includes railway stations, ports, railway lines, and shipping routes as basic elements. A railway line passes through several stations, and a shipping route passes through several navigation points. The organizational relationship of the coal-iron-water combined transportation network is shown in Figure 1:

Figure 1. Organizational relationship chart.

Applying complex network theory to describe the coal-iron-water combined supply chain network, assume each navigation point and station is represented by the node set M, $M = \{v_1, v_2, \cdots, v_n\}$. The railway lines and shipping routes are denoted by the set N, $N = \{u_1, u_2, \cdots, u_n\}$. Together, a non-empty set of nodes M is formed, and an undirected graph G is constituted by the element points in M and set N is formed, where $G = (M, N)$. Through these steps, the complex network of coal-iron-water combined transportation is transformed into a topological structure, establishing the complex network model.

The topological data of the RWCTN is represented in the form of an adjacency matrix and stored on the computer for identification and processing by the computer. Use A to represent the adjacency matrix of the RWCTN. a_{ij} represents the connection between nodes v_i and v_j. When node v_i is connected to node v_j, then $a_{ij} = 1$; otherwise, $a_{ij} = 0$. Then the adjacency matrix of the coal transportation network can be represented as follows:

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix}. \tag{1}$$

3. Results

Considering that a single importance index cannot fully reflect the importance of nodes, this paper proposes a method based on gray correlation and entropy for evaluating the importance of nodes in RWCTN. The method is used to identify influential nodes in complex networks. The specific steps are as follows:

Step 1: Draw the topology of the RWCTN, select the node importance evaluation indicators, and calculate the indicator values for each node;

Step 2: The correlation between each pair of nodes was calculated using gray correlation and entropy methods to construct a weighted adjacency matrix for the network;

Step 3: Starting from the weighted adjacency matrix, the weighted TOPSIS method is used to obtain the comprehensive importance evaluation value of the nodes in the RWCTN, and the importance of the nodes is comprehensively evaluated.

The comprehensive evaluation method process of nodes' importance in RWCTN is shown in Figure 2:

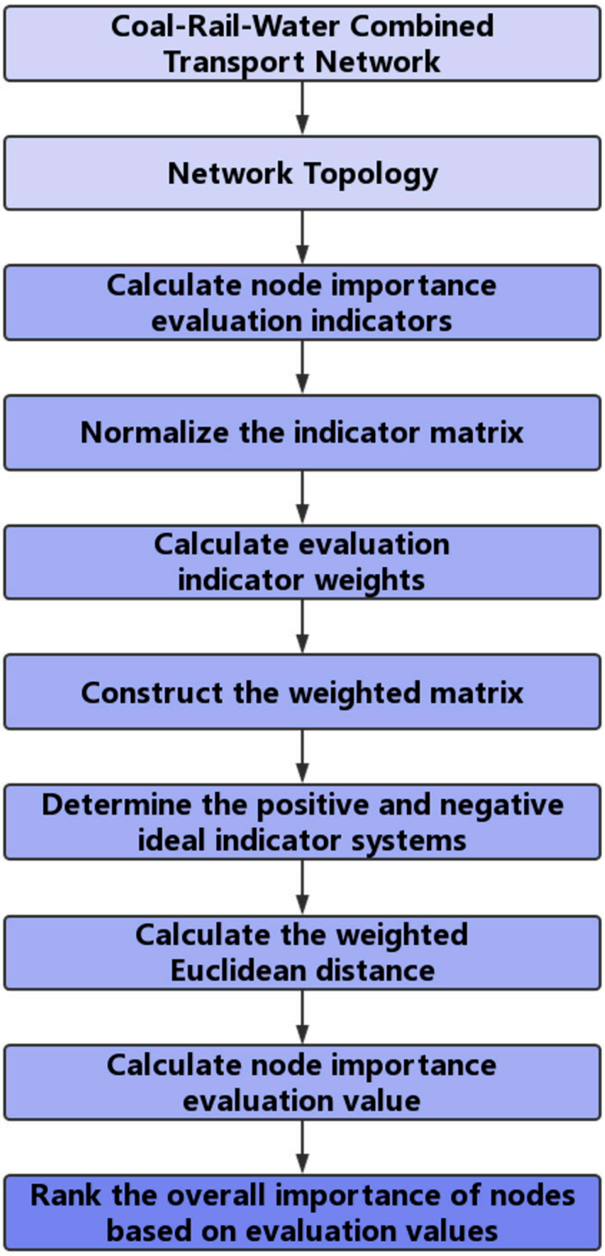

Figure 2. GRE-TOPSIS Flow Chart.

3.1. Selection of Node Importance Evaluation Indicators

There are many nodes in the coal transportation chain, and the roles that each node plays in the transport network also vary. Some nodes are more important in the transport network. In the face of sudden events, such as severe weather and natural disasters, it is easy for the node unit to fail, causing significant damage to the normal operation of the entire transport network. However, for other nodes whose role in the transport network is not prominent, the failure of the node unit does not have much impact on the operation of the entire transport network. Therefore, in the study of the importance of nodes in the coal transportation chain, not all node units need to be analyzed. It is only necessary to screen out the important nodes and analyze their importance [30]. To measure the importance of nodes in the coal-rail-water combined transport network, this paper selects important evaluation indicators from various aspects such as degree, betweenness, clustering coefficient, and node centrality [31].

3.1.1. Degree

In complex networks, the degree of a node is defined as the number of direct connections between a node and other nodes in the network, i.e., the number of connecting lines owned by the node. Node degree is an important indicator of the influence of a node in the network. In general, the greater the degree of a node, the more nodes it is connected to, and the more important node v_i is, the more influence it has in the network. It can be written as follows:

$$D(v_i) = \sum\nolimits_{i \neq j} a_{ij}, \tag{2}$$

where $D(v_i)$ denotes the degree of node v_i. a_{ij} denotes the element in the adjacency matrix A. When node v_i is connected to node v_j, then $a_{ij} = 1$; otherwise, $a_{ij} = 0$.

3.1.2. Betweenness Centrality (BC)

In complex networks, the number of shortest paths through a node as a percentage of the number of all shortest paths is defined as the inter-node centrality of that node. In practice, inter-node centrality is an important global geographic metric. It better reflects the importance of individual nodes in the network and is a statistical indicator of the importance of nodes or edges in the entire network. It can be written as follows:

$$BC(v_i) = \sum\nolimits_{s \neq i \neq t} \frac{N^{(i)}{}_{st}}{N_{st}}, \tag{3}$$

where $BC(v_i)$ denotes the BC of node v_i. $N^{(i)}{}_{st}$ denotes the number of shortest paths between nodes v_s and v_t that through node v_i. N_{st} denotes the total number of shortest paths between nodes v_s and v_t.

3.1.3. Closeness Centrality (CC)

The CC of a node reflects the proximity between the node and other nodes in the network. If a node has a short distance from all other nodes in the network, then this node is not constrained by other nodes. It can be written as follows:

$$CC(v_i) = \frac{1}{\sum_{j=1}^{n} S_{ij}}, \tag{4}$$

where $CC(v_i)$ denotes the CC of node v_i. S_{ij} denotes the shortest distance between nodes v_i and v_j.

3.1.4. Clustering Coefficient

In complex networks, the clustering coefficient is defined as the ratio of connections between neighboring nodes of a given node in the network and is used to describe the degree of aggregation of nodes in the network. If node v_i is directly connected to nodes v_s and v_t, then nodes v_s and v_t are likely to be directly connected. This phenomenon reflects the dense connectivity characteristic between certain nodes, i.e., the clustering characteristic of complex networks. The larger the clustering coefficient, the greater the influence of the node on network connectivity. The clustering coefficient can vividly describe the closeness of the pivotal nodes of the network, which can better portray the aggregation characteristics of the RWCTN. It can be written as follows:

$$CL(v_i) = \frac{2E_i}{k_i(k_i - 1)}, \tag{5}$$

where $CL(v_i)$ denotes the clustering coefficient of node v_i. k_i denotes the number of nodes adjacent to node v_i. E_i denotes the actual number of edges connected to nodes k_i. If these nodes k_i are all interconnected, there are up to $k_i(k_i - 1)/2$ edges between them.

3.2. Improved GRE-TOPSIS Method

When selecting indicators to identify vulnerability sources, it is necessary to consider the basic features of node units in complex networks. Hence, this paper selects node degree, betweenness, clustering coefficient, and closeness centrality as indicators for identifying vulnerability sources. In addition, the TOPSIS method is used to fully assess the importance of nodes and complete the identification of critical nodes.

The TOPSIS method, proposed by C. L. Hwang and K. Yoon in 1981 [32], is a typical multi-attribute decision-making method. Using the TOPSIS method, the problem of evaluating the importance of each node in a network can be transformed into a multi-attribute decision-making problem, in which each node is a decision option. The importance of each selected node serves as the evaluation index for this option. Based on each evaluation index of this option, ideal positive (best option) and negative (worst option) solutions are derived. The decision solutions are then ranked according to the proximity of each decision scheme to the option. The options are ranked by calculating how close each decision option is to that option. The traditional TOPSIS method did not consider the contribution of each evaluation indicator to the scheme, and there are differences in the contribution of each evaluation indicator to the importance of evaluating nodes. To address this issue, this project proposes using the entropy-weighted TOPSIS method based on gray correlation to calculate the importance evaluation value of nodes in the iron-water transportation network.

3.2.1. Determining the Initial Evaluation Indicator Matrix

Assume there are m nodes in the coal logistics network, and each node has n evaluation indicators. Where x_{ij} represents the data value of the j-th evaluation indicator of the i-th node ($i = 1, 2, \cdots, m$; $j = 1, 2, \cdots, n$). Therefore, the initial evaluation indicator matrix X can be represented as follows:

$$X = \left(x_{ij}\right)_{m\times n} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}. \tag{6}$$

3.2.2. Standardization of the Evaluation Indicator Matrix

To facilitate the comparison between the evaluation indicators of various nodes and avoid the effects of different dimensions of the indicators, all evaluation indicators are standardized. Positive evaluation indicators are those that are better with larger values, and negative evaluation indicators are those that are better with smaller values.

For those negative evaluation indicators, it can be processed as follows:

$$u_{ij} = \frac{\max\left(x_{ij}\right) - x_{ij}}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)}. \tag{7}$$

For those positive evaluation indicators, it can be processed as follows:

$$u_{ij} = \frac{x_{ij} - \min\left(x_{ij}\right)}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)}, \tag{8}$$

where u_{ij} is the standardized value of x_{ij}, $\min\left(x_{ij}\right)$ and $\max\left(x_{ij}\right)$ indicate the maximum and minimum values for all nodes of the j-th evaluation indicator. The standardized evaluation indicator matrix $U = \left(u_{ij}\right)_{m\times n}$ can then be constructed.

3.2.3. Construct the Weighted Evaluation Indicator Matrix

To accurately calculate the importance evaluation value of the nodes, this paper calculates weights using both the gray correlation and entropy weight methods. The entropy weight method objectively determines the weight based on the amount of information difference between the indicators. The gray correlation method, as an evaluation method measuring the similarity or difference in development trends between factors, can reflect the changes in the indicators contained within the evaluation scheme and can comprehensively evaluate multi-indicator problems.

First, $U = (u_{ij})_{m \times n}$ is normalize to obtain the sample data value of the i-th node under the j-th evaluation indicator as a proportion of that indicator as:

$$P_{ij} = \frac{u_{ij}}{\sum\limits_{i=1}^{m} u_{ij}}, \tag{9}$$

where $0 \leq P_{ij} \leq 1$, $\sum\limits_{i=1}^{m} P_{ij} = 1$. Then the entropy of each evaluation metric is calculated by column, then the entropy value of the j-th evaluation metric of the node is formulated as follows:

$$E_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij}, \tag{10}$$

where $0 \leq E_j \leq 1$, $k = \frac{1}{\ln m}$. The information redundancy of the $j-$th evaluation indicator is calculated as $R_j = 1 - E_j$. The greater the value of redundancy, the greater the impact of the evaluation metric on the evaluation of node importance and the greater the weight attached to it. Thus, the first part of the weights is obtained, and the entropy weight of the $j-$th evaluation indicator is calculated as follows:

$$\alpha_j = \frac{R_j}{\sum\limits_{j=1}^{n} R_j} \tag{11}$$

where $\sum\limits_{j=1}^{n} \alpha_j = 1$.

Moreover, for the calculation of the gray correlation weight, the largest element of each row of the matrix $U = (u_{ij})_{m \times n}$ is selected as the reference object Z:

$$Z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix} \tag{12}$$

where $z_i = \max(u_{ij}), i = 1, 2, \cdots, m, j = 1, 2, \cdots, n$. Then, the gray correlation coefficient ξ_{ij} between u_{ij} and the reference object z_i is calculated as follows:

$$\xi_{ij} = \frac{\min\limits_{i=1,2,\cdots,m} \min\limits_{j=1,2,\cdots,n} |z_i - u_{ij}| + \rho \max\limits_{i=1,2,\cdots,m} \max\limits_{j=1,2,\cdots,n} |z_i - u_{ij}|}{|z_i - u_{ij}| + \rho \max\limits_{i=1,2,\cdots,m} \max\limits_{j=1,2,\cdots,n} |z_i - u_{ij}|} \tag{13}$$

where ρ is the resolution factor and is usually set as 0.5.

Thus, the gray correlation weight is obtained as $\beta_j = \sum\limits_{i=1}^{m} \xi_{ij}, j = 1, 2, \cdots, n$. Combining the two methods to calculate the weight makes the calculation results more objective. Determine the weight of each indicator as $\omega_j = a\alpha_j + b\beta_j$, $j = 1, 2, \cdots, n, a + b = 1$, then

$\omega = (\omega_1, \omega_2, \cdots, \omega_n)$. Weight the matrix U to obtain the weighted matrix $Q = (q_{ij})_{m \times n}$, as follows:

$$Q = (\omega_j u_{ij})_{m \times n} = \begin{pmatrix} \omega_1 u_{11} & \cdots & \omega_n u_{1n} \\ \vdots & \ddots & \vdots \\ \omega_1 u_{m1} & \cdots & \omega_n u_{mn} \end{pmatrix} = \begin{pmatrix} q_{11} & \cdots & q_{1n} \\ \vdots & \ddots & \vdots \\ q_{m1} & \cdots & q_{mn} \end{pmatrix}. \tag{14}$$

3.2.4. Determining the Ideal Indicator System and the Negative Ideal Indicator System

Filter the reference sequence Q_i from the matrix Q. Select the optimal value of each evaluation index of the node to form an ideal index system; select the worst value of each evaluation index of the node to form a negative ideal index system, that is:

Ideal Indicator System can be calculated as follows:

$$Q_j{}^+ = \max(q_{1j}, q_{2j}, \cdots, q_{mj}), j = 1, 2, \cdots, n \tag{15}$$

The negative ideal indicator system can be calculated as follows:

$$Q_j{}^- = min(q_{1j}, q_{2j}, \cdots, q_{mj}), j = 1, 2, \cdots, n. \tag{16}$$

3.2.5. Calculation of Comprehensive Importance Evaluation Value for Nodes

Calculate the Euclidean distance from each node to the ideal and negative ideal indicator systems as follows:

$$d_i{}^+ = \sqrt{\sum_{j=1}^{n} \omega_j{}^2 (Q_j{}^+ - q_{ij})^2}, i = 1, 2, \cdots, m, \tag{17}$$

$$d_i{}^- = \sqrt{\sum_{j=1}^{n} \omega_j{}^2 (Q_j{}^- - q_{ij})^2}, i = 1, 2, \cdots, m. \tag{18}$$

The proximity R_i of each scenario to the ideal scenario is calculated as an assessment of the importance of the node v_i in this network layer, that is:

$$R_i = \frac{d_i{}^+}{d_i{}^+ + d_i{}^-}. \tag{19}$$

The importance of the network nodes is ranked according to the value of R_i. The larger R_i is, the more important the node is, thus identifying the key nodes in the RWCTN. Note that in this place, a simple type of decision surface is adopted, which may cause steep ups and downs. Some improved versions can be found in the literature [33].

4. Case Analysis

In multi-modal transport links, if sudden situations occur, it may result in some transshipment nodes failing or some transport modes being unable to complete their transport tasks. The stable operation of key nodes and key edges will ensure the smooth operation of the multi-modal transport network to the greatest extent. Therefore, it is necessary to identify and study the key nodes in the network to further improve the accuracy of network performance analysis.

4.1. Network Model Construction

This article selects the main domestic railway and waterway coal transport channels, including Daqin Line, Shenshuo-Huanghua Line, Taiyuan-Jiaozuo Line, Longhai Line, Beijing-Kowloon Line, etc. Using the main cities, major coal mines, railway hubs, important coastal ports, and border land ports reached by the route as nodes, the nodes are numbered. Using Google Maps to find the latitude and longitude of each node, we constructed a topological map of the RWCTN and assessed the importance of 84 nodes in the network, as shown in Figure 3.

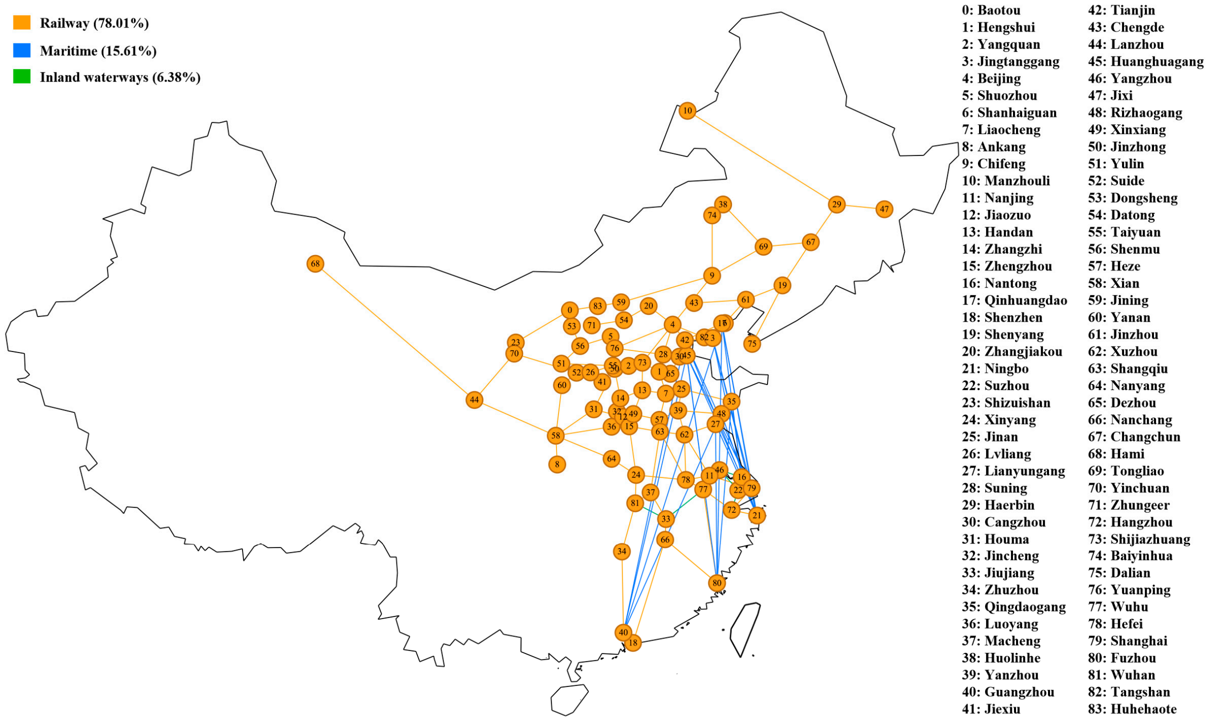

Figure 3. Topology diagram of coal rail-water transportation network. (Using Gephi v0.9.2 with the latitude and longitude from Google Maps).

4.2. Construction of Node Importance Evaluation System

In traditional node identification research, researchers usually use node betweenness, node degree, clustering coefficient, and node centrality as topology structure or vulnerability indicators for importance analysis and ranking. In the complex network G studied in this article, the indicator data distributed by nodes is shown in Figure 4.

Next, the decision matrix is constructed according to the calculated values of the indicators at each node, and the indicators in the matrix are normalized to obtain the normalized decision matrix. The calculation results of the relevant indicators are shown in Table 1.

Table 1. Table of normalized decision matrix calculation results (partial).

	Node	Degree	Betweenness	Clustering Coefficient	Closeness Centrality
0	Baotou	3	0.056518598	0	0.177350427
1	Hengshui	4	0.035033769	0	0.228021978
2	Yangquan	2	0.063446958	0	0.226775956
3	Jingtang Port	5	0.00753872	0.4	0.238505747
4	Beijing	7	0.357347351	0.047619048	0.284246575
5	Shuozhou	2	0.039244655	0	0.20906801
6	Shanhaiguan	2	0.079075885	0	0.213367609
7	Liaocheng	4	0.043588158	0	0.229916898
8	Ankang	1	0	0	0.163064833
9	Chifeng	4	0.205155118	0	0.24702381
10	Manzhouli	1	0	0	0.133440514
11	Nanjing	5	0.049207013	0.2	0.239884393
12	Jiaozuo	3	0.028218839	0	0.205445545
13	Handan	4	0.105028972	0	0.24340176
			…		
81	Wuhan	4	0.038749177	0.166666667	0.220159151
82	Tangshan	3	0.024198284	0	0.249249249
83	Hohhot	2	0.052658149	0	0.189066059

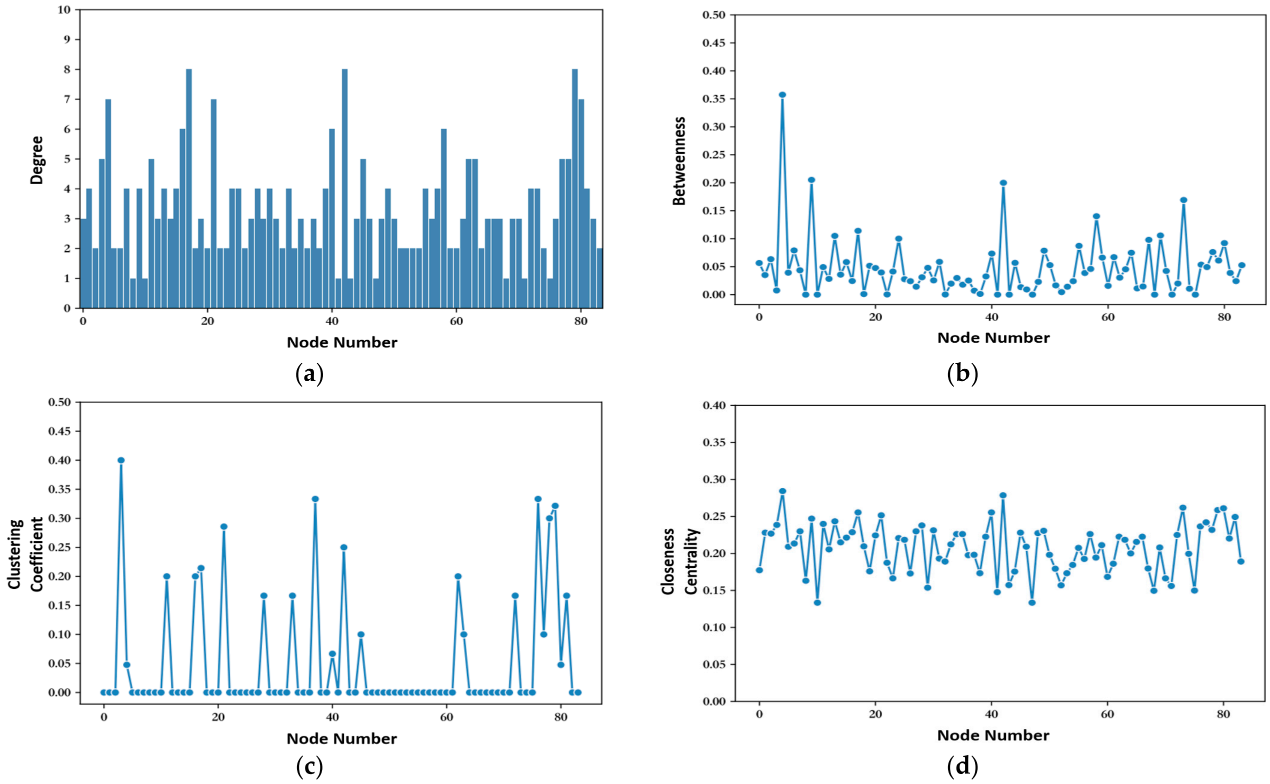

Figure 4. Topology diagram of coal rail-water transportation network: (**a**) Degree; (**b**) Betweenness; (**c**) Clustering Coefficient; (**d**) Closeness Centrality.

To mitigate the potential weight error when using a single model for evaluation, this paper adopts two different analytical methods: the entropy weighting method and the gray relational degree method. We determine the weight value for each indicator and then average the weights of the two methods to achieve a comprehensive assessment of node importance. The calculated weights are shown in Table 2.

Table 2. Table of weight calculation results.

	Entropy Weight Method	Grey Relational Degree	Average Weight
Degree	0.111596374	0.261344274	0.186470324
Betweenness	0.202804217	0.204224974	0.203514595
Clustering Coefficient	0.635896556	0.203578962	0.419737759
Closeness Centrality	0.049702853	0.330851791	0.190277322

The rankings and weights of the indicators are as follows: (1) Clustering Coefficient, with a weight of 0.4198; (2) Betweenness, with a weight of 0.2035; (3) Closeness Centrality, with a weight of 0.1903; (4) Degree, with a weight of 0.1865.

By inputting the metric weights into the corresponding decision matrix, we can calculate the importance values for each node in the basic network, as shown in Table 3.

Table 3. Table of node importance rating value (partial).

	Node	Importance
0	Baotou	0.144993345
1	Hengshui	0.23362258
2	Yangquan	0.206337677
3	Jingtang Port	0.670792346
4	Beijing	0.467186198
5	Shuozhou	0.170671759

Table 3. *Cont.*

	Node	Importance
6	Shanhaiguan	0.189919413
7	Liaocheng	0.237802713
8	Ankang	0.066450504
9	Chifeng	0.312029063
10	Manzhouli	0
11	Nanjing	0.483998803
12	Jiaozuo	0.178951363
13	Handan	0.271262416
	…	
81	Wuhan	0.400494313
82	Tangshan	0.244860113
83	Hohhot	0.140081314

4.3. Calculation of Comprehensive Node Importance Evaluation Value

Based on Equations (15) and (16), the matrix is normalized. According to Equations (17)–(19), the comprehensive importance evaluation value of each node in the coal-iron-water combined transport network is calculated and used as the node importance ranking. Research shows that if 15–20% of the key nodes in a network fail, the network will become paralyzed. Therefore, this paper lists nodes with the top 20% of comprehensive importance, as shown in Table 4.

Table 4. Table of importance ranking of coal-rail-water intermodal transport network nodes (top 20%).

	Node	Degree	Betweenness	Clustering Coefficient	Closeness Centrality	Importance
79	Shanghai	8	0.060963036	0.321428571	0.258566978	0.686753598
42	Tianjin	8	0.199926829	0.25	0.27852349	0.681208111
3	Jingtang Port	5	0.00753872	0.4	0.238505747	0.670792346
21	Ningbo	7	0.039638435	0.285714286	0.251515152	0.625456251
78	Hefei	5	0.076080383	0.3	0.231843575	0.621380689
76	Yuanping	3	0.053550659	0.333333333	0.236467236	0.614669238
17	Qinhuangdao	8	0.114059577	0.214285714	0.255384615	0.581799947
37	Macheng	3	0.007026713	0.333333333	0.198090692	0.571283504
11	Nanjing	5	0.049207013	0.2	0.239884393	0.483998803
16	Nantong	6	0.024352186	0.2	0.228650138	0.482679645
4	Beijing	7	0.357347351	0.047619048	0.284246575	0.467186198
62	Xuzhou	5	0.030384287	0.2	0.222520107	0.464014772
28	Suning	4	0.03107626	0.166666667	0.23782235	0.414215146
81	Wuhan	4	0.038749177	0.166666667	0.220159151	0.400494313
72	Hangzhou	4	0.0199362	0.166666667	0.224932249	0.399612576
33	Jiujiang	4	0.019723843	0.166666667	0.212276215	0.388402187

Finally, the node importance topology is plotted based on the calculation results. The larger and darker the node, the higher its importance. As shown in Figure 5, the comprehensive evaluation results are highly consistent with the complex network topology indicators. Nodes with larger degree and betweenness values are generally more critical and essential and require special protection and maintenance. However, ports like Jingtang Port (3) and Qinhuangdao (17), which have larger maritime transport volumes than rail transport, also need special attention. Furthermore, intermediate nodes like Yuanping (76), Macheng (36), and Suning (28) can't be overlooked. They effectively connect inland coal mines and central railway lines and hold a significant position in the coal transport network.

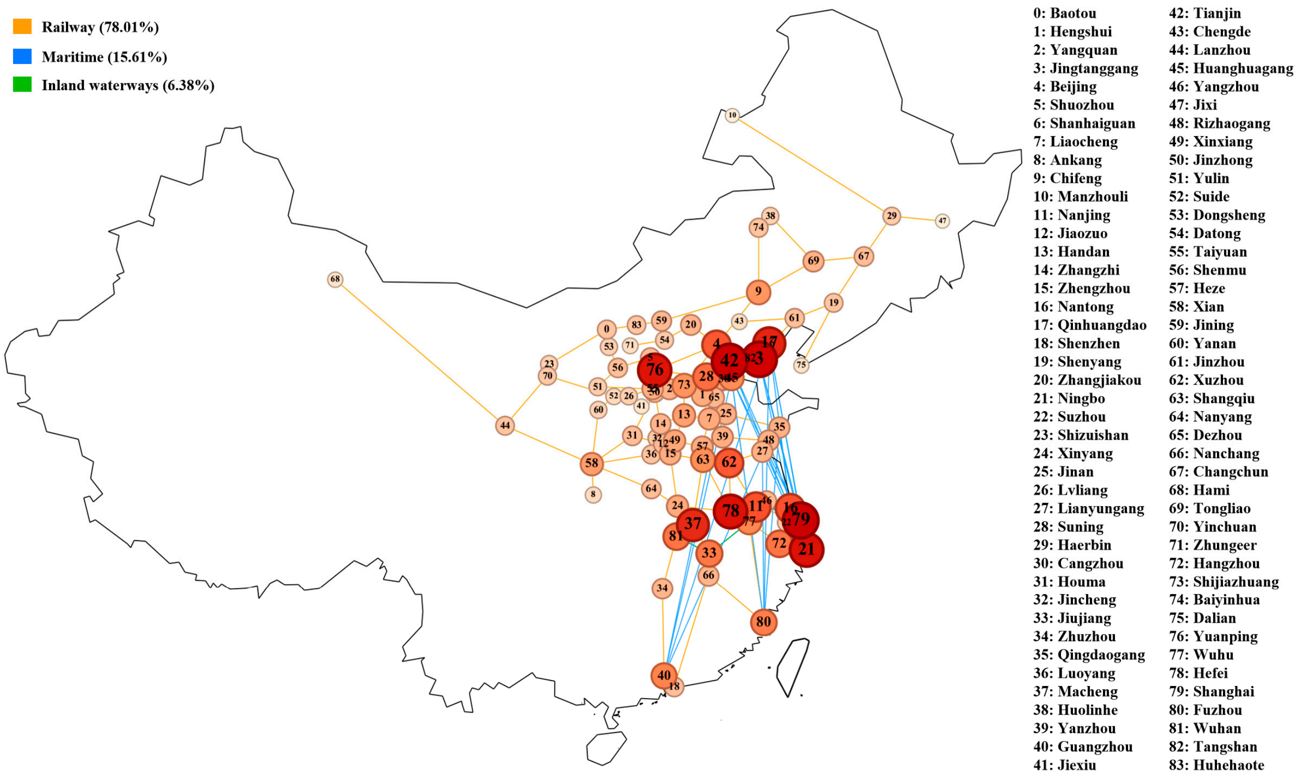

Figure 5. Node importance topology diagram (Using Gephi v0.9.2 with the latitude and longitude from Google Maps).

4.4. Simulation Attack and Performance Analysis

4.4.1. Network Performance Indicators

Network performance indicators reflect the network's operational capabilities. These indicators tend to decline as nodes or edges fail, as reflected in the network's robustness, reliability, resistance to destruction, and vulnerability. While these indicators are independent, they complement each other and are somewhat interconnected. Therefore, studying the changes in these key indicators is crucial for measuring the performance of complex networks.

Robustness, vulnerability, and resistance to destruction: robustness indicates the fault tolerance of the metro network when facing random attacks; vulnerability reflects the survivability of the transport network when targeted, showing the fault tolerance and survival of the stations and the overall network; destruction resistance is the ability of a network to maintain or restore its performance to an acceptable level when deterministic or random failures occur.

Network attack: This often involves simulating random or deliberate attacks to observe the overall network performance's decline after an attack. Random attacks refer to unforeseen major incidents in the metro network, such as equipment failures, force majeure, severe weather conditions, etc.; deliberate attacks are the purposeful human destruction of key nodes. After a node is damaged, adjacent relationships are severed, resulting in isolated points.

The metrics commonly used to describe network performance after node damage include network efficiency, network connectivity, maximum connectivity subgraph, and natural connectivity. Among them, network efficiency and connectivity reflect the utility and connectivity of the network, while maximum connectivity subgraph and natural connectivity reflect the damage resistance and overall operational performance of the network [34].

Network connectivity is the ratio of the number of connected edges l_G formed by the remaining nodes when some nodes in the network fail to the number of connected edges

l_G when the network is intact. The larger the value, the more complete the mesh formed by the remaining nodes and the smaller the network performance loss. The formula can be written as follows:

$$\varphi = \frac{l_G}{l_{G\max}}. \tag{20}$$

Network efficiency reflects the transmission efficiency of the entire network. The higher the value of network efficiency, the lower the transmission difficulty and the higher the transmission efficiency, which can be used to measure network performance. The formula can be written as:

$$E(G) = \frac{1}{N(N-1)} \sum_{i \neq j \neq G} \frac{1}{d_{ij}}. \tag{21}$$

The size of the maximum connected subgraph is the number of nodes in the subgraph that has the highest number of nodes among the various connected subgraphs decomposed from the network. It primarily measures the network's resistance to damage. The larger the value, the more complete the network formed by the remaining nodes and the smaller the network performance loss. The formula can be written as:

$$J = \frac{N'}{N}, \tag{22}$$

where N and N' denote the size of the maximum connected subgraph before and after node damage, i.e., the number of nodes in the maximum connected subgraph formed by the network. The coal-rail-water intermodal network has realized a fully connected subgraph, so the initial N is 84.

The relative maximum connectivity subgraph aims to explain network performance in terms of the network topology level. Since it's a ratio, it can directly characterize the change in network performance. Natural connectivity starts with the internal structural attributes of the complex network and has a clear physical and mathematical meaning, as in the following formula:

$$q = \ln\left(\frac{1}{N} \sum_{i=1}^{N} e^{q_i}\right), \tag{23}$$

where q is the natural connectivity, and q_i is the eigen-root of the network adjacency matrix.

4.4.2. Analysis of the Impact of Deliberate Attacks on Network Performance

Using the method of identifying key nodes mentioned earlier, we observe the extent to which the global performance of the transportation network changes under deliberate attacks on different nodes as follows:

Step 1: Select the top 16 nodes in terms of importance as key nodes;

Step 2: Carry out deliberate attacks on the key nodes in descending order of importance, that is, continuously remove key nodes;

Step 3: Calculate the network performance indicators after removing the nodes;

Step 4: Plot and analyze to obtain the results.

Based on the level of importance, the key nodes calculated in the article are deliberately damaged in ascending order, that is, deliberate attacks, causing them to fail and compromising the network's connectivity performance. Assuming the initial performance is 100%, 16 key nodes are subjected to deliberate attacks, causing node damage and failure. Analyze the relationship between network performance degradation and the number of attacked critical nodes, as shown in Figure 6.

The change in network performance after damage to each node in Figure 6 is not consistent. Critical nodes with higher importance have a greater negative impact on the overall network performance. Network efficiency and network connectivity follow a similar trend in the early stages, dropping quickly to 70%. Afterward, the former continues to rapidly decline to around 40%, while the latter gradually drops to 60%. In comparison, natural connectivity changes faster, and the final network performance remains around 50%. Overall, network efficiency and network connectivity have similar characteristics. Natural connectivity doesn't change much under deliberate destruction, with the decline being relatively steady.

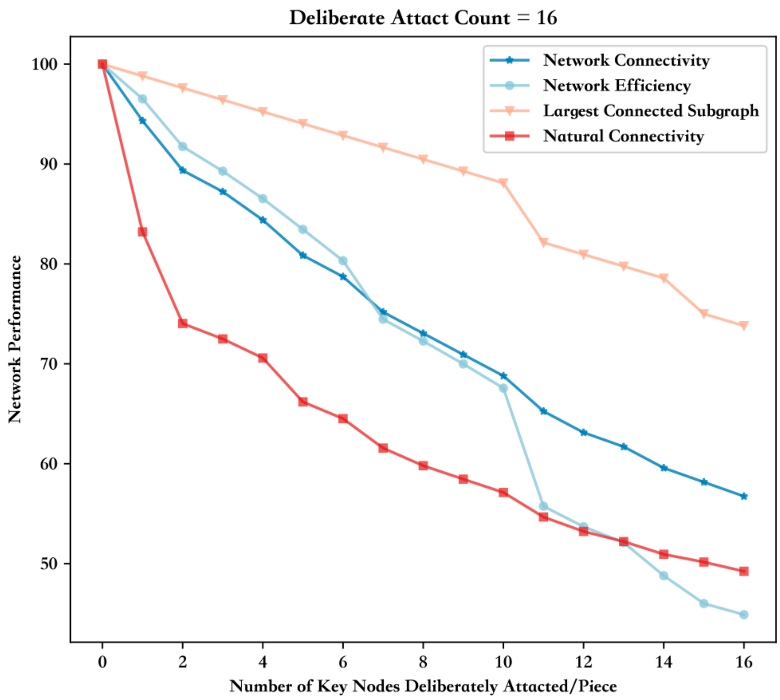

Figure 6. Deliberate attack on key nodes results graph.

4.4.3. Analysis of the Impact of Random Attacks on Network Performance

After focusing on protecting and maintaining 16 critical nodes, we simulated a random attack on the transport network and analyzed the impact of the damage to the remaining 68 common nodes on the overall network performance, as shown in Figure 7.

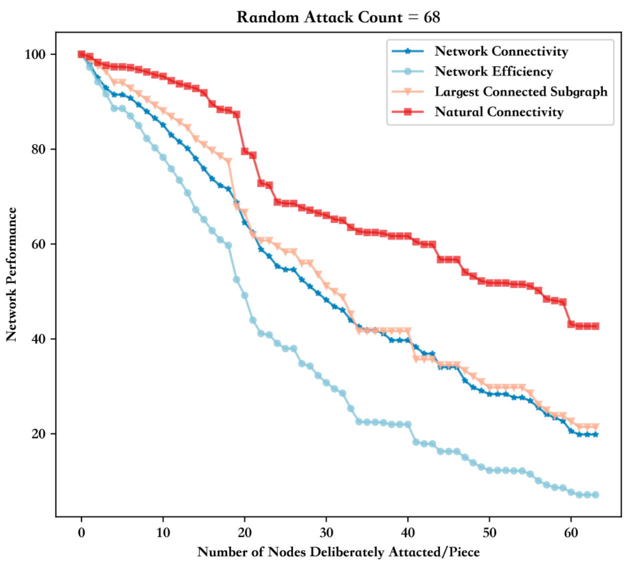

Figure 7. Random attack on key nodes results graph.

From Figure 7, it can be seen that the trends of network efficiency and network connectivity show the same randomness under random attacks. However, after the failure of important nodes, these two indicators show a significant decline. This confirms that the decline in network performance will accelerate with the failure of important nodes. Compared with the network performance changes brought about by deliberate attacks, the decay rate of network performance under random attacks is slower. This also implies that after focusing on protecting and maintaining the key nodes, when nodes in the network fail randomly, the overall performance decline trend will slow down, exhibiting a certain degree of resilience.

From Figure 7, it can be observed that under random attacks, network connectivity and natural connectivity still maintain similar change characteristics, and the overall rate of network performance paralysis remains nearly unchanged, displaying a linearly declining trend. This indicates that the importance of nodes has little effect on connectivity. The decrease in network efficiency and maximum connectivity subgraph is initially faster and then slows down. After maintaining some stability, the largest connected subgraph drops sharply, indicating that after randomly attacking some important nodes, network performance deteriorates significantly. Compared to deliberate attacks, the overall decline rate of network performance is noticeably slower. To reduce the performance to around 50%, nearly 40 stations need to be damaged, whereas, with deliberate attacks, nearly 16 stations can achieve the same effect. This shows that after protecting the key nodes, the network exhibits a certain resilience.

5. Conclusions

Based on complex network theory, this paper constructs a model for key node identification and resilience study in RWCTN and solves the problem of complex network resilience analysis in the context of RWCTN. Specifically, this study first analyzes the network structure and characteristics of RWCTN and establishes a static topological model and diagram of CTN involving maritime and railroad transportation based on complex network theory. It then tackled vulnerability and resilience from network resilience theory, identifying key nodes in the network by developing a node importance evaluation model. Using major domestic railway and waterway coal transportation channels, including the Daqin Line, Shenshuo-Huanghua Line, Taiyuan-Jiaozuo Line, Longhai Line, and Beijing-Kowloon Line, and taking the major cities, coal mines, railway hubs, important coastal ports, and border crossings that these lines pass through and arrive at as nodes, the coal-water-iron transport network topological diagram was constructed using the latitudes and longitudes of each node. The proposed GRE-TOPSIS method is used to identify critical nodes. The effectiveness of the algorithm is verified through deliberate and random attack simulation experiments based on the metrics of network efficiency, network connectivity, maximum connectivity subgraph, and natural connectivity.

The main contributions of this paper include:

- Firstly, introducing the Grey Relational Analysis and entropy weighting method, integrating existing methods to propose an improved GRE-TOPSIS method, and enhancing the objectivity of the TOPSIS method's calculations;
- Secondly, breaking through the analysis of single-medium network performance and studying the iron-water combined transport network, aligning more with China's coal transportation mode;
- Thirdly, this research, based on China's real coal transportation network, evaluates and ranks 84 nodes comprehensively. By analyzing network performance changes through deliberate and random attacks, the effectiveness of the method and its feasibility for application in real-world complex networks have been validated.

The main conclusions and insights derived from this study are:

- Firstly, by constructing a compound network for coal-water-iron transportation, the main coal transport network-related indicators were obtained, including network degree, betweenness centrality, and other topological structure characteristics, as well as network efficiency, network connectivity, and natural connectivity performance indicators. These indicators reveal connectivity issues in the iron-water transportation network, overloads on important nodes, and can guide future construction, development, and planning of iron-water transportation.

- Secondly, the entropy method objectively determines weights based on indicator variance, while the gray relational analysis evaluates the similarity or dissimilarity of development trends between factors. This paper proposes combining gray relational analysis and entropy weighting to calculate weights, enhancing the objectivity of the GRE-TOPSIS method in selecting key nodes and achieving a more accurate and objective calculation of node importance.
- Thirdly, through the comprehensive evaluation system for key nodes in the network, after comprehensive evaluation and ranking of key nodes in the network, it was found that nodes like Yuanping (Node 76), Macheng (Node 36), and Suning (Node 28) may not rank highly based on topological characteristics, but due to their strong freight capacity and connections to central and western parts, they also rank highly in comprehensive evaluations. GRE-TOPSIS can identify these key nodes, providing an essential theoretical reference for targeted protection in practical applications.
- Finally, network performance analysis reveals that network efficiency and maximum connectivity subgraphs, as well as network connectivity and natural connectivity, have similar trends, especially under deliberate attacks. However, after protecting the critical nodes, random attacks on other network nodes greatly reduced network paralysis, proving the effectiveness of the GRE-TOPSIS approach.

In conclusion, coal is a focal point in the energy system. The study of its network can improve the resilience of the RWCTN and contribute to the development of an energy strategy. In the future, based on resilience research, the focus will be extended to optimize network resilience so as to improve the overall resilience of the RWCTN and enhance its anti-interference ability.

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