Key Node Identification and Toughness Analysis of China Railway Express Transportation Network

Dongdong Tong, Xiangfei Yang

***Abstract*—The Chin-Europe Railway Express transportation network (CRETN) is a core component of the "Belt and Road Initiative". The identification of its key nodes and toughness assessment are crucial for enhancing the network's risk resistance capacity. This study proposes a key node identification method based on the CRITIC-TOPSIS method, comprehensively evaluates the importance of nodes by combining multiple indicators such as degree centrality and betweenness centrality, and constructs a dynamic toughness assessment model to quantitatively analyze the impact of attack and recovery strategies on network performance. Research shows that: (1) The network density (0.0037) and efficiency (0.0511) of the CRETN are relatively low, presenting a sparse structure and inefficient information transmission; (2) The CRITIC-TOPSIS method can effectively identify key hubs such as Xi 'an and Moscow. Its failure will lead to a sharp decline in network toughness (the minimum toughness of the IARR model is 0.1938). (3) Prioritizing the recovery of the IR mode of key nodes can significantly enhance toughness (the toughness of the JAIR mode can reach up to 1). It is suggested to strengthen the protection of key nodes and the connection between stations in the CRETN, providing theoretical support for network optimization.**

***Index Terms*—the Belt and Road Initiative, China Railway Express, toughness evaluation, key node identification, CRITIC-TOPSIS method**

I. Introduction

As a core component of the country's "Belt and Road Initiative", the China-Europe Railway Express (CRE) has become a key land transportation channel connecting the Eurasian continent. As of 2022, it has operated over 60,000 trains in total, covering more than 200 cities in 24 European countries, and has undertaken 76% of the land transportation volume of trade between China and Europe. However, the CRE is gradually forming a network layout of "trunk and branch lines combined, hub and distribution", which has a relatively high operational efficiency but poor risk resistance. Meanwhile, in recent years, sudden events such as geopolitical conflicts (such as the Russia-Ukraine war) and natural disasters have occurred frequently. This has led to a sharp increase in the risk of failure at key nodes, for instance, in 2022, the civil unrest in Kazakhstan caused over 300 trains to be stranded at the Alashankou Port, resulting in direct economic losses of 210 million US dollars. This exposes the vulnerability of the CRE network, which is characterized by "strong hub dependence and insufficient route redundancy". There is an urgent need to enhance the network's risk resistance capacity by scientifically identifying key nodes and quantifying the toughness level.

The essence of the CRETN is transportation network, and a large number of scholars have done depth research on the application of complex networks in transportation networks, including network structure analysis, key node identification and toughness research. Effective analysis of network structure is of great significance for reasonable planning and development of network. Qian et al. (2024) studied the structure and evolution of the China Railway Express network, and found that the network has small-world and scale-free characteristics, which provides reference for the construction of the CRETN in this study; Li et al. (2024) analyzed the topological attributes of three different networks: aviation network, traffic flow network, and time-delayed propagation network and discussed the interrelationships between attributes. Wang et al. (2022) improved node degree, considered the influence of neighbor nodes, proposed a new network topology importance evaluation model and proved the validity of the model. Existing studies have analyzed the common structural characteristics of various networks, but have not revealed their correlation with toughness, and the overall evaluation of the networks is lacking.

Key nodes are the core of network operation, and effective identification of key nodes can alleviate or even avoid the impact caused by network fluctuation. Wang et al. (2024) proposed an improved weighted K-shell model to identify key nodes of multimodal transport network in combination with network topology and traffic demand. Zhang et al. (2024) proposed a comprehensive voting rating (CVR) algorithm to identify key stations of Shanghai City subway network and verified the effectiveness of the method Wang et al. (2021) proposed a new key node identification method based on TOPSIS method in combination with the topological structure and industry characteristics of air cargo network, which provides a reference for the construction of CRITIC-TOPSIS evaluation model in this study. All the existing methods for identifying key nodes remain at the static index level and lack consideration of dynamic failure scenarios.

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Toughness was firstly proposed by Holling et al. (1973), and then gradually extended to various fields. In terms of transportation network, network toughness is studied by simulation attack with the help of complex network theory; Ma et al. (2022) proposed a multi-dimensional evaluation model, considering multi-source data to evaluate urban rail transit network toughness and reduce URT time risk. Hou et al. (2024) analyzed the toughness of rail transit network after earthquake, and concluded that the protection of important units can increase the network seismic resistance, but cannot effectively improve the network toughness and recovery ability. Wang et al. (2024) formulated the urban road network toughness optimization strategy under traffic accidents based on the toughness triangular framework, optimized the elastic loss and improved the network toughness. Yang et al. (2024) constructed a rainfall model based on data-driven and infiltration theory, proposed a method for evaluating and improving road network toughness under rainfall, and verified the feasibility and novelty of the method by taking the British East Midlands Highway Network as an object. However, all kinds of traffic network research focus on single angle, pay less attention to the overall analysis of the network, and lack of integrity and coherence of network research. Overall, most of the existing study adopts a single indicator to evaluate the importance of nodes, ignoring the coupling influence of multiple attributes. The research on the toughness of the network focuses on static assessment, lacking the dynamic simulation of "attack - recovery", and has not formed a closed-loop structure of "structural analysis - node identification - toughness optimization", lacking integrity.

This study breaks through the limitations of traditional single-dimensional analysis and realizes a trinity research framework of "topological structure - key nodes - dynamic toughness" firstly. By combining the objective weighting of CRITIC with the multi-attribute decision-making of TOPSIS, a key node identification model of CRITIC-TOPSIS is constructed, and the influence of nodes is quantified by indicators such as degree centrality and betweenness centrality. Meanwhile, based on the toughness triangle theory, three indicators, namely network connectivity rate, efficiency and the average number of independent paths, are introduced to simulate the toughness evolution under deliberate and random attacks and different recovery strategies. The accuracy of the identification model is verified through the failure experiments of key nodes, and accordingly, the toughness improvement strategy is proposed. The achievements can provide the operation department of the CRE with a list of key hub hierarchical protection and the optimal recovery path method, and offer a basis for network redundancy optimization, contributing to the security and stability of the supply chain along the Belt and Road Initiative.

II. Transportation Network Construction And Node Importance Evaluation Methods

A. Construction of the China Railway Express transportation network

The study uses Space-L model which can reflect the actual spatial characteristics of the network to construct the CRETN. Taking the cities of the CRE route cities as nodes, if there is a channel between two cities, there is a connecting edge between the nodes. Considering the actual situation, transportation between cities can be carried out in both directions. Therefore, the CRETN is constructed as a non-directional network, that is, bidirectional transportation and information transmission can be realized between nodes.

B. Evaluation method of node importance

The structure of the CRETN is complex, and it is difficult to evaluate the nodes objectively and comprehensively by using a single evaluation index and evaluation method. This paper proposes a CRITIC-TOPSIS evaluation method to evaluate the importance of the nodes in the CRETN. The specific steps are as follows:

Step1: Construct the CRETN, select appropriate node importance evaluation indexes and calculate them.

Step2: Use CRITIC method to weight the evaluation indexes of each node importance.

Step3: Using TOPSIS method, combined with the weights calculated by CRITIC method, calculate the importance evaluation value of nodes and determine the importance ranking of nodes.

The specific flow of the evaluation method is shown in Figure 1.

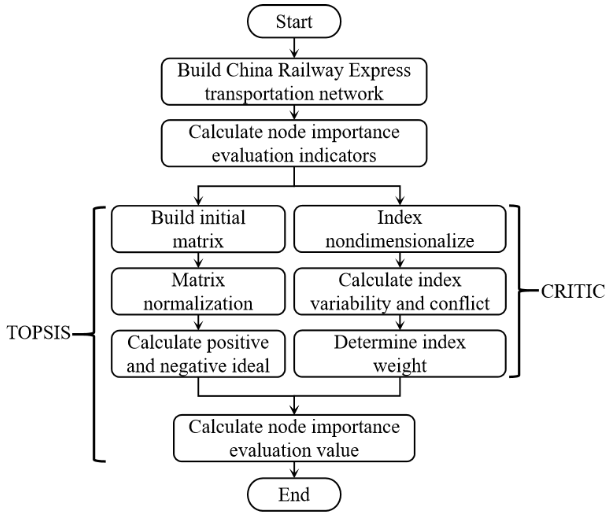


Fig. 1. Identification process of key nodes in the China Railway Express transportation network

Selection of node importance evaluation indexes

There are many indexes for evaluating node importance, such as betweenness, degree value, network constraints, etc. Different indexes represent different meanings, and different indexes are used differently in different networks. At the same time, a single index is difficult to reflect the importance of network nodes comprehensively and realistically. In order to measure the importance of nodes in the CRETN more reasonably, based on complex networks theory, four evaluation indexes of node importance are selected from the aspects of node itself, its influence on neighboring nodes and the whole network, namely degree centrality, betweenness centrality, near-centrality and eigenvector centrality. Among them, degree centrality measures the degree of connection between nodes and other nodes, and is the most direct index to describe node centrality. The higher degree centrality is, the more important node is. Betweenness centrality shows the bridging and mediating function of nodes. The higher the betweenness centrality, the better the transfer function of nodes and the more important nodes are. Closeness centrality measures the distance between nodes and other nodes, that is, the speed of information transmission. The higher the closeness centrality, the shorter the distance between nodes and other nodes, the faster the information transmission, the higher the network efficiency, and the more important the nodes. Eigenvector centrality reflects the transfer influence between nodes and the connectivity of the network. Considering the relationship between nodes and neighbors, the higher the eigenvector centrality, the more important the neighbors and the more important the nodes. The calculation formulas of each index are shown in Table 1.

CRITIC-TOPSIS method

CRITIC method is an objective weighting method proposed by Diakoulaki, which is suitable for determining attribute weights in multi-attribute decision making problems (Zhang et al., 2015; Lin et al., 2018). This method mainly determines objective weights of indicators by comparing strength and conflict between indexes (Wang et al., 2017). TOPSIS method is a multi-attribute comprehensive evaluation method, which was first proposed by C. L. Hwang and K. Yoon in 1981. It is used to compare the distance between the evaluation object and the positive and negative ideal solutions and rank them, so it is also called the approximate ideal solution ranking method (Arslan, 2017). This method can make full use of the original information and accurately reflect the gap between the solutions through the distance to the positive and negative ideal solutions.

Traditional TOPSIS method fails to consider the contribution of each index to the scheme, but in complex networks, the contribution of different indexes to the evaluation of node importance is different (Feng et al., 2022), and different indexes of the network are closely related and influence each other. CRITIC method pays attention to the interaction between attributes, which can clearly measure the correlation of different indexes, and give objective weights to different indexes to measure the contribution of different indexes. Therefore, this paper proposes TOPSIS method based on CRITIC method weighting. CRITIC method is used to evaluate the contribution degree of different indicators from the network structure nature, and then TOPSIS method is used to calculate the importance of nodes in the network and evaluate the importance of different nodes in the Central European train transportation network. The specific steps of CRITIC-TOPSIS method are as follows:

Step1: Evaluation index weight determination

1) Construct initial matrix

In the CRETN, assuming that the number of network nodes is N, the number of node importance evaluation indexes is M, and the evaluation index value of each node is x_{ij} (i = 1, 2, 3, ..., N; j = 1, 2, 3, ..., M), the initial matrix X is obtained, that is:

$$X = \left(x_{ij}\right)_{N\times M} = \begin{bmatrix} x_{11} & \cdots & x_{1M} \\ \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{NM} \end{bmatrix} \tag{5}$$

2) dimensionless index

In order to eliminate the influence of dimensionality on evaluation results, dimensionless treatment is carried out on each index of initial matrix X, namely:

Positive indexes:

$$x'_{ij} = \frac{x_{ij} - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{6}$$

Negative indexes:

$$x'_{ij} = \frac{\max\left(x_j\right) - x_{ij}}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{7}$$

3) Calculating Index Variability and Conflicts

(1) Index variability

The standard deviation is used to express the fluctuation of the internal value of each index, which is expressed as:

$$\bar{x}_j = \frac{1}{N}\sum_{i=1}^{N} x_{ij} \tag{8}$$

$$S_j = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_{ij} - \bar{x}_j\right)^2} \tag{9}$$

Where: $\bar{x}_j$ is the mean value of the j evaluation index; S_j is the standard deviation of the j evaluation index, the larger the standard deviation, the greater the difference in the value of the index, the more information can be projected, the stronger the evaluation strength of the index itself, and the more weight allocated to the indicator.

(2) Index Conflict

The correlation coefficient is used to express the correlation between the indexes. The stronger the correlation with other indexes, the smaller the conflict between this

TABLE I
INDICATOR FORMULA

Index	Formula	Parameter meaning
betweenness centrality	$BC_i = \sum_{s\neq i\neq t} \frac{n_{st}^i}{g_{st}}$ (1)	n_{st}^i —The number of shortest paths passing through node i; g_{st} —The number of shortest paths connecting nodes s and t;
degree centrality	$DC_i = \frac{k_i}{N-1}$ (2)	k_i —The number of edges connected to node i; N —The number of nodes in the network;
closeness centrality	$CC_i = \frac{N-1}{\sum_{j=1}^{N} d_{ij}}$ (3)	d_{ij} —Distance from node i to node j;
eigenvector centrality	$EC_i = \frac{1}{\lambda}\sum_{j=1}^{N} a_{ij}x_j$ (4)	a_{ij} —The weight of an arc that starts at i and ends at j; λ —The maximum eigenvalue of the network adjacency matrix;

indicator and other indicators. It is expressed as:

$$R_j = \sum_{i=1}^{N}\left(1-r_{ij}\right) \quad i \neq j \tag{10}$$

Where: r_{ij} represents the correlation coefficient between the evaluation indexes i and j. The larger r_{ij}, the smaller R_j, the smaller the conflict, reflecting, the more the same information is reflected, the more the evaluation content can be reflected, and to a certain extent, the evaluation intensity of the index is weakened, and the weight assigned to the index is less.

4) Calculation of index information and weight

(1) Amount of information

The information content of an index is the product of index variability and index conflict. The greater the information content of an index, the greater the role of the index in the whole evaluation index system and the more the assigned weight. It is expressed as:

$$C_j = S_j \sum_{i=1}^{N}\left(1-r_{ij}\right) \quad i \neq j \quad j=1,2,\cdots,M \tag{11}$$

(2) Weight

The objective weight of an indicator is the ratio of the information amount of the indicator to the total information amount. The higher the weight, the stronger the importance of the indicator. It is expressed as:

$$W_j = \frac{C_j}{\sum_{j=1}^{M} C_j} \quad j = 1,2,\cdots,M \tag{12}$$

Step2: Calculation of Comprehensive Evaluation Index by TOPSIS Method

1) Combined with the index weights, a standardized weighting matrix Z is constructed. It is expressed as:

$$Z = \left[Z_{ij}\right]_{N\times M} = \left[x'_{ij} \times W_j\right]_{N\times M} \tag{13}$$

2) Calculate positive and negative ideal solutions

Compute the maximum and minimum values of each metric to determine the positive ideal solution Z^+, and the negative ideal solution Z^-, that is:

$$Z^+ = \max\left\{z_{1j}, z_{2j}, \cdots, z_{Nj}\right\} \quad j = 1,2,\cdots,M \tag{14}$$

$$Z^- = \min\left\{z_{1j}, z_{2j}, \cdots, z_{Nj}\right\} \quad j = 1,2,\cdots,M \tag{15}$$

3) Calculate the distance

Calculate the distance of each node from the positive ideal solution and the negative ideal solution, that is.:

$$D_i^+ = \sqrt{\sum_{j=1}^{M} \mathrm{W}_j \left(Z_j^+ - z_{ij}\right)^2} \tag{16}$$

$$D_i^- = \sqrt{\sum_{j=1}^{M} W_j \left(Z_j^- - z_{ij}\right)^2} \tag{17}$$

4) Calculate node importance evaluation value

The score of each node is calculated as the importance evaluation value of the node, namely:

$$T_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad , \quad T_i \in [0, 1] \tag{18}$$

where the greater the D_i^- value, the farther the i node is from the worst solution, the greater the comprehensive evaluation index T_i value of the node, the higher the importance of nodes in the network.

III. Network Toughness Assessment Methodology

Toughness assessment of the CRETN includes four stages: initial phase, attack phase, recovery phase and stabilization phase. Each attack or recovery stage is a unit time. State changes of the CRETN is shown in Fig. 2.

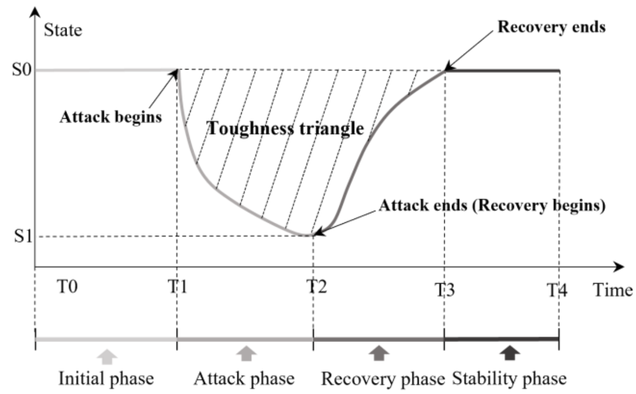


Fig. 2. State of the China Railway Express transportation network

1) Initial phase

T0-T1, the China Railway Express transport network is not subject to fluctuations, and is in a static state, with stable network structure and efficiency.

2) Attack phase

T1-T2, the CRETN is attacked, and there are two main attack modes: deliberate attack and random attack. Deliberate attack simulates the impact on the network due to operational accidents, deliberate strikes and regional conflicts, including three attack strategies: degree attack (DA), median attack (JA) and importance attack (IA); random attack (RA) reflects the impact on the network due to various natural disasters and other random factors, and randomly ranks the network nodes, and then deletes them to simulate the nodes failing due to attacks. The nodes are randomly sorted and then sequentially deleted to simulate the failure of nodes under attack.

3) Recovery Phase

T2-T3, the attack is over, the CRETN is restored, and there are two recovery methods: deliberate recovery and random recovery. Deliberate recovery simulates the situation where nodes regain their functions due to human involvement, and includes the three recovery strategies of degree recovery (DR), centroid recovery (CR), and importance recovery (IR); random recovery (RR) indicates the situation where nodes regain their abilities due to the network's own recovery ability, and due to the unknown nature of the recovery, the nodes of the network are randomly sorted and then recovered sequentially.

4) Stabilization phase

Recovery ends, the network reaches stability, and the properties of the entire network are consistent with the initial state of the network. the recovery capacity, absorptive capacity and buffering capacity of the whole process network were calculated statistically, and the spatial vector method was used to calculate the toughness of the network under each mode.

A. Toughness assessment indicators

1) Recovery capacity

Recovery capacity refers to the ability of a network to adjust and adapt to and be able to quickly recover to the normal level after being attacked. The network connectivity ratio is the ratio of the maximum connected subgraph size to the total number of nodes in the original network, reflecting the topology change after the network suffers from an attack, and the larger the value indicates that the network has better connectivity and stronger recovery capacity (Li et al., 2019). Therefore, the network connectivity is used to characterize the recovery capacity, denoted as:

$$C(t)=\frac{M(t)}{n} \tag{19}$$

Where: $M(t)$ is the size of the maximum connected subgraph of the network at moment t, and n is the number of network nodes at the initial moment.

2) Absorptive capacity

Absorption capacity refers to the ability to resist the reduction of network level after the network is attacked. Network efficiency reflects the information transfer performance of network nodes, the higher the network efficiency, the stronger the network transferability, the faster it can reflect to external stimuli and resist the reduction of the network operation level. Therefore, the network efficiency is used to characterize the absorption capacity, expressed as:

$$E(t)=\frac{\sum_{i\neq j\in G}\frac{1}{d_{i,j}(t)}}{N(t)\left(N(t)-1\right)} \tag{20}$$

Where: G is the set of neighboring nodes of the node V_i, $N(t)$ is the number of nodes in the network at time t, $d_{i,j}(t)$ is the shortest path length from the node V_i to the node V_j at time t.

3) Buffering capacity

Buffering capacity refers to the ability of a network to quickly adapt and be able to improve the reduced level of operation of the network due to an attack by choosing alternative paths to reach the target (Stubbs et al., 2018; Ma et al., 2023). The average number of independent paths in the network can characterize the buffering capacity, denoted as:

$$P(t)=\frac{\sum_{i\neq j\in G}\mathrm{I}_{i,j}(t)}{N(t)\left(N(t)-1\right)} \tag{21}$$

Where: $I_{i,j}(t)$ is the number of independent paths between node V_i and node V_j at time t.

4) Toughness index

From the theory of toughness triangle, it is known that improving the performance of the system, or reducing the time of network recovery, can reduce the area of the toughness triangle, thus improving the toughness of the network (Wang et al., 2023). In this paper, we characterize the different toughness of the network in terms of the degree of change of the three capabilities over time as the network undergoes the destruction and recovery phases, and the larger each toughness indicator is, and the smaller the area of the toughness triangle is in that interval, the greater the toughness of the network is. Three toughness metrics are denoted as:

$$R_C=\int_0^t C(t)dt \tag{22}$$

$$R_E=\int_0^t E(t)dt \tag{23}$$

$$R_P=\int_0^t P(t)dt \tag{24}$$

B. Global toughness assessment

Recovery capacity (R_C), absorptive capacity (R_E), and buffering capacity (R_P) are important indicators to measure the network structure toughness, and all three are positive indicators. By analyzing the physical structure characteristics and service efficiency of the CRETN, using the network stress test method, corresponding weights are assigned to the evaluation indicators and placed in the same spatial coordinate system. Through the method of spatial vector superposition, the toughness vector of the CRETN is obtained. Finally, the modulus of the toughness vector is taken as the network toughness value. This reflects the toughness level of the network under different attack and recovery modes (Ma et al., 2022; Ji et al., 2019). The specific relationship between the three indicators and toughness is shown in Figure 3.

Toughness of the CRETN can be expressed as follows:

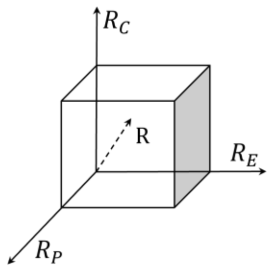


Fig. 3. Toughness evaluation model of the China Railway Express transportation network

$$R=\sqrt{\theta_1 R_C^{\ 2}+\theta_2 R_E^{\ 2}+\theta_3 R_P^{\ 2}} \tag{25}$$

Where, θ_1, θ_2, θ_3 are the weights of recovery capacity (R_C), absorptive capacity (R_E), and buffering capacity (R_P) (Ma et al., 2022). Because the network index will have a certain impact on the toughness R, in order to clearly analyze the impact of different indicators, the normalization of each indicator is carried out.

IV. Example Analysis

A. The China Railway Express transportation network construction

In order to reflect the latest dynamics of the operation of China Railway Express, this study obtains the line situation of each liner train as of November 2022 from the official website of the "Belt and Road Initiative" and the China Railway Express Branch of China Railway Lanzhou Group Co., LTD., and constructs the CRETN, which contains a total of 583 city nodes and 627 edges. Each node is numbered, and the latitude and longitude data of each city is obtained by using Gaode map, and Gephi is used to visualize the transport network of China Railway Express using Fruchterman Reingold (FR) layout and Geo Layout-Map of Countries (GM) layout respectively, and the results are shown in Fig. 4, with the FR layout on the left and the GM layout on the right. From the FR layout, the relative position of each node in the network can be seen, and several cities with large degree values, such as Xi'an, Moscow, Lanzhou, Warsaw, etc., can be clearly seen. From the GM layout, the specific geographic location and relative distance of each node can be seen, as well as the relationship between clusters and groups in the CRETN.

B. Topology analysis of the China Railway Express transportation network

Node topology characterization

The topological characteristics of each node in the CRETN are shown in Fig. 5. The degree value of 80% of the nodes in the CRETN is distributed between 1-2, the median is distributed between 2-3, the degree centrality and eigenvector centrality are concentrated around 0.1, and the distance centrality is concentrated around 0.3, which indicates that most of the nodes in the network are more dispersed, which has less influence on the overall efficiency of the network, and the network is more decentralized. Among them, Xi'an, Jining, Moscow, Warsaw and other city sites have higher topological characteristics at the same time, Xi'an has the highest degree value and eigenvector centrality, and Moscow has the highest median, which is of great utility in the network; Rome, Munich, Lyon and Madrid have the lowest topological indexes in the network, and their utility in the network is lower.

Network topology characterization

The topological characteristic indexes of the CRETN are shown in Table 2. The CRETN has 583 nodes, 627 edges, and the network density is 0.0037, indicating that the CRETN is relatively sparse. The average distance of the network is 34.4171, indicating that any two cities in the network need to pass through 34 cities to reach each other, while the efficiency of the network is 0.05117, which means that the distance between the nodes of the network is larger, the speed of information transfer and exchange is slower, the efficiency

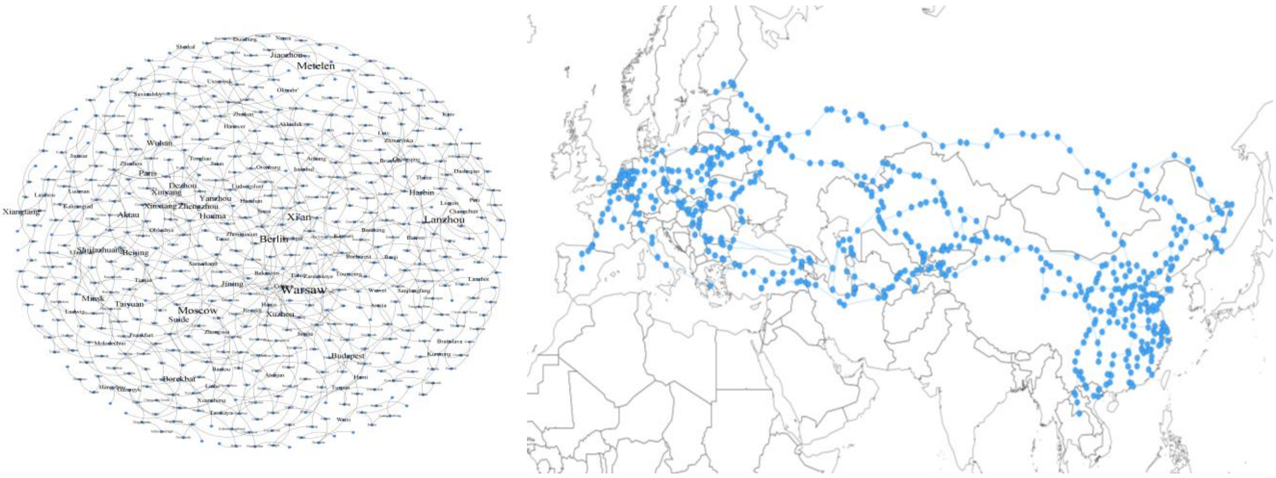
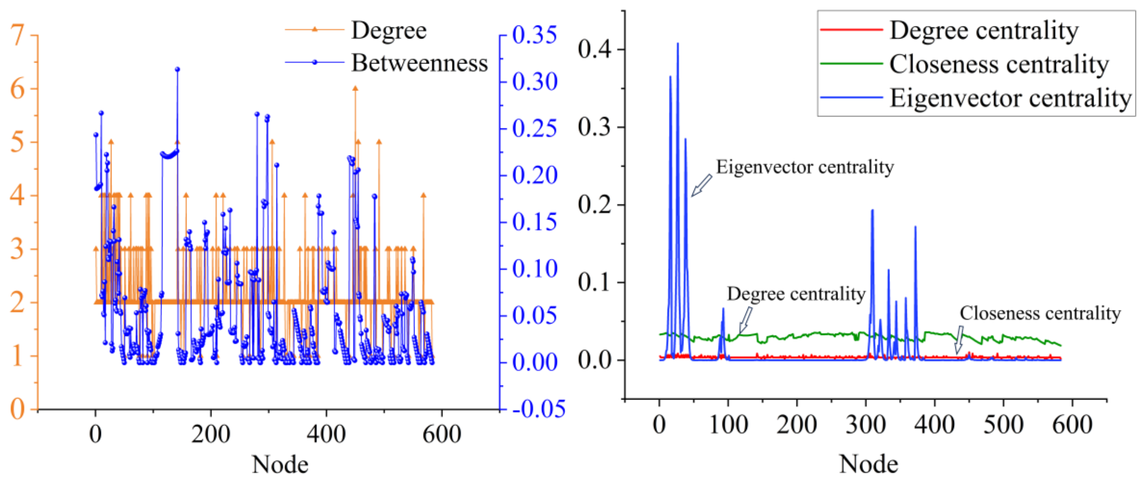


Fig. 4. Topology diagram of China Railway Express transportation network



(a) Degree and betweenness

(b) Centrality

Fig. 5. Topological properties of nodes in the China Railway Express transportation network

TABLE 2
PARAMETERS OF THE CHINA RAILWAY EXPRESS TRANSPORTATION NETWORK

Index	Value	Index	Value
network size	583	network mean distance	34.4171
edge quantity	627	network clustering coefficient	0
network density	0.0037	average number of independent paths on a network	1.4512
network efficiency	0.0511		

of the network is reduced, and the stability of the network as a whole is poor.

The clustering coefficient of the network is 0, which means that the nodes in the network do not form a close community and the network is more decentralized; the average number of independent paths in the network is 1.4512, which says that the number of independent paths between the nodes in the people's network is approximated to be 1, which further indicates that the network is less stable.

C. CRITIC-TOPSIS based identification of key nodes in the China Railway Express transportation network

According to the constructed transport network of China Railway Express, from equation (1)-equation (4), the degree centrality, median centrality, proximity centrality, and eigenvector centrality of each node in the network are calculated by calling Networkx through Python to get the node importance evaluation index data. On the basis of obtaining the index data of each node, the initial matrix is constructed and normalized to obtain the standardized decision matrix Z.

$$Z=\begin{vmatrix} 0.055272 & 0.114323 & 0.045869 & 3.912986e-06 \\ 0.036848 & 0.087339 & 0.046023 & 7.840203e-06 \\ 0.036848 & 0.087536 & 0.046208 & 1.874180e-05 \\ \vdots & \vdots & \vdots & \vdots \\ 0.036848 & 0.003220 & 0.027086 & 4.811927e-08 \\ 0.036848 & 0.001613 & 0.026570 & 2.368250e-08 \\ 0.018424 & 0.000000 & 0.026072 & 9.733634e-09 \end{vmatrix}$$

The weights of each indicator were calculated by Python programming using the CRITIC method. The corresponding weights of each indicator are 1) degree centrality: 0.1861; 2) betweenness centrality: 0.2317; 3) closeness centrality: 0.3815; and 4) eigenvector centrality: 0.2007. The weights of each indicator computed by CRITIC are brought into the corresponding decision matrix Z of TOPSIS to compute the importance rating value of each node and used as the node's importance ranking. Studies have shown that when about 5% of the key nodes in a network fail, the network faces paralysis (Rek et al., 2002). Therefore, this paper lists the data of nodes with top 5% importance ranking and the results are shown in Table 3.

As can be seen from Table 3, the top 5% of key nodes in the CRETN are mainly distributed in China, Russia, Germany, Poland and Belarus, of which more than 70% of the key nodes are distributed in China. Xi'an, Zhengzhou and other nodes have become the hub cities of the China Railway Express with superior geographic location, and these nodes occupy an important position in CRETN. Effective management and protection measures should be taken for these key nodes to ensure the safe and smooth operation of China Railway Express and improve the overall toughness of CRETN, as well as to strengthen the construction of infrastructure and accelerate the construction of an efficient transport. The national policy promotes the strengthening of infrastructure construction, accelerates the construction of efficient transportation organization system, and promotes the high-quality and high-level development of China Railway Express (Feng et al., 2022).

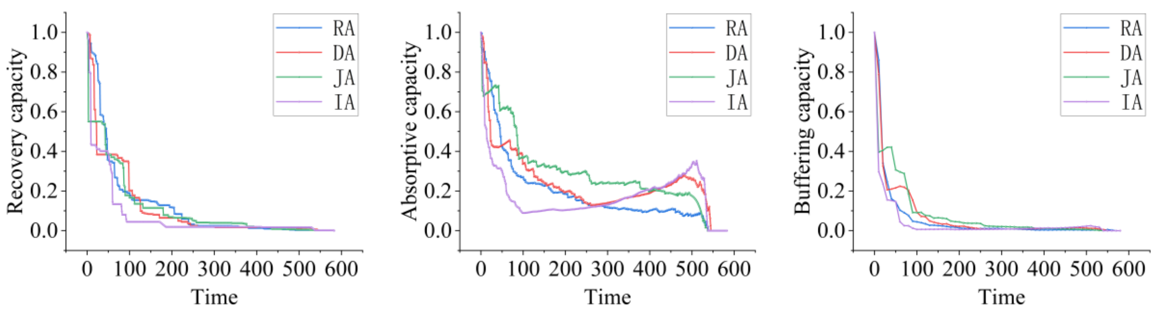
D. Toughness assessment of the China Railway Express transportation network

Analysis of the CRETN in the attack phase

In order to verify the effectiveness of the CRITIC-TOPSIS critical node identification method proposed in this paper as well as to reasonably assess the toughness of the CRETN, random and deliberate attacks are carried out on the CRETN, and by default the attack stops when no node exists in the network. Under the four attack modes of random, degree,

TABLE 3
RANKING OF THE IMPORTANCE OF NODES IN THE CHINA RAILWAY EXPRESS TRANSPORTATION NETWORK

ID	City	Importance degree	Ranking	ID	City	Importance degree	Ranking
27	Xi'an	0.8124	1	24	Suide	0.2828	16
16	Houma	0.7388	2	10	Jining	0.2818	17
26	Zhongjiacun	0.6776	3	450	Warsaw	0.2771	18
17	Huashan	0.6458	4	37	Tangyin	0.2716	19
38	Xinxiang	0.6395	5	280	Turpan	0.2627	20
39	Zhengzhou	0.5505	6	298	Hami	0.2609	21
309	Baoji	0.4373	7	333	Heze	0.2598	22
28	Ankang	0.4286	8	455	Berlin	0.2538	23
310	Luoyang	0.4101	9	297	Yadong	0.2494	24
372	Shangluo	0.3844	10	1	Ulan-Ude	0.2468	25
15	Jiexiu	0.3370	11	446	Minsk	0.2439	26
25	Yan'an	0.3328	12	19	Baotou	0.2381	27
41	Xinyang	0.3236	13	311	Shangqiu	0.2375	28
142	Moscow	0.3141	14	42	Wuhan	0.2365	29
40	Luohe	0.2848	15	373	Nanyang	0.2330	30



(a) Recovery capacity (b) Absorptive capacity (c) Buffering capacity

Fig. 6. Network toughness indexes change under four attack modes

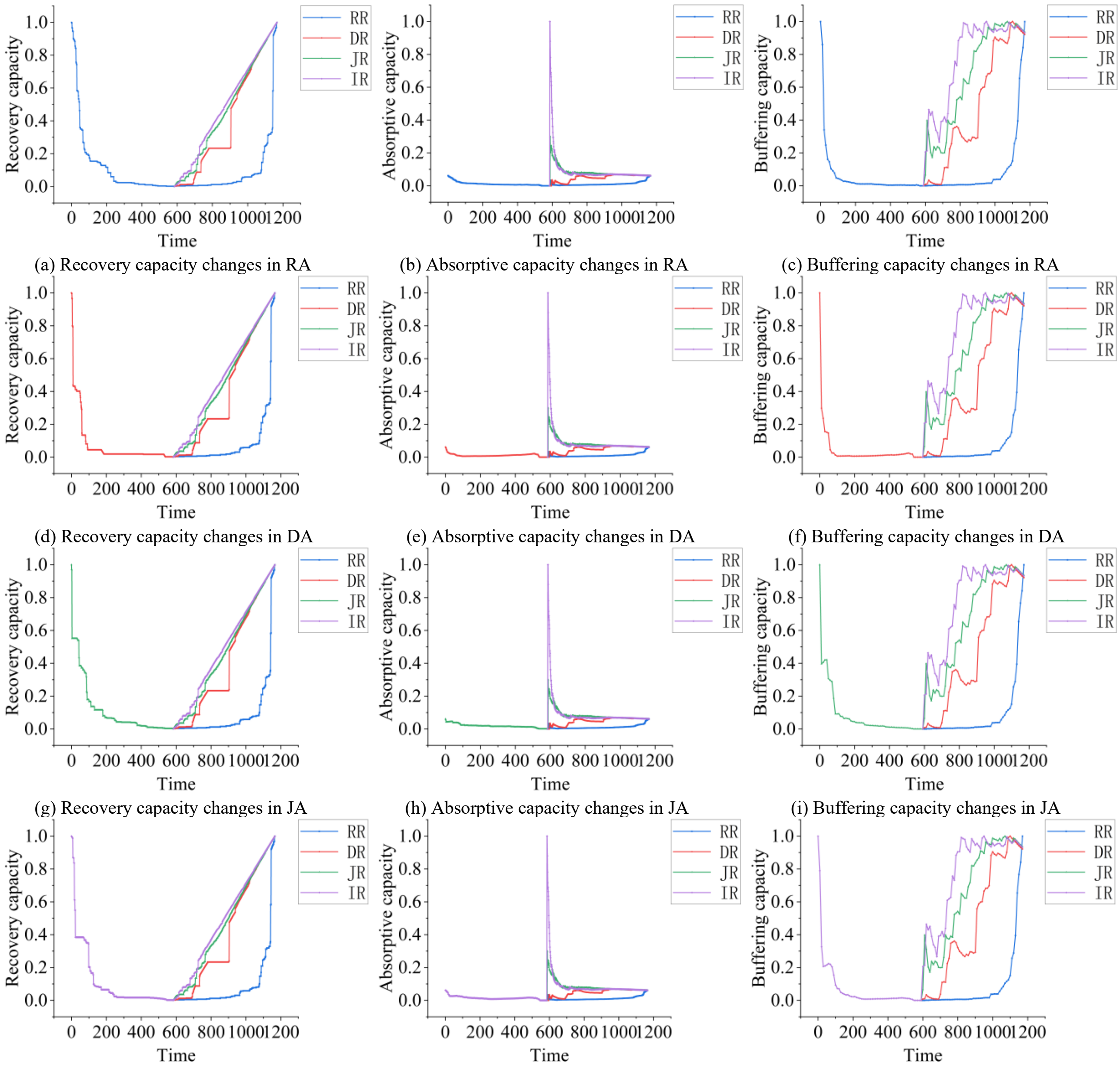
median and criticality, the changes of the three indicators of recovery capacity, absorptive capacity and buffering capacity of CRETN are shown in Fig. 6.

As can be seen from Fig. 6, recovery capacity and buffering capacity of the CRETN decrease the fastest when it suffers from IA attack, and the slowest when it suffers from JA attack. When subjected to IA attack, when the attack time is 257 units, recovery capacity of the CRETN basically decreases to 0. When the attack time is 103 units, buffering capacity of the CRETN basically decreases to 0, and the network is completely paralyzed. When subjected to DA attack and IA attack, absorptive capacity of the CRETN are both rapidly declining first, and the IA attack declines more quickly, then when the damage nodes reach about 90%, the network efficiency appears to be transiently rebounded phenomenon and then rapidly reduces to 0, which is different from the phenomenon of gradual decline of RA and JA, which is due to the fact that the structure of the CRETN is more decentralized, and the initial network efficiency is relatively low, and at the beginning of the damage, the network is relatively stable, but when less than 10% of the network stations are left, the lines between the network are reduced at a slower speed, resulting in a sudden increase in network efficiency until the stations are destroyed one after another, and the network efficiency plummets to 0 again.

The performance of each index of the CRETN under different attack modes is highly differentiated, showing the vulnerability of the network when subjected to IA attacks, with a huge drop in each index and poor resistance to attacks, which is sufficient to show that according to the sabotage of key nodes identified by CRITIC-TOPSIS, it is very destructive to the network, i.e., the identified key nodes affect the whole network in a more generalized and efficient, confirming the effectiveness of the CRITIC-TOPSIS method.

Analysis of the CRETN in the recovery phase

Fig. 7 shows the change curves of recovery capacity, absorptive capacity, and buffering capacity during the process of the CRETN suffering from four modes of attack RA, DA, JA and IA and then recovering to the initial network with four modes of RR, DR, JR and IR. By default, the



(a) Recovery capacity changes in RA (b) Absorptive capacity changes in RA (c) Buffering capacity changes in RA

(d) Recovery capacity changes in DA (e) Absorptive capacity changes in DA (f) Buffering capacity changes in DA

(g) Recovery capacity changes in JA (h) Absorptive capacity changes in JA (i) Buffering capacity changes in JA

(j) Recovery capacity changes in IA (k) Absorptive capacity changes in IA (l) Buffering capacity changes in IA

Fig. 7. Network toughness indicators change under different modes

network starts to recover when the attacks endured by the network stop.

As can be seen from Figure 7, under the same attack mode, the recovery speed of the recovery capacity, absorption capacity and buffer capacity of the CRETN is the fastest under the IR recovery mode; under the same attack, the recovery speed of the three capabilities under the random recovery mode is the slowest. Therefore, in the face of network node damage in practice, network city stations can be repaired according to the key node sequence identified by CRITIC-TOPSIS method. For example, Xi'an, Zhengzhou, Moscow and other city stations should strengthen protection and guarantee efforts to improve the connectivity and efficiency of the network, so that the damaged network can maintain a relatively stable state, adjust the network capacity in time, and facilitate the information transmission between the CRETN. This increases the toughness of the network.

Overall, the changes in the indicators vary greatly when the CRETN is subjected to different attack-recovery modes. Combining the three metrics, the IR mode recovery is the most effective, and the RR mode has the slowest recovery speed and the worst effect. Meanwhile, in the process of recovery, when the second node is recovered the absorptive capacity indicators appear to climb sharply eventually with the increase in the number of nodes and then gradually decline to the initial value of the situation, this is because, according to the different modes of the network node recovery, the nodes with higher degree and criticality will be recovered first, and these nodes are very strong connectivity, so at first when recovering the first node recovery when the efficiency of the network is 0, when the second node appears, there is an edge between the two nodes, the network efficiency plummets to 1, but when the nodes gradually increase, the nodes with small connectivity are more and more, which ultimately leads to a gradual decrease in the density and efficiency of the network and eventually reaches the initial level.

Global toughness analysis

To analyze the whole process of the state change of the CRETN, three toughness indicators of CRETN are calculated according to the formulas (22)~(24), so as to portray the toughness of the whole network in different attack-recovery processes, and a comparison of toughness characteristic indicators of the CRETN is obtained as shown in Table 4. From Table 4, it can be seen that the CRETN has the highest recovery capacity under the same recovery mode when attacked by RA; the absorptive capacity and buffering capacity are the highest when attacked by JA; at the same time, the three toughness metrics are at the lowest in IA attack mode, which indicates that IA attack mode has the strongest destructive effect on the toughness of the network, and the greatest impact on the network. Under the same attack mode, RR recovery mode, the three toughness indicators are at the lowest, and IA recovery mode, the three toughness indicators are at the highest, which indicates that under different attack conditions, the network recovery capacity absorption capacity, and buffering capacity under IA recovery mode are at the best, and the restorative nature of the network is the best. Therefore, when the network faces unknown attacks resulting in reduced effectiveness, the IR recovery mode can be adopted to prioritize the recovery and protection of cities with higher criticality, such as Xi'an, Zhengzhou, Warsaw, Moscow, etc., so as to improve the efficiency and toughness of the overall network and to maintain the smooth operation of the CRETN.

After obtaining the values of the three toughness indicators of CRETN in different attack-recovery modes, the weights of each indicator are calculated by Python programming using the network stress testing method. The corresponding weights of each indicator are 1) recovery capacity: 0.32; 2) absorptive capacity: 0.34; and 3) buffering capacity: 0.34. Using the spatial vector modeling calculation method, the three toughness indicators and the corresponding weights are brought into formula (25) to obtain the toughness values of the CRETN under different attack-recovery modes, and the normalization processing is performed on them. The final result is shown in Figure 8.

TABLE 4
COMPARISON OF NETWORK TOUGHNESS CHARACTERISTICS

Mode \ Toughness		Recovery capacity	Absorptive capacity	Buffering capacity
RA	RR	123.990	13.437	82.563
	DR	311.077	35.473	314.973
	JR	343.576	54.338	418.893
	IR	358.930	60.449	483.981
DA	RR	116.655	15.208	90.233
	DR	303.743	37.244	322.643
	JR	336.242	56.109	426.563
	IR	351.595	62.220	491.651
JA	RR	116.508	16.910	96.333
	DR	303.595	38.946	328.743
	JR	336.094	57.811	432.663
	IR	351.448	63.922	497.751
IA	RR	93.907	12.993	73.113
	DR	280.995	35.029	305.522
	JR	313.494	53.894	409.442
	IR	328.847	60.005	474.530

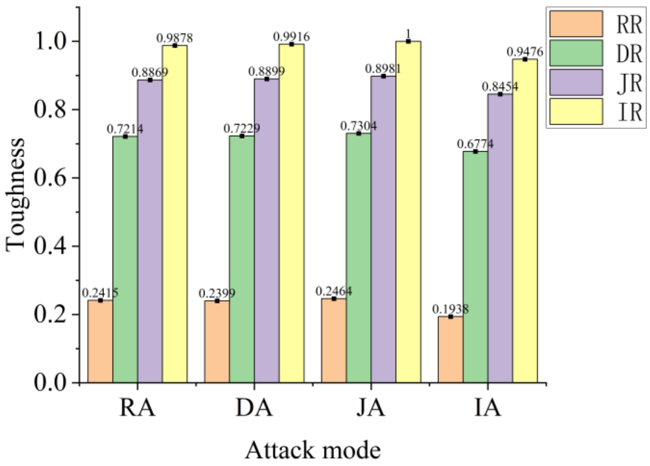


Fig. 8. Transport network toughness comparison

Figure 8 shows that the network toughness of the CRETN varies under different attack-recovery modes. Under the same attack mode, IR recovery mode has the highest network toughness, RR recovery mode has the lowest network toughness, and the toughness value difference is about 80%, which is very large; under the same recovery mode, IA attack mode has the lowest network toughness, JA attack mode has the highest network toughness, indicating that IA attack mode has the strongest destructive power, the highest damage to the network, and the most severe impact; In JAIR mode, the network toughness reaches the highest, 1, and in IARR mode, the network toughness reaches the lowest, 0.1938. IA mode has the strongest aggressiveness among the four modes, IR mode has the highest toughness among the four recovery modes, further verifying that CRITIC-TOPSIS method can effectively characterize the core of the network. By priority the recovery of core stations, the absorption, buffering and recovery capabilities of the whole network can be effectively improved, and finally improve the network toughness. Therefore, the protection and maintenance of stations in cities with high criticality should be strengthened at ordinary times, and in case of network damage, the IR mode can be used to repair the network preferentially, so as to improve the toughness and information transmission speed of the network more quickly, thus effectively ensuring the normal operation of the CRETN.

V. Conclusion

This study takes the CRETN as the research object. By combining network topology analysis, key node identification and dynamic toughness assessment, it systematically reveals the characteristics of the network structure, the distribution of key hubs and the evolution law of toughness. The main conclusions are as follows:

1) Network topology characteristics reveal efficiency bottlenecks. The CRETN presents a sparse structure with low density (0.0037) and low efficiency (0.0511), resulting in low information transmission efficiency. The network clustering coefficient is 0, the average number of independent paths is only 1.45, the connection redundancy between nodes is insufficient, the anti-interference ability is weak, and it is easy to cause global paralysis due to local failure. The connection of sites can be optimized, such as adding branch connections or enhancing the radiation capacity of hubs, thereby improving the network connectivity.

2) The validity of key node identification. The CRITIC-TOPSIS method based on multiple indicators can objectively quantify the importance of nodes and identify core hubs such as Xi 'an (importance 0.812), Zhengzhou (0.55), and Moscow (0.314). Meanwhile, IA attacks led to a sudden drop in network resilience (with a minimum of 0.1938), and their destructive power was significantly higher than that of random attacks, confirming the accuracy of the model.

3) Resilience evolution laws and optimization strategies. Through simulating attack and recovery scenarios, it was found that IA attack was the most destructive, followed by JA, and RA was the weakest. The IR mode that prioritizes the recovery of key nodes can maximize resilience (JAIR mode resilience reaches 1), which is over 400% higher than random recovery (RR). It is suggested to establish a "graded protection - intelligent recovery" mechanism (such as implementing real-time monitoring of key nodes and presetting emergency resources) and strengthen international cooperation to jointly build a risk prevention system with countries along the route.

4) Research Limitations and Future Prospects. The method proposed in this study has fixed weights. In the future, real-time traffic data can be introduced to dynamically correct the index weights. Meanwhile, this study only focuses on the railway transportation part of the CRE and does not analyze the resilience of the multimodal transport network in combination with sea transportation, air transportation, etc. In the future, it can be combined to explore the resilience and risk resistance mechanism of the "land-sea-air" collaborative network.

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