Academic Journal of Management and Social Sciences
ISSN: 2958-4396 | Vol. 14, No. 3, 2026

Resilience Evaluation of the Railway Transport Network of the New Western Land-Sea Corridor

Ming Chen [1, *], Yutong Luan [2]

[1] School of Economics and Management, Chongqing Jiaotong University, Chongqing, China
[2] New Land-Sea Corridor Operation Co., Ltd., Chongqing, China
[*] **Corresponding author**: Ming Chen (Email: chenming190810@gmail.com)

Abstract: Rail transport along the New Western Land-Sea Corridor serves as the core transportation mode connecting China's inland regions with coastal ports, playing a vital role in ensuring the corridor's efficient and stable operation. This paper constructs an evaluation index system for node importance within the corridor's rail transport network. Utilizing the entropy-weighted TOPSIS method, it identifies critical nodes and high-risk nodes. K-means clustering is then applied to group nodes based on their comprehensive risk levels. Furthermore, regional belt analysis is employed to examine the spatial distribution characteristics of rail transport risks. Simultaneously, leveraging resilience triangle theory and employing network dynamic evolution simulation, the study assesses the evolution of railway transport network efficiency under various disturbance and recovery strategies, calculating network resilience indices. Research findings indicate: The railway transportation network of the New Western Land-Sea Corridor exhibits strong dependency on core hub nodes, with high-importance and high-risk nodes clustering toward core hubs along main corridors. Railway transportation risks display pronounced spatial heterogeneity: border port areas concentrate relatively high-risk nodes, seaport areas harbor extremely high-risk points, while inland transshipment zones maintain overall controllable risk levels. Simulation experiments reveal that under targeted attack scenarios, the network exhibits weaker disturbance resistance and more pronounced efficiency degradation, whereas targeted recovery strategies effectively accelerate network efficiency restoration. Finally, policy recommendations to enhance the resilience of the railway transportation network along the New Western Land-Sea Corridor are proposed across three dimensions: resource allocation, operational efficiency, and sustainable development.

Keywords: New Western Land-Sea Corridor; Railway Transportation Network; Network Efficiency; Transportation Network Resilience.

1. Introduction

The 15th Five-Year Plan explicitly calls for accelerating the construction of the New Western Land-Sea Corridor. As a vital maritime corridor linking China's southwest region with Southeast Asia, South Asia, and the wider world, this channel serves as a pivotal vehicle where the national strategies of "Western Development," "Transportation Powerhouse," and "Chengdu-Chongqing Metropolitan Area" converge. Railways serve as the primary transportation mode linking western inland regions with coastal ports, offering high capacity, low cost, and strong stability—crucial guarantees for the corridor's efficient operation. Compared to highways, railway networks feature more complex structures and concentrated nodes. Once disrupted, rail failures pose greater challenges in recovery and broader impacts, highlighting more pronounced resilience issues.

The word resilience comes from the Latin word "resilire," which means that an object can bounce back to its original state after being compressed or disturbed. In 1973, ecologist Holling[1] first introduced the concept of resilience into ecosystem analysis, emphasizing the system's ability to resist shocks and maintain balance in the face of environmental changes. As research deepened, the concept of resilience was also introduced into the study of transportation system resilience. In the field of engineering, resilient systems focus on maintaining a certain equilibrium state near a certain equilibrium state[2]. For example, transportation networks can still operate under the influence of extreme weather and have the ability to recover quickly from shocks[3]. Relying on scientific response and recovery mechanisms, we can promote the rapid recovery and optimization of service levels, thereby effectively coping with future uncertainties[4]. Railway resilience research has gradually risen from the facility level to the system level, involving infrastructure, transportation organization, traffic flow scheduling, and logistics coordination. By using complex network theory to analyze the structural resilience of key nodes in China's high-speed rail network, "vulnerable core" nodes are identified[5]. Real-time optimization scheduling and station congestion problems are achieved through railway scheduling simulation platforms, thereby effectively assessing the system's recovery capacity and adaptability to responding to emergencies[6]. Simulation models can also be used to analyze changes in railway transportation functions and verify the system's operational recovery speed in extreme events such as floods[7]. Feng et al.[8] studied the resilience of the China-Europe freight train and revealed the system's response characteristics under compound risks. Knoester et al. [9] proposed the "Resilience Curve" method based on historical operating data, and assessed the efficiency and robustness of the disturbance recovery process by the trajectory of network operating state changes. With the deepening of research, more attention has been paid to the system operating logic and functional degradation process in recent years. For example, Bešinović et al. [10] proposed the scheduling-infrastructure-recovery linkage mechanism to realize the system-level resilience assessment of functional and structural coupling. Network science methods play an increasingly important role in resilience assessment due to their ability to characterize system structure [11]. Currently, research on railway trunk lines and high-speed rail systems is relatively mature, but research on regional corridors and intermodal transport corridors is relatively limited.

This study aims to construct a railway transportation network resilience evaluation framework adapted to the operational characteristics of the New Western Land-Sea Corridor, revealing the vulnerability characteristics of key nodes and critical lines. Based on simulation, it proposes effective resilience enhancement strategies to improve the transportation system's resistance to disturbances and its recovery capabilities, ensuring the safe, stable, and efficient operation of the corridor.

During the research process, in conjunction with the geographical scope defined by the "13+2" joint construction mechanism of the New Western Land-Sea Corridor, and based on the route information of the China Railway 95306 network in September 2024, 71 nodes were finally identified. The cities where the nodes are located were used as the node names. Then, the data information, such as train numbers of the nodes, is matched to form the data basis of this study.

2. Identification of Key Nodes in the Railway Transportation Network

2.1. Node Importance Evaluation

Table 1. Weights of Network Node Importance Evaluation Indicators

Primary Indicator	Secondary Indicator	Tertiary Indicator	Weight Value
Network Structural Characteristics	Local Network Characteristics	Degree	0.148
		Clustering Coefficient	0.130
	Global Network Characteristics	Betweenness Centrality	0.385
		Closeness Centrality	0.021
		Eigenvector Centrality	0.307
Urban Economic Characteristics	Economic Growth Characteristics	GDP growth rate	0.009

Table 2. Evaluation Results of the Importance of Railway Network Nodes (Top 20)

Ranking	Node	Ranking	Node
1	Qinzhou	11	Urumqi
2	Fangchenggang	12	Hotan
3	Zhanjiang	13	Karamay
4	Chengdu	14	Aksu Prefecture
5	Xi'an	15	Xilingol League
6	Kunming	16	Kashgar
7	Ili Prefecture	17	Luoyang
8	Bortala Prefecture	18	Bayingolin Prefecture
9	Chongqing	19	Shihezi
10	Turpan	20	Wuzhong

To assess the importance of railway transportation nodes within the New Western Land-Sea Corridor railway network, an evaluation index system for node significance was developed based on network structural characteristics and urban economic features. The entropy weight method was employed to determine the specific weight of each indicator, as shown in Table 1. Subsequently, the TOPSIS method was applied to calculate the evaluation scores for each railway network node, listing the top 20 ranked node cities as presented in Table 2.

Table 2 shows that port nodes such as Qinzhou, Fangchenggang, and Zhanjiang scored significantly higher, reflecting Haikou's prominent role as a hub for transport, transfer, and terminal aggregation at the end of the New Western Land-Sea Corridor. Following Haikou are Chengdu, Xi'an, Kunming, and Chongqing, all occupying key transshipment positions on the inter-regional trunk corridor. Xi'an serves as a crucial link between the Northwest and the national backbone, Chengdu connects Chengdu and Chongqing with multiple directions of southwest traffic, and Kunming plays a significant role in organizing and converging southward traffic. All three possess substantial connectivity and strong route resource allocation capabilities. Thirdly, Xinjiang cluster nodes are prominent, with several nodes from Xinjiang ranking in the top 20. Overall, high-scoring nodes are mainly clustered along the backbone and outbound sea directions; from a regional perspective, Xinjiang has leveraged its railway network to achieve a leap from the periphery of the network to a transportation hub.

2.2. K-means Clustering Analysis

Based on the entropy-weighted TOPSIS comprehensive risk score of railway transportation nodes, K-means clustering is further used to group and identify the risk levels of the nodes. Using the node's TOPSIS comprehensive score as the clustering input variable, and comparing the silhouette coefficients under different cluster numbers, railway transportation nodes are ultimately divided into five risk levels: low risk, relatively low risk, medium risk, relatively high risk, and high risk.

To characterize the spatial distribution of railway transportation risk, this paper combines the geographical location and functional attributes of the nodes, dividing all railway nodes into three regional zones: border ports, seaports, and inland transit zones. Based on this, the K-means risk grouping results are cross-statistically analyzed with the regional zones to obtain Table 3, analyzing the risk level composition of railway transportation nodes within different regional zones, thereby identifying high-risk areas and their structural characteristics in the railway transportation system.

Table 3. Regional zone-risk group cross-statistic results

Regional Zone	Low Risk	Lower Risk	Medium Risk	Higher Risk	High Risk
Border Ports	10	13	8	2	0
Seaports	7	0	0	2	1
Inland Transit	13	11	2	2	0

Based on the cross-statistical results of risk grouping and regional zones (Table 3), the risk level distribution of railway transportation nodes in different regional zones shows significant differences: the border port area has the largest number of high-risk nodes, with a significantly higher proportion than other regional zones. Disturbances at border port railway nodes can easily amplify the overall connectivity and stability of the railway transportation system; therefore, border ports are the primary focus of railway transportation risk prevention and control. While the overall number of nodes at seaports is relatively small, they are the only high-risk nodes. These nodes are typically located at key points connecting railways, ports, and the industrial chain, and are highly sensitive to external shocks (such as port congestion and international logistics fluctuations), exhibiting typical characteristics of "extreme risk points." Compared to border ports and seaports, low-risk and relatively low-risk nodes dominate in inland transit areas, with significantly fewer high-risk nodes. This indicates that although inland transit nodes play a certain hub and distribution role in the railway network, their risks are more dispersed, and the overall risk level is relatively controllable. The above results indicate that in risk prevention and resource allocation in the railway transportation system, priority should be given to border ports and seaports, and differentiated control strategies should be implemented for the risk characteristics of different regions.

3. Resilience Evaluation of the Railway Transport Network

3.1. Methodology

3.1.1. Simulation Experiment Design

The resilience evaluation of the railway transportation network is divided into three stages: absorption, recovery, and stability. First, it is assumed that nodes cannot immediately recover after failing due to a disaster, and that the nodes are independent of each other. Then, a simulation experiment is designed to simulate the evolution of nodes in the three stages, progressively introducing node attacks and recovery, and calculating the performance level of the railway network in each stage. The calculation methods for the three stages are as follows:

(1) Absorption phase: The failure of disturbed nodes will lead to a decrease in network performance. The study uses two methods to simulate the interference process: targeted attack (denoted as A1, nodes and connected edges are removed according to the importance of nodes from high to low) and random attack (denoted as B1, each node has an equal probability of being removed). The network performance index after interference is calculated until the network performance drops to 0.

(2) Recovery phase: In this phase, after the interference, the connected nodes and edges are restored one by one. Two strategies are adopted: directional recovery (denoted as A2, which restores nodes from high to low importance) and random recovery (denoted as B2, which restores each node with equal probability) until all nodes are restored.

(3) Stable phase: After the absorption and recovery phases, the performance of the railway transportation network gradually stabilizes and forms a resilience triangle. The resilience index Re represents the ratio of the area enclosed by the actual network performance curve and the ideal baseline within the range of [t_0, t_1]. The calculation is shown in (1).

$$R_e = \frac{\int_{t_0}^{t_1} Q_{(t)}dt}{\int_{t_0}^{t_1} Q_{(0)}dt} \quad (1)$$

R_e is the network resilience index. The closer its value is to 1, the stronger the network's ability to recover its functions after interference occurs. $Q_{(t)}$ is the curve of network performance change after interference, and $Q_{(0)}$ is the initial level of network performance without interference.

3.1.2. Selection of Network Performance Evaluation Metrics

Network performance evaluation metrics are core elements for measuring system operational capabilities. To measure the accessibility and timeliness of railway transportation networks and to clearly capture performance fluctuations during the attack-recovery process, network efficiency was selected as the core performance metric.

Network efficiency is a core indicator for measuring the connectivity and operational effectiveness of a railway transportation network. A higher value indicates shorter transport paths between nodes, higher resource flow efficiency, and greater accessibility and timeliness of goods transported between nodes. The calculation formula is shown in (2).

$$E = \frac{1}{N(N-1)}\sum_{i\neq j}\frac{1}{d_{ij}} \quad (2)$$

E represents network efficiency; the closer its value is to 1, the better the network connectivity and the shorter the shortest path between nodes. N represents the total number of nodes in the network. d_{ij} represents the shortest path length from node i to node j.

3.2. Network Efficiency Evolution in the Absorption Stage

During the absorption phase, targeted attacks (A1) and random attacks (B1) were conducted on the railway transportation network. The network efficiency was calculated using formula (2), and the change process was recorded as shown in Figure 1.

Under targeted attacks, the network efficiency curve declines most rapidly in the initial stage. During the attack period from t=0 to t=10, network efficiency drops rapidly from 100% to about 25%, indicating that continuous damage to critical nodes can cause a jump in efficiency. Subsequently, the attack period from t=10 to t=30 enters a "low-level plateau," with efficiency loss of only about 10%. In the stage from t>30, a long-tail decay begins, and network efficiency gradually approaches 0, demonstrating that after the critical structure of the network is damaged, the remaining part can only provide limited transportation capacity, which continues to weaken.

Under random attacks, the curve is smoother overall. The network efficiency remains at 65% at t=10, approximately 34% at t=20, and approximately 16% at t=30, after which it continues to decline slowly and approaches 0 at t=60. Compared to targeted attacks, random attacks have a more dispersed effect on network efficiency and are less likely to trigger structural collapse in a short period of time. Therefore, they are more resilient in the early stages, and the decay process is more gradual.

In summary, transportation networks are more dependent on "critical nodes," and once targeted, network efficiency will collapse rapidly in the early stages. Under random disturbances, the network can still maintain its efficiency for a longer period of time by relying on redundant paths, but eventually it will also decay and fail due to the accumulation of damage.

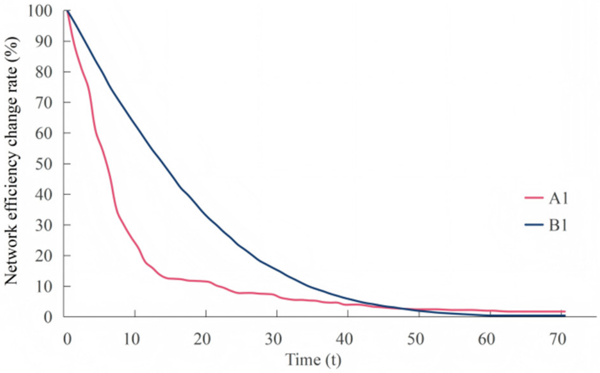

Figure 1. Evolution of network efficiency under different attack strategies

3.3. Network efficiency evolution in the recovery stage

During the recovery phase, the railway transportation network was subjected to directional recovery (A2) and stochastic recovery (B2), and the changes in network efficiency are shown in Figures 2 and 3.

In Figures 2 and Figures 3, from t=70 to t=150, the performance of the targeted attack and random attack strategies is as follows: The targeted recovery strategy recovers faster in the early stages, reaching approximately 63% recovery at t=100 and nearly 100% recovery at t=130; the random recovery strategy recovers more slowly, reaching about 50% recovery at t=100 and nearing full recovery only at t=140. The results indicate that after a targeted attack on critical nodes, prioritizing the repair of critical elements can significantly shorten network function recovery time and reduce losses during the recovery period.

Comparing the two sets of curves reveals significant differences in the attack phase while exhibiting a high degree of similarity in the recovery phase. This is because targeted attacks, prioritizing the destruction of critical nodes in the network, rapidly weaken the optimal path system and trigger structural breaks, leading to a precipitous drop in network efficiency. Random attacks, on the other hand, are more likely to first target non-critical or redundant connections, allowing the network to maintain connectivity through alternative paths, resulting in a smoother and more gradual efficiency decline. Upon entering the recovery phase, both scenarios begin with inefficiency, but efficiency recovers as critical channels and nodes are gradually repaired. Therefore, the attack phase reflects the network's structural sensitivity to critical elements, while the recovery phase is more driven by recovery strategies and reconnection patterns, hence the similar curve changes.

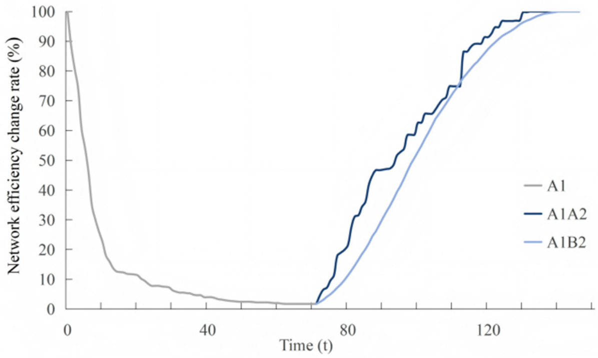

Figure 2. Evolution of network efficiency of recovery strategies after targeted attacks

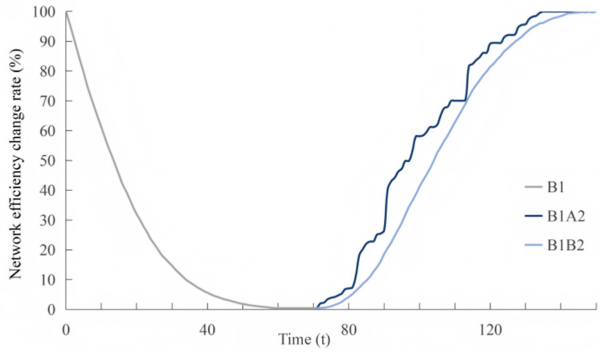

Figure 3. Evolution of network efficiency of recovery strategies after random attacks

3.4. Network Resilience Evaluation in the Stabilization Stage

The resilience level of the network under different attack and recovery strategies was calculated using formula (1), and the results are as follows: the network resilience index is highest at 0.411 when a targeted recovery strategy is used under a random attack strategy, and lowest at 0.358 when a random recovery strategy is used under a targeted attack strategy. This shows that both attack targeting and recovery priority have a certain impact on the resilience of the transportation network.

4. Conclusion

The study found that high-scoring nodes and main corridors in the New Western Land-Sea Corridor railway transportation network are significantly clustered towards core hubs, mainly concentrated in the "Xi'an-Chengdu-Chongqing-Kunming" axis in the central and western regions, with Xinjiang forming a dense hub area. Among the top 20 nodes in terms of node importance, port nodes such as Qinzhou, Zhanjiang, and Fangchenggang scored higher, reflecting their port collection and transfer capabilities; Xi'an, Chengdu, and Kunming undertake cross-regional transfer and route control, and the cluster nodes in Xinjiang are closely connected. Simulation experiments in the final network resilience evaluation stage show that the network is significantly dependent on key nodes. Targeted attacks cause a sharp drop in network efficiency in the early stages, while random attacks cause a smoother decline; although the recovery phases converge, targeted recovery is superior, indicating that prioritizing recovery is crucial for improving resilience. Based on the above conclusions, strategies to improve the resilience of the New Western Land-Sea Corridor railway transportation network are proposed from the following three aspects:

(1) Resource Allocation: Implement priority protection and pre-position resources centered on high-impact nodes. For risk-sensitive areas such as border crossings and seaports, establish a tiered protection list covering "critical nodes—key links—vital systems." Incorporate traction power supply, communication signals, and station equipment as the foundation of resilience under stricter threshold controls and preventive maintenance mechanisms to enhance the system's shock absorption capacity during normal operations. During emergencies, deploy rescue teams, spare parts, and emergency rolling stock in high-risk zones to form a support network capable of reaching targets within specified timeframes. Through cross-departmental coordination and resource synergy mechanisms, ensure resources are

prioritized for critical breakpoints and backbone corridors during sudden disruptions, minimizing fault propagation and cascading failure probabilities. For extremely high-risk points at seaports, promote “port-rail coordination” resource linkage by establishing rapid coordination mechanisms between port operation rhythms, train arrival/departure capacity, and storage buffers to mitigate the transmission of port congestion to the rail network.

(2) Operational Efficiency: Enhance connectivity and organizational resilience through “addressing weaknesses + phased recovery.” Prioritize engineering measures such as adding redundancy to single corridors, completing connecting lines, and optimizing station facilities based on regional development positioning and node functional differences. Adopt a “function-first, efficiency-restoration” approach to enhance alternative routes and detour capabilities, strengthening structural resilience. During the emergency restoration phase, prioritize repairing backbone connectivity and access to critical nodes. Pre-plan emergency detour routes and timetables to ensure uninterrupted cross-border/ocean-bound critical logistics chains. During the stabilization phase, dynamically optimize transport capacity and schedules while implementing tiered priority dispatch (e.g., prioritizing essential goods and critical industrial chains, granting priority clearance at key bottlenecks) to prevent secondary congestion during recovery. Simultaneously, achieve shorter recovery times and minimize cumulative losses through dynamic optimization of recovery sequencing and transport organization (yard operations, marshaling plans, train operation structures). For inland transshipment zones, focus on optimizing operations and enhancing capacity at locally medium-risk nodes under overall controllable conditions to achieve higher resilience gains at lower costs.

(3) Sustainable Development: Integrate resilience building with green and low-carbon initiatives to achieve simultaneous improvements in safety, efficiency, and emissions reduction. Resilience enhancement should extend beyond emergency preparedness to include concurrent energy-saving retrofits, equipment upgrades, and redundancy configurations at critical hubs and disaster-prone zones. This enhances the reliability and self-healing capabilities of traction power supply, signaling, and communication systems. Promote energy efficiency management and emergency energy storage facilities to reduce operational downtime risks while lowering peak-period energy consumption and carbon emission intensity. Introduce a comprehensive evaluation system centered on recovery time, energy consumption intensity, and carbon emissions per unit of transport turnover. Implement differentiated performance assessments for different regional zones to drive synergistic optimization of operational safety, organizational efficiency, and green transformation.

This study has several limitations: First, the analysis primarily focuses on resilience identification and zoning based on domestic transport nodes and network structures, with relatively limited consideration of factors such as port rule differences, foreign infrastructure constraints, and multilateral coordination mechanisms in cross-border transportation scenarios. Second, this paper employs static indicators and predetermined scores for risk grouping, without incorporating dynamic disturbance factors such as extreme weather, policy adjustments, and demand shocks into multi-scenario simulations. Consequently, it struggles to comprehensively reveal evolutionary pathways under varying disturbance intensities and recovery strategies. Future research should expand the scope by integrating cross-border corridor nodes and external constraints into a unified network framework. Combining static structural identification with dynamic simulation modeling, a scenario-based analysis system incorporating multi-source disturbances, recovery strategies, and performance evaluation should be developed. This approach will enable a more comprehensive assessment of the resilience of the New Western Land-Sea Corridor railway transportation network and validate the effectiveness of proposed strategies.

Acknowledgments

Major Scientific and Technological Research Project of Chongqing Education Commission (KJZD-M202500705).

Major Project of Chongqing Social Science Planning “Construction of Western Land-Sea New Passage” (2023ZD LH06).

Graduate Research Innovation Project of Chongqing Jiaotong University (2025S0080).

References

[1] Holling, C. S. (1973, November). Resilience and stability of ecological systems.

[2] Murray-Tuite, P. M. (2006, December). A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions. In Proceedings of the 2006 winter simulation conference (pp. 1398-1405). IEEE.

[3] Diab, E., & Shalaby, A. (2020). Metro transit system resilience: Understanding the impacts of outdoor tracks and weather conditions on metro system interruptions. International Journal of Sustainable Transportation, 14(9), 657-670.

[4] Jenelius, E., & Mattsson, L. G. (2020). Resilience of transport systems. Encyclopedia of Transportation, 1-16.

[5] Zhang, J., Hu, F., Wang, S., Dai, Y., & Wang, Y. (2016). Structural vulnerability and intervention of high speed railway networks. Physica A: Statistical Mechanics and its Applications, 462, 743-751.

[6] Liu, E., Lin, Z., Wang, J. Y., & Chen, H. (2023). A Mobile Data-Driven Hierarchical Deep Reinforcement Learning Approach for Real-time Demand-Responsive Railway Rescheduling and Station Overcrowding Mitigation. arXiv preprint arXiv:2308.11849.

[7] Bi, W., Schooling, J., & MacAskill, K. (2024). Assessing flood resilience of urban rail transit systems: Complex network modelling and stress testing in a case study of London. Transportation Research Part D: Transport and Environment, 134, 104263.

[8] Feng, F., Fang, Y., Zhang, Z., et al. (2025). Resilience assessment of China-Europe freight train transportation network from the perspective of risk disturbance. Journal of Transportation Systems Engineering and Information Technology, 25(2), 338-351.

[9] Knoester, M. J., Bešinović, N., Afghari, A. P., Goverde, R. M., & van Egmond, J. (2024). A data-driven approach for quantifying the resilience of railway networks. Transportation Research Part A: Policy and Practice, 179, 103913.

[10] Bešinović, N. (2020). Resilience in railway transport systems: a literature review and research agenda. Transport Reviews, 40(4), 457-478.

[11] Peng, C., Lin, Y. Z., & Gu, C. L. (2018). Resilience evaluation and optimization strategy of urban network structure in the middle reaches of the Yangtze River. Geographical Research, 37(6), 1193-1207.