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Research on multi-layer network topology optimization strategy for railway internet of things based on game theory benefits

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In the railway system environment, the interconnection of a vast array of intelligent sensing devices has brought about revolutionary changes in the management and monitoring of railway transportation. However, this also poses challenges to the communication service quality within the railway Internet of Things (IoT). Through collective intelligence and collaboration, the nodes within the railway IoT can not only share data and information but also work synergistically to enhance the overall intelligence level and improve decision-making quality of the network. Therefore, this paper proposes a reconnection mechanism based on the computation of node game-theoretic benefits and optimizes this process with the concept of swarm intelligence collaboration. Initially, the game-theoretic benefit values of the nodes in the railway IoT network are calculated. Subsequently, based on the weight priority of the edges, the two edges with the larger weights are selected, and connections are established between nodes with similar game-theoretic benefit values to enhance the network's robustness. This approach enables rapid networking and efficient communication transmission within the railway IoT, providing robust assurance for the safe and stable operation of the railway.

1 Introduction

With the rapid development of new generation information [1] and communication technologies (5G), the scale of Internet of Things (IoT) applications in the railway environment has increased dramatically [2]. The rapid expansion of IoT applications, while enhancing network service quality, also brings greater risks of network paralysis [3]. Device nodes in network applications are susceptible to failure due to various factors, such as natural disaster activities, node malfunctions, and malicious attacks. Moreover, since IoT applications are interconnected, the paralysis of a single network can easily lead to a chain reaction causing the collapse of the entire railway IoT system [4]. Therefore, in the face of partial device node failures, how to improve the quality of service (QoS) of complex IoT applications and their robustness against network attacks [5], and to maximize the maintenance of network topology communication capabilities, has become a bottleneck in the development of large-scale railway IoT applications [6].

When the topological structure of IoT applications is attacked, measuring and optimizing the robustness and reliability of the network topology is an important means to minimize the risk of network failures [7]. In practical dynamic issues such as the propagation and immunity of complex networks [8], and link control [9], different topological structures exhibit different levels of robustness in the face of deliberate attacks or random failures. Therefore, altering the network's topological structure is of significant importance for enhancing the robustness of complex networks.

The robustness of complex networks measures the network's ability to respond to external disturbances, such as deliberate attacks or random failures [10]. Networks that maintain their functionality under such changes (by removing some nodes or edges) are considered more robust than those that do not. Current research on improving the robustness of complex networks is mainly divided into two categories: increasing the connections within the network and reconnecting the network's edges. Many infrastructures have capacity limitations, such as transmission lines of power plants and the number of flights in aviation systems, making it impractical to increase the number of connections in a network. A substantial amount of research has confirmed that the reconnection mechanism [11] is a simple and effective method often used to adjust the network's topological structure to enhance its robustness. For the topological structure of complex dynamic networks, it is generally described by a coupling matrix, and most of the existing literature discusses the case of constant coefficient coupling matrices. In actual complex dynamic networks, due to the influence of external environments, the topological structure cannot remain constant. Therefore, it is necessary to introduce the concept of time-varying topological structures in complex dynamic networks. Some scholars have begun to consider this issue. For example, Refs. [12,13] discuss the time-varying coupling strength in complex dynamic networks, using adaptive laws to identify unknown parameters, achieving adaptive synchronization of complex dynamic networks; Ref. [9] discusses the control of complex networked supply chains with multiple time-delay couplings and time-varying topological structures, thereby enhancing the network's ability to resist collaborative attacks; and how the network's performance in the dynamics process feeds back and affects the evolution of the topological structure.

Currently, IoT topology optimization methods [12] primarily use the largest connected subgraph as a robustness metric to quantify and optimize network topologies. Since the IoT topology optimization problem is an NP-hard problem [14], to seek approximate optimal solutions, most IoT topology optimization methods are based on heuristic algorithms [15,16]. Meanwhile, in complex networks, the scale-free network model more closely resembles the structure of real-world networks and performs well in resisting random network attacks (where each device node fails or leaves the network with equal probability). However, it is prone to network paralysis when facing malicious attacks (where important nodes fail first). A multitude of researchers have proposed efficient strategies to enhance the stability and resilience of IoT topological structures. Rong et al [14] first classified the edges in the network as effective, ineffective, and flexible edges, and then proposed a heuristic optimization algorithm based on edge classification (EC), designed to enhance the robustness of scale-free (SF)

networks against malicious attacks (MA). Qiu et al. [13] introduced the ROSE strategy, an enhancement method for wireless sensors in scale-free networks, which identifies and protects key nodes in the network and optimizes the connection structure to fend off malicious attacks. Zhao et al studied [17] a specific type of network attack under the knapsack constraint—the maximum vertex cover attack, which aims to maximize the number of links associated with removed nodes under a limited budget. Game theory, which describes the micro-interactions of network nodes, is naturally a powerful tool to guide the adjustment of topological structures, and applying cooperative game theory to the optimization of IoT topologies will also face greater opportunities and challenges.

Based on this, to address the failure of some critical equipment nodes and the chain reaction collapse effect of network attacks, which affect the service quality of railway system communication applications, this paper proposes a reconnection mechanism calculated based on the measurement of game-theoretic benefits between nodes. The first chapter introduces the essential knowledge of complex networks and model construction, and on this basis, constructs a cooperative game strategy, including interaction strategies, transformation rules, and equilibrium balance analysis. The second chapter proposes the initialization of the model and the reconnection edge mechanism. The third chapter verifies the optimized network robustness based on the game value reconnection edge mechanism using Monte Carlo experiments in complex networks.

2 Construction of multi-layer topological network model in the railway internet of things environment

2.1 Network representation

The network is modeled as a weighted graph $G = (V, E)$, where $V = \{e_1, e_2, e_3..., e_n\}$ represents the set of nodes in the network and $E = \left\{(e_i, e_j) \mid e_i, e_j \in V\right\}$ represents the set of edges. Let $N = |V|$ denote the number of nodes and $M = |E|$ denote the number of edges. Each edge e_{ij} connects nodes e_i and e_j, and has a weight w_{ij}, which reflects the importance of the connection between the nodes.

This paper only considers simple connected undirected graphs without duplicate edges or self-loops, meaning that there is at most one edge between any pair of nodes in the network, each edge has two distinct endpoints, and there is at least one path between any two nodes. The neighborhood of a node v_i in the network G is denoted as $N_{v_i} = \{(u, v_i) \in E, u \in V\}$, representing the set of nodes adjacent to node v_i in the network G. To avoid confusion, it is simply noted as N_i. The degree $d_{v_i} = |N_i|$ of a node v_i, denoted as d_i, represents the number of edges associated with node v_i in the network G.

2.2 Game strategy

Swarm intelligence collaboration is a large-scale sensing and computing model based on collective intelligence, emphasizing the completion of complex sensing and computing tasks through the

TABLE 1 Rules of cooperative evolution in network structure.

Color	Previous round strategy	Current round strategy
Blue	Cooperate	Cooperate
Red	Defect	Defect
Green	Defect	Cooperate
Yellow	Cooperate	Defect

participatory and collaborative nature of the group. This model typically involves a large number of individuals who are interconnected through communication technologies such as the Internet, collectively engaging in a particular task or goal. The core of swarm intelligence collaboration lies in how to effectively organize and motivate these participants, as well as how to process and analyze the vast amounts of data they generate.

By integrating swarm intelligence collaboration with cooperative game theory, a more efficient and fair system can be created. In this system, participants (who can be humans or intelligent devices) are motivated to cooperate and jointly complete tasks or solve problems. Cooperative game theory provides the tools and methods to design such incentive mechanisms.

In the cooperative evolution within network structures, it is assumed that each individual engages in a round of public goods games with its neighbors at each clock cycle, where the neighbors are the subjects of the individual's game, related to the social network structure that hosts the gaming group. The model includes three types of topological structures for the gaming group: regular lattice networks, BA scale-free networks, and WS small-world networks. In each round of the game, there is no central leader to control; individuals have two choices: to cooperate or to defect. The specific strategy an individual chooses is related to a series of factors, which is also what the experiment will investigate. The strategies adopted will have an impact on neighboring subjects; adopting a cooperative strategy generates positive externalities, from which other subjects can benefit. These externalities reflect the social ability of subjects to interact with their adjacent subjects. After multiple rounds of the game, whether a stable evolutionary outcome can be achieved is also influenced by the introduction of incentive mechanisms in the experiment, which aim to shift the original evolutionary outcome from defection to cooperation. Each subject in the model is described by four elements:

1) The strategy for this round is either cooperation or defection;
2) The strategy from the previous round was either cooperation or defection;
3) The score for this round;
4) To facilitate the observation of results during the simulation process, subjects are also assigned different colors for distinction. The specific rules are as shown in Table 1.

2.3 Interaction and strategy transition rules

The most important part of evolutionary game theory is the interaction between individuals (interact) and the selection stage of the next round of strategy. Assuming all individuals are

homogeneous and have the same set of strategies. When an individual adopts a cooperative strategy, the net benefit it receives is the cooperative benefit R minus the cooperation cost c. For the convenience of studying the problem, let the benefit R be the total number of all neighboring nodes plus one (which is itself), and the cooperation cost is 1, so the net benefit for each node is its total number of neighboring nodes. When a node chooses a defection strategy, the defector will gain a certain benefit, and due to the cooperation of neighboring nodes, the defector will free-ride and enjoy the positive external benefits from the cooperating neighbors, so its benefit is the defection incentive multiplied by the total number of cooperators among its neighboring nodes.

Therefore, for each individual, the number of cooperators among its neighboring nodes is counted, and if the individual is a cooperator, its score is the total number of cooperators among its neighbors; if the individual is a defector, its score is the product of the defection benefit and the total number of cooperating neighbors. In this paper, we mainly adopt the strategy of choosing the one with the highest score among the neighboring nodes as the strategy for the next round, characterizing the feature of learning from the strong in evolutionary games.

2.4 Strategy space and equilibrium analysis

The incentive rules here are refined into rewards (R) and punishments (P). The incentive policy will either reward cooperators as the sole strategy or punish defectors as the sole strategy. Individuals will react to external stimuli, that is, they will consider the rewards or punishments given by the central authority before making decisions. The model compares three scenarios: no policy, reward policy, and punishment policy, to determine which one achieves the optimal outcome (the optimal outcome is determined by the number of cooperators), in order to identify the best solution. When a reward mechanism is introduced into the model, corresponding to rewards for cooperators in reality, a reward (reward) is introduced, and the utility function of cooperators increases, while the utility function of individuals adopting a defection strategy remains unchanged. When a punishment mechanism is introduced into the model, corresponding to punishments for defectors in reality, a punishment (punishment) is introduced, and the utility function of defectors will decrease by a value P, while the utility function of individuals adopting a cooperation strategy remains unchanged.

The individual payoff is characterized as follows:

TABLE 2 Experimental parameters and their value ranges.

Network structure parameters	Parameter meaning	Random network	BA scale-free network	WS small-world network
Num-nodes	Total Number of Network Nodes, Initial	500	1,000	1,500
Initial-cooperation	Cooperation Probability	0–1	0–1	0–1
Defection-award	Defection Reward	B	B	B
Reward	Reward	R	R	R
Punishment	Punishment	P	P	P

$$p_{xy} = p_x p_y R + (1 - p_x) p_y T + p_x (1 - p_y) S + (1 - p_x)(1 - p_y) P \tag{1}$$

The average revenue is as follows:

$$r_x = \sum_{y=1}^{|\Omega_x|} p_{xy} \Big/ |\Omega_x| \tag{2}$$

where $|\Omega_x|$ is the number of neighbors of node x.

The expected outcome is related to the number of initial cooperators, the size of the group, the magnitude of the defection payoff, and the network's topological structure. Subsequently, targeted improvements in parameter settings, as well as the magnitude of imposed incentives, expected rewards, and punishments, will also affect the final evolutionary outcome.

2.5 Paramter settings

The previous section introduced the algorithms of game theory; now we will begin to set initial values for the relevant parameters of network initialization, representing their meanings and ranges.

1) Num—nodes: It represents the total number of nodes in the network, which is also the scale of the gaming group, and its value range varies slightly depending on the network;
2) Initial—cooperation: It represents the initial probability of cooperation, with a value range between 0% to 100%;
3) Defection—award: It represents the defection payoff, with a value range between 0 to 10;
4) In models with incentive mechanisms, there are also parameters for reward and punishment.

Table 2 displays the experimental parameters and their value ranges.

3 Topology reconstruction of railway internet of things based on cooperative benefits
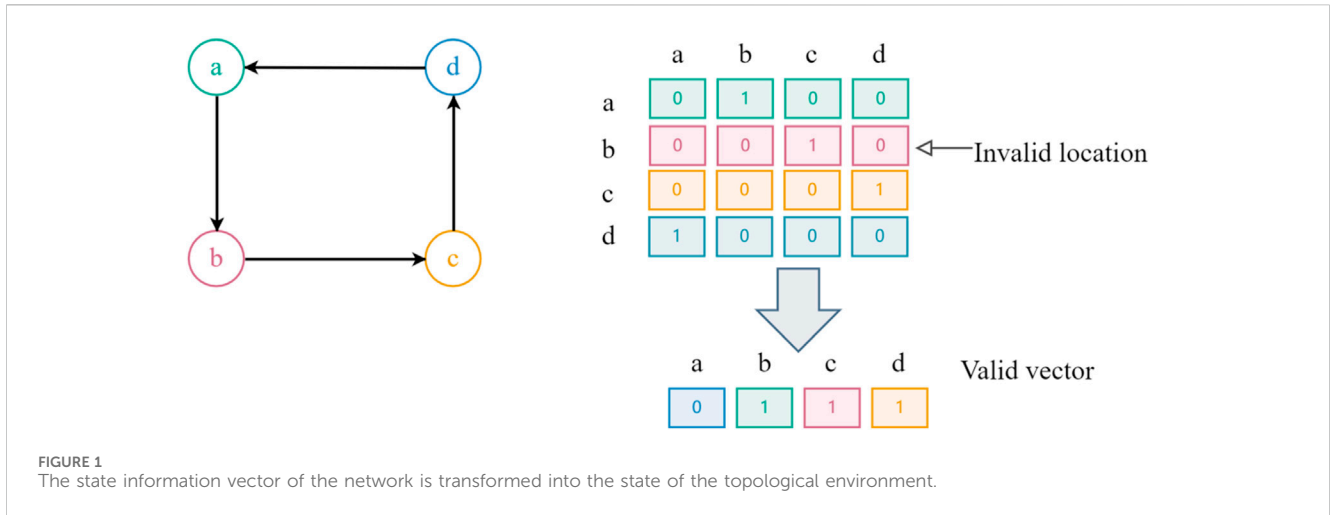
3.1 Network state initialization

Initializing the network requires setting the network's state information vector to the topological environmental state. The following description details how to convert the IoT topology structure into the corresponding environmental state vector, as shown in Figure 1. It is essential to reduce the storage space of the topology structure for large-scale topologies. First, the topology structure is converted into an adjacency matrix, an operation frequently used in other IoT applications. In this paper, by analyzing the network topology structure and optimization action operations, it is found that only network nodes within each other's communication range can have a connection relationship. Therefore, information from other nodes within the node's communication range is of significant value. As shown in Figure 1, node a's upper triangular relationship is [1, 0, 0, 0], but since a is not within the communication range of c and d, the only effective position is b with [1]; similarly, node b has no connection with node d and node e, so its effective position is c with [1]; node c's effective position is d with [1]; node d's effective position is a with [1], and node d has no effective position because it only considers the upper triangular matrix. In summary, finally, the topology is linked in the order of the adjacency matrix numbers to form an environmental vector of [0, 1, 1, 1].

3.2 Initialization of network edge weights

In the analysis of complex networks, the degree of a node plays a fundamental and crucial role. BA scale-free networks [17] typically exhibit scale-free characteristics, with a degree distribution that follows a power-law rule, indicating that most nodes in the network have only a few connections, while a small fraction of nodes have a large number of connections. In the context of cooperative and competitive relationships between nodes, the most important factor is the expected benefit of cooperation with neighbors. According to the clustering effect reflected in Ref. [18], it is known that the more neighbors a node has, the easier it is to form a cluster, so nodes with a higher degree may often generate better benefits over time. This paper assigns weights to each edge in the network by calculating the absolute difference in the expected benefits of node cooperation, thereby characterizing the similarity between nodes, and using the magnitude of edge weights to measure whether nodes have the conditions for reconnection, as shown in the following formula:

$$w_{ij} = |r_i - r_j| \tag{3}$$

FIGURE 1
The state information vector of the network is transformed into the state of the topological environment.

where r_i represents the degree value of node v_i, and w_{ij} represents the weight of edge (v_i, v_j). The larger the weight value of the edge, the greater the difference between the two endpoints of that edge.

3.3 Edge selection strategy

To enhance the stability of the network, the strategy for selecting edges to swap is to disconnect edges with a large difference in expected benefits, while nodes with similar benefit values are more likely to connect with each other. The algorithm proposed in this paper assigns weights to each edge using Formula 3, and when selecting edges for reconnection, the decision is based on the weight of the edges. The probability of choosing two edges is directly proportional to the weight of the edges, following the rule as stated.

$$\Pi_{ij} = \frac{w_{ij}}{\sum_{(u,v)\in E} w_{uv}} \qquad (4)$$

According to Formula 4, edges with larger weights have a higher probability of being selected, and these edges typically connect two nodes with a large deviation in benefit values. Therefore, the algorithm can quickly identify the edges with larger differences and then select the two edges with the highest edge weights (requiring at least four nodes and two edges for disconnection and reconnection), and reconnect their endpoints. This can eliminate the benefit gap and rapidly enhance the stability of the network.

3.4 Node homophily

Homophily can analyze and understand the connection preferences between nodes, which is the phenomenon that similar nodes tend to connect with each other. Connection preferences also stem from the attributes of nodes, such as routing frequency, bandwidth, climatic environment, antenna technology, etc. This can help designers optimize network structures and improve network efficiency and performance. According to Formula 5, prioritize the reconnection operation of

four distinct nodes connected by two edges with larger weights. According to the benefit values, the four nodes are sorted in non-decreasing order, i.e., $r_1 \geq r_2 \geq r_3 \geq r_4$. Then, there are three ways for the reconnection mechanism to connect these four nodes: (1) $(v_{r_{(1)}}, v_{r_{(2)}})$ and $(v_{r_{(3)}}, v_{r_{(4)}})$; (2) $(v_{r_{(1)}}, v_{r_{(3)}})$ and $(v_{r_{(2)}}, v_{r_{(4)}})$; (3) $(v_{r_{(1)}}, v_{r_{(4)}})$ and $(v_{r_{(2)}}, v_{r_{(3)}})$. Therefore, this paper determines the optimal connection method between nodes by comparing the changes in the homophily coefficient of the three edge connection methods.

The homophily coefficient is an indicator that measures the similarity or difference in connections between nodes in a network. Choosing the reconnection method that results in the smallest change in the homophily coefficient can be considered optimal. The homophily coefficient reveals the preference for connections between nodes in the network. When nodes with higher connectivity in the network tend to connect with other nodes of similar connectivity, the network is referred to as a homophilous network. As shown in Formula 6.

$$\rho = 1 - \frac{\sum_{(i,j)\in E} \left(r_i - r_j\right)^2}{\sum_{i=1}^{N} r_i^3 - \frac{1}{2M}\left(\sum_{i=1}^{N} r_i^2\right)^2} \qquad (5)$$

where r_i represents the expected benefit value of node v_i , N represents the number of nodes in the network, and M represents the number of edges in the network.

Since the reconstruction mechanism in this paper does not change the degree values of the nodes during the reconnection process. Therefore, $\sum_{i=1}^{N} r_i^3 - \frac{1}{2M}(\sum_{i=1}^{N} r_i^2)^2$ is a constant during the calculation process. The network's homophily coefficient is only related to the square of the difference in degree values at the two endpoints of each edge. Consequently, the difference in the homophily coefficient for the three edge connection methods is as shown in Formulas 6–8.

$$\rho_{(1)} - \rho_{(2)} = \frac{2\left(r_{(2)} - r_{(3)}\right)\left(r_{(1)} - r_{(4)}\right)}{\sum_{i=1}^{N} r_i^3 - \frac{1}{2M}\left(\sum_{i=1}^{N} r_i^2\right)^2} \geq 0 \qquad (6)$$

$$\rho_{(2)} - \rho_{(3)} = \frac{2\left(r_{(1)} - r_{(2)}\right)\left(r_{(3)} - r_{(4)}\right)}{\sum\limits_{i=1}^{N} r_i^3 - \frac{1}{2M}\left(\sum\limits_{i=1}^{N} r_i^2\right)^2} \geq 0 \qquad (7)$$

$$\rho_{(1)} - \rho_{(3)} = \frac{2\left(r_{(2)} - r_{(4)}\right)\left(r_{(1)} - r_{(3)}\right)}{\sum\limits_{i=1}^{N} r_i^3 - \frac{1}{2M}\left(\sum\limits_{i=1}^{N} r_i^2\right)^2} \geq 0 \qquad (8)$$

From Formulas 6–8, it can be seen that $\rho_{(1)} \geq \rho_{(2)} \geq \rho_{(3)}$, which means that the first reconnection method will cause the greatest increase in homophily. Therefore, this paper performs the reconnection operation based on the first method of edge connection, which is to sort the four nodes selected by edge weight in non-increasing order according to their degree values, creating two edges between nodes with similar game-theoretic benefits. Similarly, during the reconnection process, the network is not allowed to have duplicate edges and self-loops, and the network must remain connected. Additionally, this paper uses the collective cooperation rate to judge the cooperative performance of the network after reconnection; if the network cooperation increases, the reconnection operation is maintained, otherwise, the reconnection operation is undone.

4 Experimental simulation

4.1 Reconstruction network statistical indicator test

The experiment is conducted using the python, where the network is modeled as a weighted graph and evolves according to the method by Nowak and May in reference [19]. This method places "agents" in a two-dimensional spatial array to explore the changing spatial patterns of nodes. In this paper's experiment, the two-dimensional grid space is replaced with a more three-dimensional BA scale-free network. In the model, when a reward system is implemented to encourage cooperative behavior, the utility function of cooperators is enhanced, manifested as an additional reward, while the utility function of individuals adopting a defection strategy remains unchanged. Similarly, when the model adopts punitive measures to sanction defection, the utility function of defectors will suffer a loss, specifically reflected in the deduction of a fixed amount P as a penalty. In this case, the utility function of individuals choosing a cooperative strategy remains unchanged. The specific value is set to $R = 1, T = b, S = 0, P = 0$. At the beginning of the experiment, an initial probability of cooperation is randomly assigned to each node in the network graph. The evolutionary game strategy introduced in Chapter 1 is then used for calculations, with the defection payoff set to b = 1.2 and the time step MCS = 5,000. Subsequently, the network begins to evolve. After the network reaches a preliminary state of stability, reconnection operations are performed based on the average payoff of each node using the algorithm from Figure 2, and the reconnected network undergoes degree distribution testing and natural connectivity testing.

The degree distribution in a communication network describes the probability distribution of the number of connections (degree) of various nodes within the network, such as routers, switches, and terminal devices. This distribution influences the efficiency of communication within the network.

Through the simulation analysis of the optimization of complex network topological structures, the following basic conclusions can be drawn:
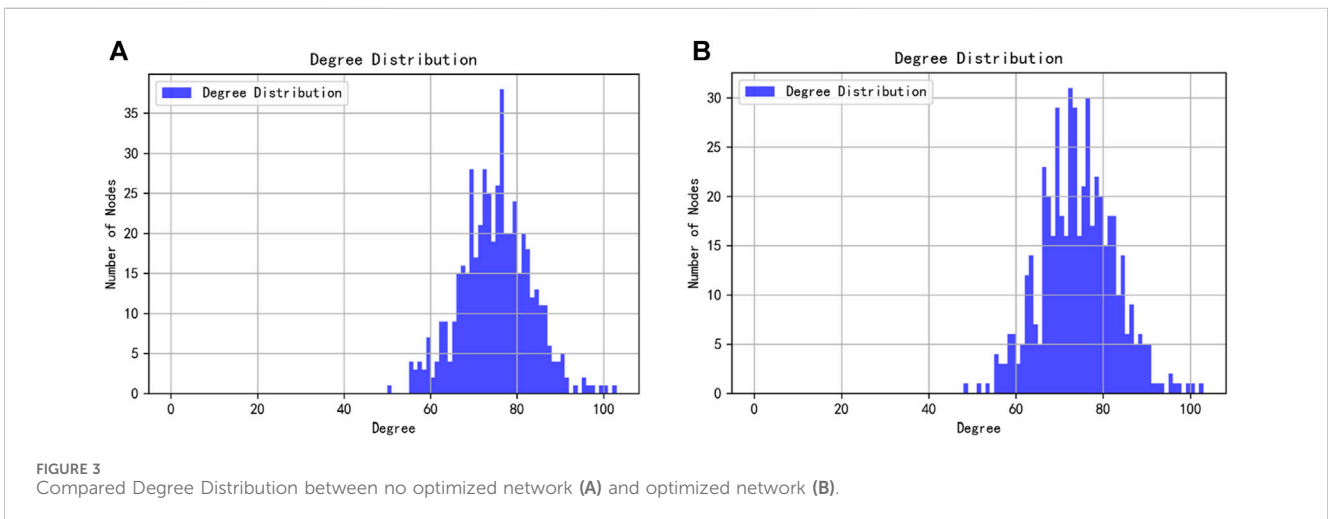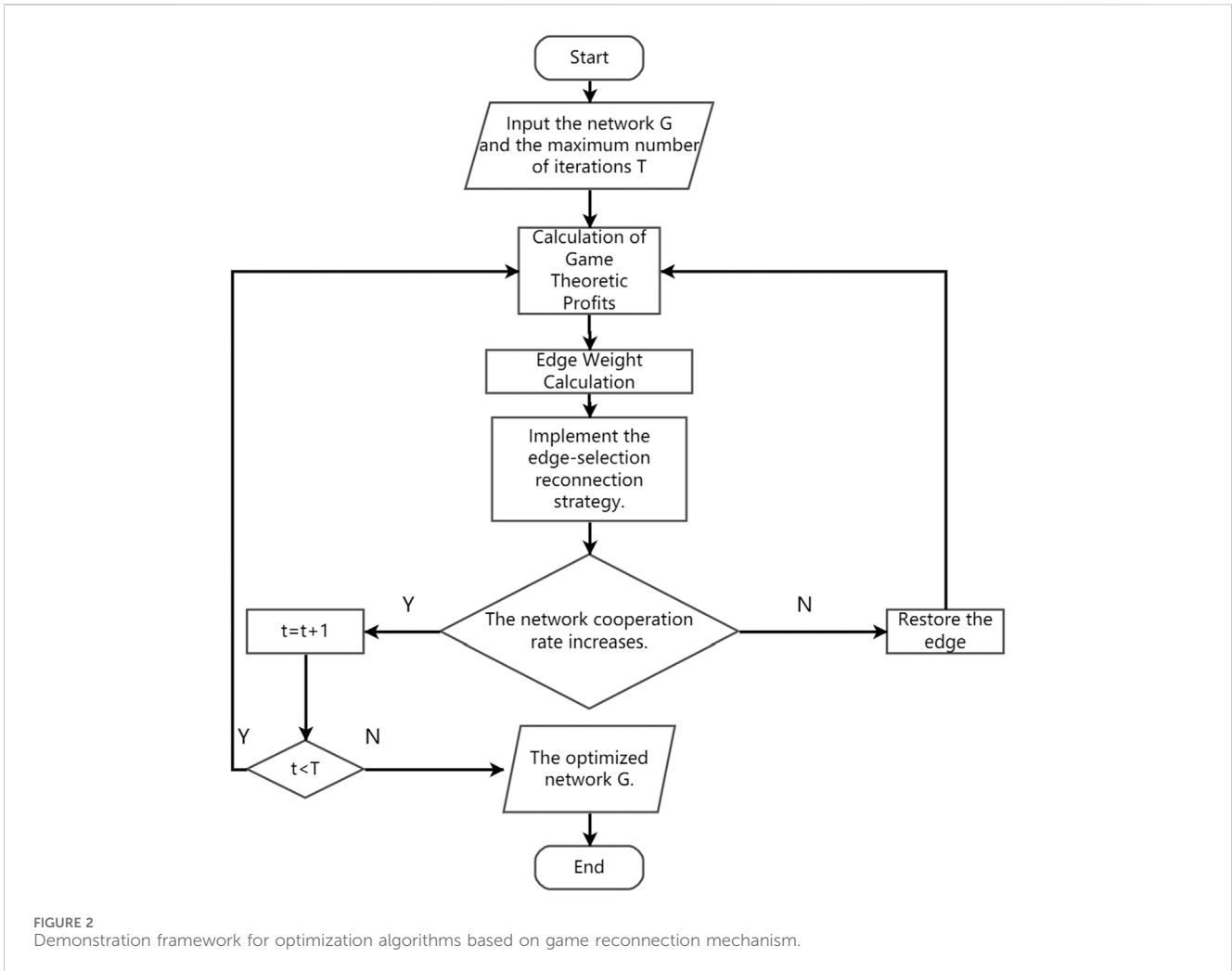
1) The simulation analysis has verified the effectiveness and feasibility of the complex network topology optimization model and the solution model. As the topological structure continues to be optimized, the natural connectivity value continuously increases, indicating that the network's resilience to destruction is constantly strengthening.

2) By comparing the results of Figures 3A, B, it can be observed that the degree distribution of the network has changed after optimization, where nodes with high degree values and those with low degree values have gradually decreased, while nodes with a moderate degree (around 74) have significantly increased. This results in the entire network's cooperation rate being in an optimal state, possibly because a very high degree value can lead to traffic congestion, which is not conducive to collective interests; too low a degree value can also affect the decrease in selfish benefits of individual entities. Therefore, the reconnection edge strategy in this paper serves as the best way to balance the interests of individuals and the collective.

3) Analyzing the relationship between natural connectivity and the number of evolutionary generations, as well as the relationship between fitness values and the number of evolutionary generations, as depicted in Figures 4, 5, reveals a common pattern. It is evident that both of these metrics increase with the increase in the number of evolutionary generations. This suggests that nodes with higher degrees are more likely to form new connections with other nodes that also have high degrees.

4.2 Robustness analysis

The purpose of complex network topology optimization is to enhance the network's resilience. The analysis mentioned above establishes a topology optimization model using natural connectivity as a measure of network resilience, significantly improving the network's resistance to destruction. Here, two types of strategies are adopted: random (node and edge removal) attacks and malicious (node and edge removal) attacks. These are implemented before and after the optimization of complex network topologies to analyze the changes in network resilience, as shown in Figures 6–9.
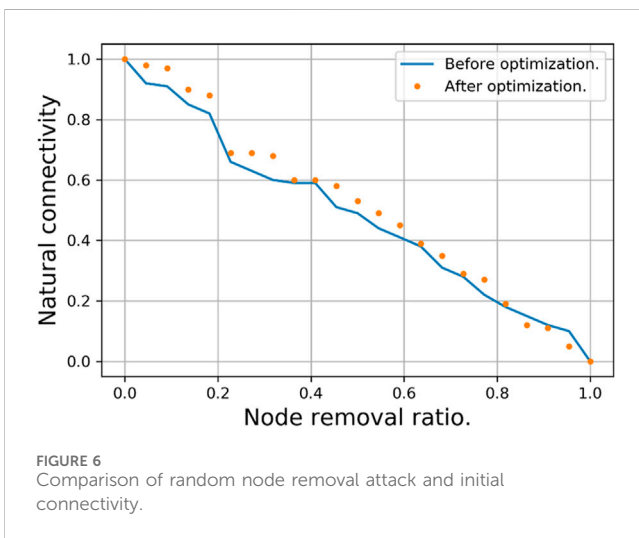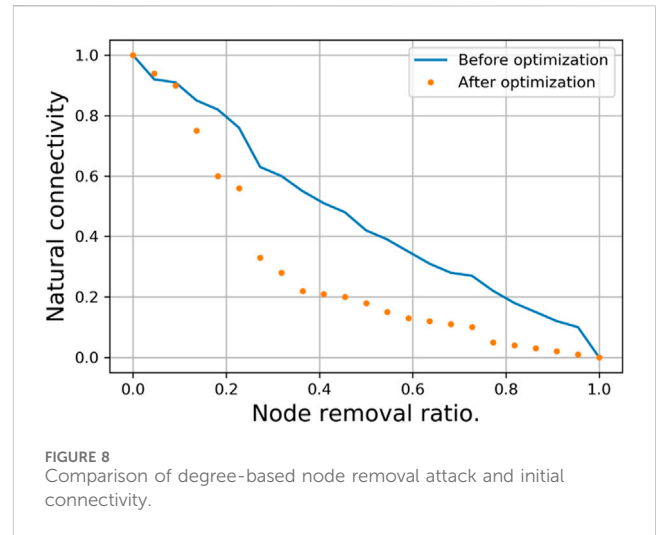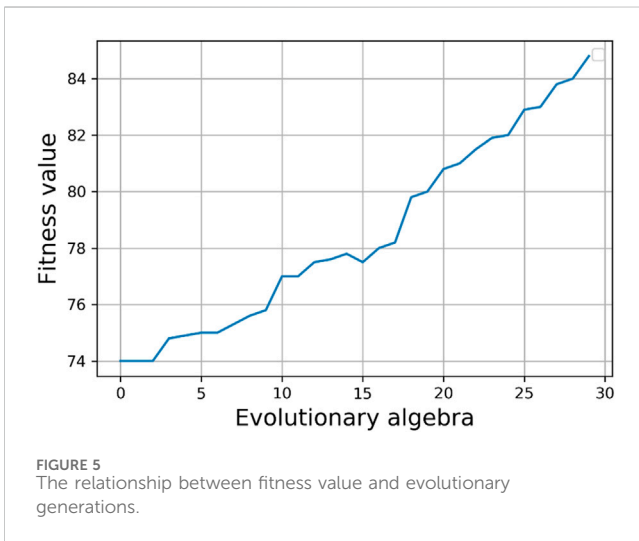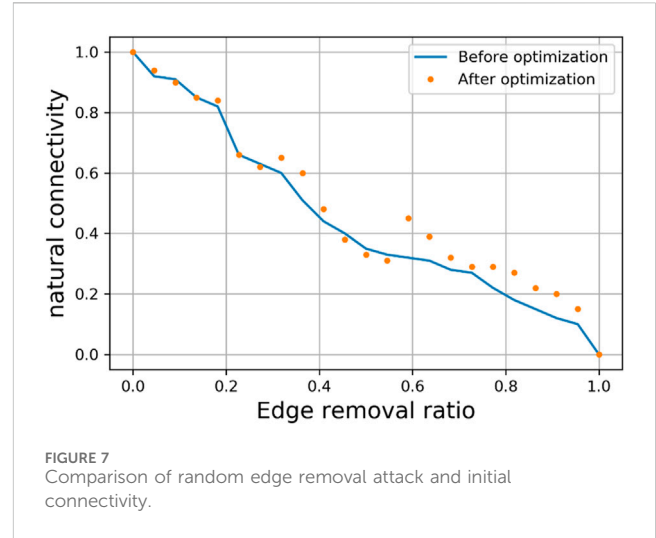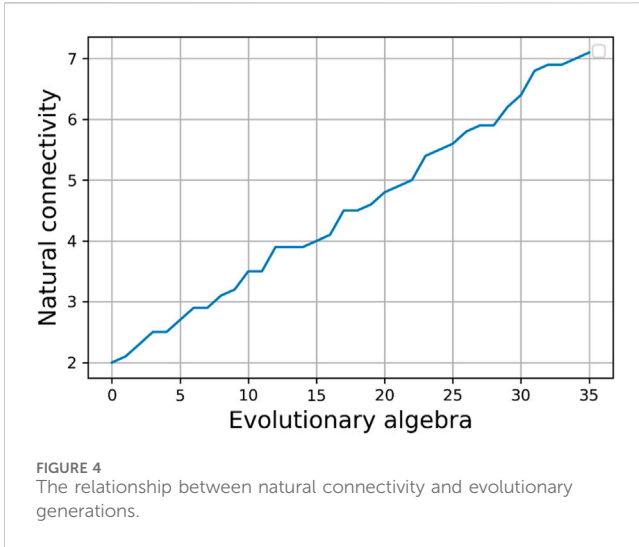
Through simulation analysis, it is known that complex network topologies before and after optimization exhibit the following characteristics when facing different attack strategies:

1) In the random node removal attack strategy (Figure 6), the optimized network's resistance to attacks is higher than the resistance before optimization, mainly reflected in the slower decline in network resilience as the proportion of node removal increases. Analyzing the network's topological structure, using the average degree as a dividing line, the proportion of nodes with low degrees in the optimized network increases, while the proportion of nodes with high degrees decreases. Therefore, under the random attack

FIGURE 2
Demonstration framework for optimization algorithms based on game reconnection mechanism.

FIGURE 3
Compared Degree Distribution between no optimized network **(A)** and optimized network **(B)**.

strategy, the average probability of low-degree nodes being attacked in the optimized network is higher than that of high-degree nodes, and the impact of low-degree nodes on network resilience is also smaller, thus demonstrating stronger resistance to attacks.

2) In the random edge removal attack strategy (Figure 7), the network's resistance to attacks is similar before and after optimization, and it is only when the edge removal ratio exceeds approximately 0.6 that the optimized network's resistance to attacks shows a slight improvement.

FIGURE 4
The relationship between natural connectivity and evolutionary generations.

FIGURE 5
The relationship between fitness value and evolutionary generations.

FIGURE 6
Comparison of random node removal attack and initial connectivity.

FIGURE 7
Comparison of random edge removal attack and initial connectivity.

FIGURE 8
Comparison of degree-based node removal attack and initial connectivity.

3) In the degree-based node removal attack strategy (see Figure 8), where nodes are removed in descending order of degree, the optimized network exhibits poorer resilience against this attack method. The removal of a small number (about 10%) of high-degree nodes leads to a significant decrease (about 40%) in network resilience, almost paralyzing the network; whereas the network before optimization demonstrates relatively stronger resilience against such attacks.

4) In the betweenness-based edge removal attack strategy (see Figure 9), where edges are removed in order of their betweenness centrality, the optimized network shows relatively stronger resilience against this attack method. The removal of a minority (about 20%) of edges with high betweenness has a limited impact on network resilience. The analysis attributes this to the tendency of low-degree nodes in the optimized network to connect with high-degree nodes, which results in the edges connecting high-degree nodes also having relatively high betweenness, thus the edges have stronger redundancy.

FIGURE 9
Comparison of betweenness-based edge removal attack and initial connectivity.
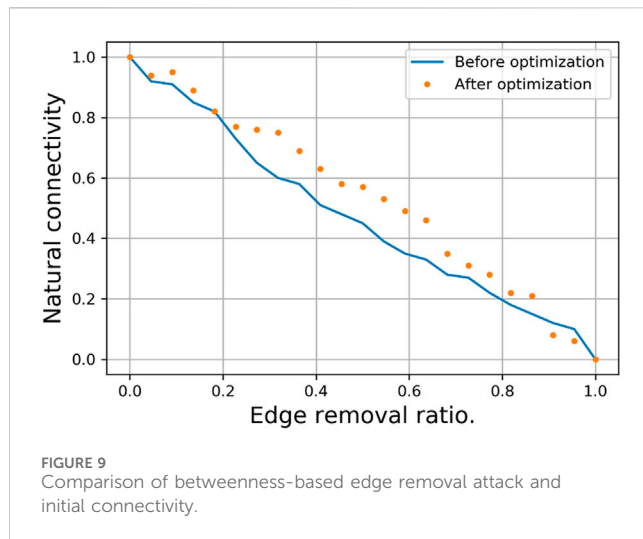
Conversely, for the network structure before optimization, the situation is the opposite.

This paper considers attack strategies, which belong to the dynamic optimization of network topological structures. The optimized network has enhanced resilience against node removal attacks.

5 Conclusion

This paper introduces a rewiring strategy based on node game payoff, which assigns initial cooperation rates to nodes through cooperative game play, and adjusts cooperation benefits during dynamic interactions. It introduces reward and punishment mechanisms to achieve average payoff. In this process, each network node not only makes decisions based on its own payoff but also considers the collective intelligence synergy of the entire network to achieve overall optimization. Building on this, the paper uses the average payoff between nodes for rewiring and evaluates the rewiring effect with the collective cooperation rate. The experimental results show that the optimization algorithm proposed in this paper performs better in terms of the proportion of nodes in natural connectivity and robustness indicators when subjected to attacks such as random node attacks, random edge attacks, degree centrality attacks, and betweenness centrality attacks on the multi-layer network topology of the Internet of Things (IoT) in the railway sector. It is also found that the network exhibits poor resistance to attacks when facing degree-based node removal attacks. Therefore, in practical applications, it is necessary to choose different network topological structures based on the specific real threats faced. In conclusion, the research findings of this paper provide a reference for achieving rapid networking, efficient transmission, and secure and stable operation of communication in the IoT for the railway sector.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

FW: Formal Analysis, Methodology, Software, Validation, Writing–original draft, Writing–review and editing. KS: Investigation, Methodology, Software, Validation, Writing–original draft, Writing–review and editing. BL: Conceptualization, Funding acquisition, Investigation, Writing–review and editing. JY: Conceptualization, Supervision, Validation, Writing–review and editing. WB: Software, Supervision, Validation, Writing–original draft, Writing–review and editing.

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Conflict of interest

Authors BL, JY, and WB were employed by China Academy of Railway Sciences Company Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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