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MODELLING AND SIMULATION OF METRO FIRE RISK PROPAGATION WITH IMPROVED SIR MECHANISMS

Jia, Q. J.*; Zhang, L.*,**,# & Liu, Z. L.*
* School of Economics and Management, China University of Geosciences (Beijing), Haidian District, Beijing, P.R. China
** Faculty of Business, City University of Macau, Macau, P.R. China
E-Mail: 2009250034@email.cugb.edu.cn, zhangl@cugb.edu.cn, 3007240020@email.cugb.edu.cn
(# Corresponding author)

Abstract
Research on the propagation mechanism of metro fire risk can assist operators in preventing and controlling fires while safeguarding public travel safety. In this paper, susceptible–infected–recovered (SIR) models incorporating the reaction-time mechanism, edge-cutting mechanism, and pre-immunization mechanism are developed and integrated with a metro fire risk complex network to simulate risk propagation and investigate its patterns. The propagation network is constructed based on the analysis of causal factors and causal chains derived from past metro fire accidents. The results show that vehicle equipment failure and electromechanical equipment failure are critical nodes within the metro fire risk complex network. Enhancing the recovery rate, edge-cutting probability, and pre-immunization probability can, to varying degrees, reduce the spread of risk across the network. These findings provide a theoretical foundation for formulating metro fire risk prevention and control measures.
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Key Words: Metro Fire, Risk Propagation, Complex Network, SIR Model, Causal Chain

1. INTRODUCTION

The metro is a crucial component of urban public transport. With advantages such as high operating speed, punctual arrivals, and affordable fares, it provides significant convenience for passengers. However, with the rapid development of rail transit, various accidents occur frequently, among which metro fire accidents account for more than 40 % [1]. These incidents not only have the highest occurrence rate but also cause the most severe losses. Metro fires are typically the result of multiple interacting risk factors. Therefore, an in-depth investigation of their propagation mechanisms is of great significance for formulating targeted prevention and control measures and for enhancing the safety and reliability of metro operations.

Current research on metro fire accidents mainly concentrates on two aspects: fire simulation and risk management. Fire simulation studies focus on smoke dispersion and passenger evacuation [2, 3]. Giachetti et al. conducted scaled model experiments of metro stations to examine the effects of factors such as metro geometry and ventilation volumetric flow rate and proposed more efficient smoke extraction strategies [4]. Zhang et al. developed a hybrid simulation method combining multiple evacuation times, multi-attribute decision analysis, and numerical modelling to identify the most adverse fire scenarios [5]. Si et al. used Pyrosim and Pathfinder software to simulate the entire process of smoke spread and passenger evacuation in an air–rail intermodal hub station, analysing the evacuation times under both smoke-extraction system failure and normal operating conditions [6]. Research on risk management has addressed issues such as safe operation, the reliability of fire alarm equipment, and methods of risk assessment. Choi et al. introduced fuzzy mathematics into metro fire studies and proposed a risk checklist and questionnaire-based approach [7]. Chai et al. put forward a hybrid FANP–FGRA–Cloud method to quantitatively evaluate fire safety in metro stations and identify the safest stations [8]. However, the above studies have primarily focused on physical scenario simulation and risk assessment of metro fires, with insufficient attention paid to causative factors and the underlying mechanisms of risk propagation.

Complex network theory has been widely applied in fields such as financial systems and stock markets for studies on risk propagation and risk assessment [9-11]. In recent years, however, it has increasingly been employed in accident causation analysis and in examining the relationships among risk factors [12]. González and De La Mota constructed a dynamic stochastic network of the Mexico City metro, analysed changes in hub index, betweenness index and clustering coefficient, and proposed recommendations for future research [13]. Ermagun et al. measured metro networks in 50 cities and built complex network models to assess their vulnerability through simulation experiments [14]. Bi et al. incorporated real-world factors into a complex network model and quantitatively evaluated the flood resilience of London's rail transit system [15]. Wang et al. applied complex network analysis to identify critical causative factors and their interrelations in urban rail transit accidents, providing a theoretical basis for risk analysis and accident prevention [16]. Most of these studies have relied on analysing the physical structures of metro systems, constructing complex networks and examining their topological features, but they lack abstraction and systematic modelling of metro fire risk factors.

The susceptible–infected–recovered (SIR) model was originally widely applied in the study of epidemics, but in recent years it has gradually been adopted by scholars for research on accident risk propagation and risk control. Berger et al. developed a susceptible–infected–susceptible (SIS) model in which nodes represented suppliers and directed edges denoted material flows. Through simulating risk infection, they found that strengthening quality control at key nodes could reduce supply chain vulnerability [17]. Chen et al. employed an SIS model to quantify panic emotions during the evacuation process and revealed their transmission patterns [18]. Wen et al. constructed a stochastic SIR model and adjusted the infection rate to quantify the propagation of risky driving behaviours [19]. Feng et al. proposed a dynamic risk diffusion model for complex industrial networks, combining propagation threshold with network average degree to provide guidance for industrial system risk management [20]. However, traditional models often overlook external intervention factors, and specific research on metro fire risk propagation remains limited [21].

The objective of this study is to examine the causal relationships among the causal factors of metro fires, construct a complex network of metro fire risk, and analyse its topological characteristics to identify key causal factors. An improved susceptible–infected–recovered (SIR) model is established and combined with the complex network to conduct SIR-based simulation experiments, with the aim of revealing the propagation mechanism of metro fire risk. Finally, based on risk management theory, this study provides overarching recommendations for metro fire prevention and control.

The contributions of this study are as follows: (1) a metro fire risk complex network is constructed by integrating accident causation theory with the "4M" management theory, and its topological characteristics are analysed to identify key control nodes; (2) an improved SIR model is developed, incorporating the reaction-time mechanism, edge-cutting mechanism, and pre-immunisation mechanism; (3) simulation experiments based on the improved SIR model are designed, and by adjusting key parameters, the propagation patterns of metro fire risk are revealed.

2. RESEARCH METHOD

This study collects metro fire incidents from both domestic and international sources, extracts their causal factors, and analyses the accident causation chains to construct a complex network of metro fire risk. An improved SIR model is then developed and applied to simulate risk propagation on the network, with the aim of examining the underlying patterns of risk transmission. The framework of this research is illustrated in Fig. 1.

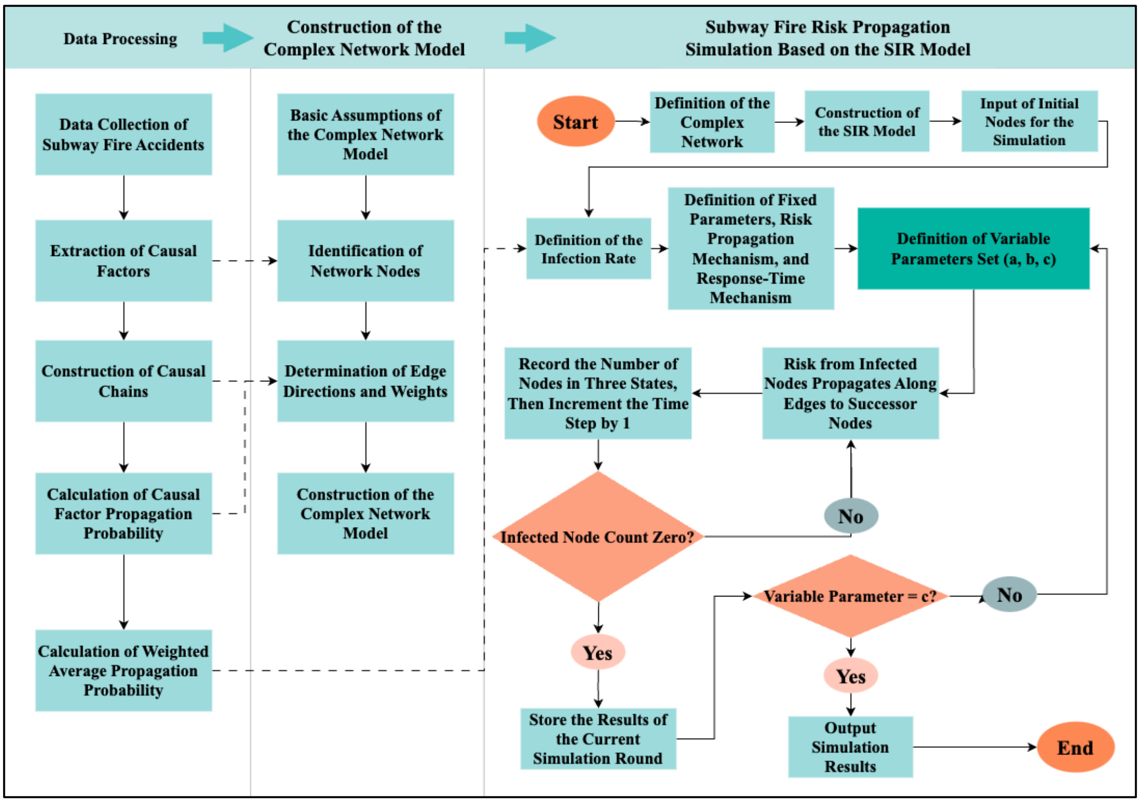


Figure 1: Research framework of metro risk propagation simulation.

2.1 Extraction of metro fire causal factors and construction of causal chains

Based on past metro fire accident cases, this study analyses accident reports in accordance with the 4M management theory and relevant regulations, delineates the accident evolution process, conceptualizes this process, extracts universal causative factors, and categorizes them into four types: human, equipment, environment, and management.

Based on the extracted metro fire causative factors, this study further analyses the causal relationships between these factors to construct accident causation chains. These chains can be categorized into single-factor causation chains and multi-factor sequential causation chains. For example, the 2004 Moscow metro fire in Russia was constructed as a single-factor causation chain: terrorist attack → fire.

The propagation probability of a metro fire accident causal factor is defined as the ratio of the number of times a causal factor leads to a chain accident to the total number of occurrences of that factor. All multi-factor accident causal chains are decomposed into single-factor accident causal chains and combined with the original single-factor chains. The frequency of each chain is then counted, and its propagation probability is calculated, which is used as the edge weight in the constructed complex network.

The propagation probabilities of individual causal factors are weighted by their frequencies to calculate the weighted average propagation probability, which is subsequently used as the infection rate in the SIR model.

2.2 Construction of metro fire risk complex network

The propagation of metro fire risk involves interactions among multiple causal factors, exhibiting complex causal relationships. Constructing a complex network of metro fire risk enables a systematic characterisation of the interconnections among causal factors and clarifies the paths and directions of risk propagation.

In the modelling process, this study is based on the assumption: each node in the network represents a causal factor of metro fire, while the edges denote the causal relationships between factors. The direction of an edge indicates the direction of risk propagation among the causal factors.

Based on the causal factors and causal chains extracted from metro fire accident data, and combined with the assumptions of the metro fire risk complex network model, the metro fire risk complex network can be constructed using Gephi software. In this network diagram, the weights of the edges are determined by the propagation probabilities of causal factors of metro fires calculated in Section 2.1.

2.3 Construction of the improved SIR risk propagation model

The SIR model is a mathematical model used to describe the process of disease transmission within a population. The risk of metro fires can spread through multiple pathways, and this risk propagation process is similar to the spread of infectious diseases, characterised by dynamism and uncertainty. The SIR model is well suited to describe this process.

SIR model considering reaction time mechanism: At the early stage of a fire, people require time to detect the fire, respond, and initiate emergency procedures. Therefore, in constructing the metro fire risk propagation model, a reaction time parameter $t_{reaction}$ is introduced. This time mechanism prevents the simulation process from being interrupted at the initial moment of risk propagation due to the immediate recovery of the initial node. Based on the evolution rules of the SIR model, this study makes the following assumptions regarding the SIR model with a reaction time mechanism: (1) The total number of nodes in the metro fire risk complex network remains unchanged. (2) Initial infected nodes are selected according to the initiating causal factors of metro fires, while all other nodes are initially in a susceptible state. (3) The infection rate is determined based on the weighted average propagation probabilities among the causal factors of metro fires. (4) Nodes do not have recovery capability during the reaction time. (5) The network model is directed, and risk propagates following the direction of edges between nodes, with no consideration of backward propagation. The system of differential equations is shown in Eq. (1).

$S(t)$ is the number of nodes in the susceptible state S at time t; $I(t)$ is the number of nodes in the infected state I at time t; $R(t)$ is the number of nodes in the recovered state R at time t; N is the total number of nodes in the network; β is the infection rate; γ is the recovery rate; and $t_{reaction}$ is the reaction time.

$$\begin{cases} \dfrac{dS(t)}{dt} = -\beta S(t)I(t)/N \\ \dfrac{dI(t)}{dt} = \dfrac{\beta S(t)I(t)}{N} - \gamma I(t)u(t - t_{reaction}) \\ \dfrac{dR(t)}{dt} = \gamma I(t)u(t - t_{reaction}) \end{cases} \tag{1}$$

Here, $u(t)$ is a step function:

$$u(t - t_{reaction}) = \begin{cases} 0 & t < t_{reaction} \\ 1 & t \geq t_{reaction} \end{cases}$$

SIR model with edge-cutting mechanism: In metro safety management, a series of fire prevention measures are usually implemented to block the propagation of risk. Therefore, an edge-cutting mechanism is added to the SIR model that already incorporates the reaction time mechanism. In addition to the previous assumptions, the following additional assumptions are made: (1) After the risk begins to propagate, at each time step, infected nodes are identified, and the outgoing edges of these nodes have a probability of being cut. Once an edge is cut, it can no longer transmit the risk. (2) To prevent the propagation process from terminating at the initial moment due to the cutting of outgoing edges from the initial nodes, the edge-cutting mechanism is not activated during the reaction time. The system of differential equations for the SIR model with the edge-cutting mechanism is given in Eq. (2):

$$\begin{cases} \dfrac{dS(t)}{dt} = -\dfrac{\beta S(t)I(t)}{N} + \delta \dfrac{\beta S(t)I(t)}{N} u(t - t_{reaction}) \\ \dfrac{dI(t)}{dt} = \dfrac{\beta S(t)I(t)}{N} - \delta \dfrac{\beta S(t)I(t)}{N} u(t - t_{reaction}) - \gamma I(t) u(t - t_{reaction}) \\ \dfrac{dR(t)}{dt} = \gamma I(t) u(t - t_{reaction}) \end{cases} \tag{2}$$

δ represents the edge-cutting probability, indicating the probability that an outgoing edge of an infected node is cut per unit time after the reaction time. The remaining parameters are the same as in Eq. (1).

SIR model with pre-emptive immunity mechanism: Before a metro fire occurs, effective preventive measures can protect causative factors from being affected by the risk propagation process. Therefore, a pre-emptive immunity mechanism is added to the SIR model that already considers the reaction time mechanism, with the following additional assumptions: (1) To prevent the propagation from terminating at the initial moment due to the initial node being pre-emptively immune, the initial node does not participate in the pre-emptive immunity mechanism. (2) Before the risk begins to propagate, all nodes except the initial node may acquire a pre-emptive immunity state with a certain probability. Nodes in the pre-emptive immunity state cannot be infected by the risk and do not propagate the risk.

The differential equations of the SIR model with the pre-emptive immunity mechanism are shown in Eq. (3):

$$\begin{cases} \dfrac{dS(t)}{dt} = -\dfrac{\beta S(t)I(t)}{N} \\ \dfrac{dI(t)}{dt} = \dfrac{\beta S(t)I(t)}{N} - \gamma I(t) u(t - t_{reaction}) \\ \dfrac{dR(t)}{dt} = \gamma I(t) u(t - t_{reaction}) \\ N = S(t) + I(t) + R(t) + P \end{cases} \tag{3}$$

N is the total number of nodes in the network model, P is the number of nodes in the pre-emptive immune state, and the remaining parameters are the same as in Eq. (1). The calculation of P is given by:

$$P = \pi(N - 1)$$

Here, π is the pre-emptive immunity probability, and $N - 1$ excludes the initial node from which the risk propagation starts.

Improved SIR Model Simulation: Due to the complexity of the model, this study employs computer simulation to capture the dynamic evolution of node states. To compare and verify the differences in risk propagation characteristics under various mechanisms, simulation experiments were designed for SIR models incorporating the reaction time mechanism, the edge-cutting mechanism, and the pre-emptive immunisation mechanism. The infection rate β is set as the weighted average propagation probability between accident causal factors, thus β = 0.645. The parameter settings for the three SIR models are presented in Table I.

Based on the statistically identified initial causal factors of metro fire incidents, each factor was individually used as the risk initiation node for simulation. The simulation was implemented using the Python programming language and its relevant modules. The entire process was set to run for 200 time steps, with each step representing 1 second, and the reaction time was set as $t_{reaction} = 3$ s. The simulation terminated when the number of nodes in the infected state I in the network dropped to zero, indicating that the risk had been completely eliminated.

Table I: Comparison of simulation parameters for the three SIR models.

Model	Recovery rate γ	Edge cutting probability δ	Pre-emptive immunity probability π
SIR model with reaction time mechanism	0.1, 0.3, 0.5	—	—
SIR model with edge-cutting mechanism	0.1	0.2, 0.4, 0.6	—
SIR model with pre-emptive immunity mechanism	0.1	—	0.2, 0.4, 0.6

To enhance the generalisability of the simulation results, each experiment was initially conducted as a single run, with the results recorded and analysed. Subsequently, 50 iterative simulations were performed, with the outcomes of each run recorded, and the average values for each time step were calculated to produce the final simulation results for validation.

3. SIMULATION EXPERIMENTS AND RESULTS

3.1 Causal factors

This study collected 90 metro fire incidents worldwide between 1903 and 2024. The data sources included: (1) literature and accident reports; (2) online searches; and (3) published books and other relevant materials. A total of 26 causal factors were identified, which are summarised in Table II.

Table II: Causal factors in metro fire incidents.

Category	ID	Causal factors	ID	Causal factors
Human	P1	Staff operational violations	P6	Passenger mental health issues
	P2	Improper operation by staff	P7	Carrying flammable/explosive items
	P3	Lack of staff responsibility	P8	Terrorist attacks
	P4	Insufficient passenger safety awareness	P9	Sabotage of facilities
	P5	Discarding unextinguished cigarette butts	P10	Arson
Equipment	Q1	Vehicle equipment failure	Q3	Electromechanical equipment failure
	Q2	Vehicle design defects	Q4	Information system failure
Environment	E1	Aging and damage of internal facilities	E5	External third-party construction impact
	E2	Internal facility malfunctions	E6	External fire spread
	E3	Poor internal hygiene conditions	E7	Foreign object intrusion
	E4	Demonstrations and social unrest	-	-
Management	M1	Inadequate emergency management	M4	Improper waste management
	M2	Insufficient supervision and inspection	M5	Incomplete management systems
	M3	Insufficient staff training	-	-

3.2 Metro fire risk complex network

Based on the accident causation chains extracted in the previous study and the assumptions of the metro fire risk complex network model, the metro fire risk complex network diagram shown in Fig. 2 was constructed using Gephi software.

The network diagram contains a total of 27 nodes, where node C represents "fire" and the remaining 26 nodes represent the causal factors of metro fire incidents. The edges between nodes indicate the causal relationships among these factors, with a total of 66 edges in the network. The thickness of each edge reflects its weight within the network.

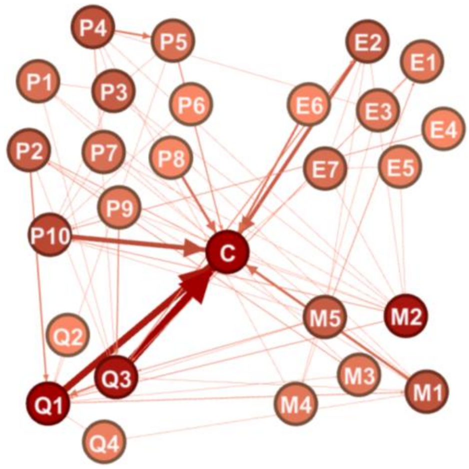


Figure 2: Metro fire risk complex network.

The network characteristic analysis indicates that the network exhibits small-world properties, with good connectivity between nodes, and that the degree distribution follows a scale-free pattern. This study conducts network reliability analysis using both deliberate attacks and random attacks. The results of deliberate attacks indicate that the metro fire risk network is sensitive to the failure of key nodes, showing a certain level of vulnerability. The results of random attacks show that the network as a whole demonstrates a degree of robustness against random node failures, with minimal changes in network parameters.

Network topological characteristics: This study selects typical indicators at both the node and network levels to analyse the topological characteristics of the subway fire risk complex network. Fig. 3 summarises the calculation results for each node indicator.

Node degree measures the importance of a node and its influence on neighbouring nodes. As shown in Fig. 3 a, nodes such as Q1, Q3, and M1 have high total and out-degree values, indicating that they occupy central positions in the network and exert strong influence on other factors, making them prone to triggering risk cascades. At the same time, nodes such as Q1, Q3, and M2 have high in-degree values, making them more susceptible to influences from other factors and increasing the difficulty of risk prevention.

The clustering coefficient measures the degree of node aggregation within a network and reflects the presence of "small groups" or communities [22]. Fig. 3 b shows that nodes Q4 and E5 have the highest clustering coefficients. This indicates that these nodes are strongly connected to their neighbouring nodes, facilitating risk transmission among them and increasing the difficulty of controlling subway fire incidents.

Eigenvector centrality evaluates the influence of a network node by considering not only its direct connections but also the importance of its neighbouring nodes. As seen in Fig. 3 c, nodes such as P2, Q1, Q3, and M1 have high eigenvector centrality. This suggests that controlling these nodes can help manage the other nodes associated with them, thereby reducing the propagation of subway fire risk.

Betweenness centrality measures the bridging role of a node within the network. As shown in Fig. 3 d, Q3 has the highest betweenness centrality, indicating that this node possesses strong transmission and control capabilities between nodes, and its state changes are most likely to trigger a cascade, thereby significantly affecting the diffusion of subway fire risk throughout the network.

At the global level, in the subway fire risk network composed of 27 nodes, the network diameter is 7 and the average path length is 2.93, indicating that risk can propagate through relatively few intermediary nodes, and the network exhibits high overall connectivity efficiency. The global clustering coefficient is 0.184, suggesting that local clustering among nodes is weak and that the risk propagation paths are relatively dispersed.

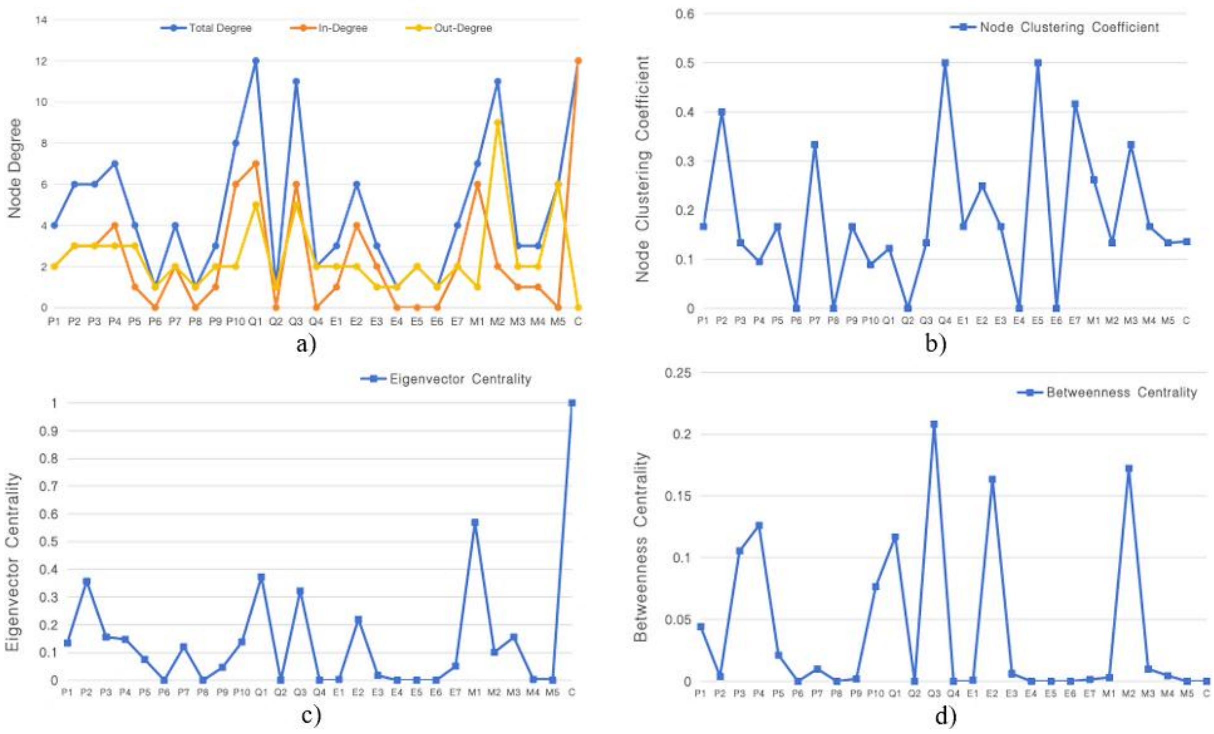


Figure 3: Analysis of network topological characteristics: a) Overview of node degrees; b) Overview of node clustering coefficients; c) Overview of node eigenvector centrality; d) Overview of node betweenness centrality.

3.3 Simulation results of metro fire risk propagation based on the improved SIR model

Simulation results of SIR model under different recovery rates: From the simulation experiments involving 19 starting nodes, this study selects the results for two typical starting nodes, P2 and E6, as examples for analysis, with the single-run simulation results shown in Fig. 4. Considering space limitations, this experiment and several subsequent experiments only present a selection of key result figures.

When risk propagates within the metro fire risk complex network, if the infection rate is fixed, an increase in the recovery rate effectively shortens the duration of risk presence in the network. When risk originates from a peripheral node (P2), corresponding to a longer accident causation chain, increasing the recovery rate helps reduce the number of infected nodes (I) in the network. However, when risk originates from a central node (E6), corresponding to a shorter accident causation chain, increasing the recovery rate does not effectively reduce the number of infected nodes (I). In the results of 50 repeated simulations, the variations in both the duration of risk presence and the number of infected nodes (I) with different recovery rates are consistent with those observed in single-run simulations.

Simulation results under different edge cut probabilities: Using P2 and E6 as the initial nodes, the single-run simulation results after adding the edge cut mechanism are shown in Fig. 5 (from a to f). Analysis of the single-run simulation figures indicates that when simulations are conducted from different initial nodes, the changes in the number of nodes in the three states, as well as the peak number of nodes in the infected state I, vary with the increase in edge cut probability. This variation is related to the eccentricity of the initial node. When the initial node has a high eccentricity, such as P2 (eccentricity of 6), increasing the edge cut probability can effectively reduce the number of nodes infected by risk and lower the peak number of nodes in the infected state I. Conversely, when the initial node has a low eccentricity, such as E6 (eccentricity of 1), the peak number of nodes in the infected state I shows no significant change.

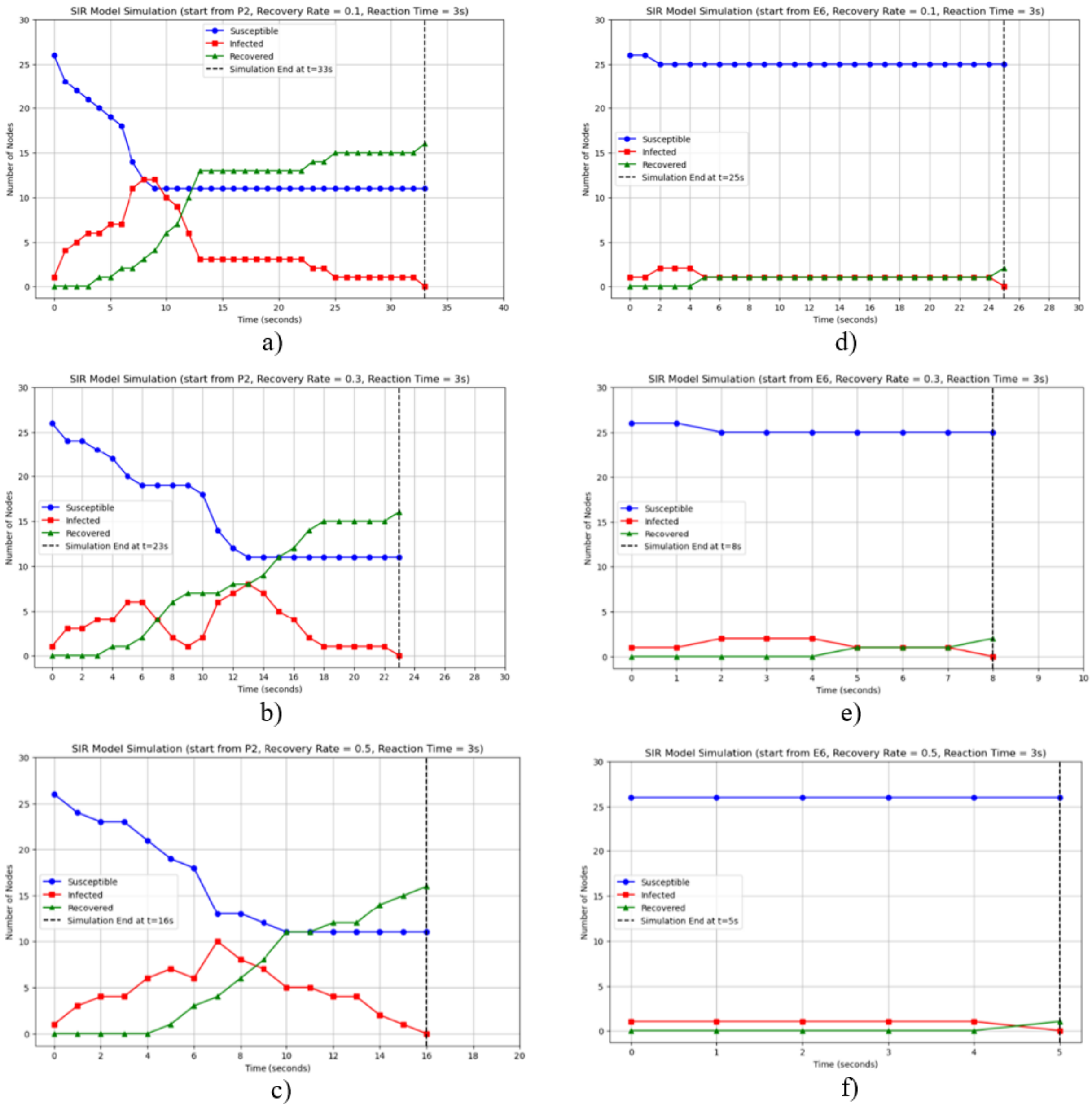
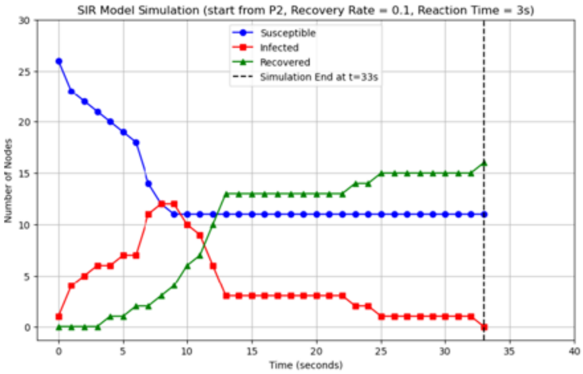


Figure 4: Single simulation results of SIR model under different recovery rates; a) to c) Starting from P2; d) to f) Starting from E6.

Simulation results under different pre-immunization probabilities: With P2 as the initial node, the single-run simulation result after adding the pre-emptive immunity mechanism is shown in Fig. 6. Analysis of Fig. 6 indicates that when P2 is the starting node, the addition of the pre-emptive immunity mechanism effectively reduces the peak number of nodes in the infected state I, and this peak decreases as the pre-emptive immunity probability increases. However, for some starting nodes, such as E6, increasing the pre-emptive immunity probability does not significantly affect the peak number of infected nodes I.

A comprehensive analysis of the all single-run simulation results shows that when simulations are conducted from different starting nodes, increasing the pre-emptive immunity probability can effectively reduce the number of nodes infected by the risk and limit the spread of risk within the network. This effect is particularly pronounced when the starting node has a larger number of outgoing edges and more complex subsequent propagation paths. The results are consistent in the 50-run cyclic simulation results.



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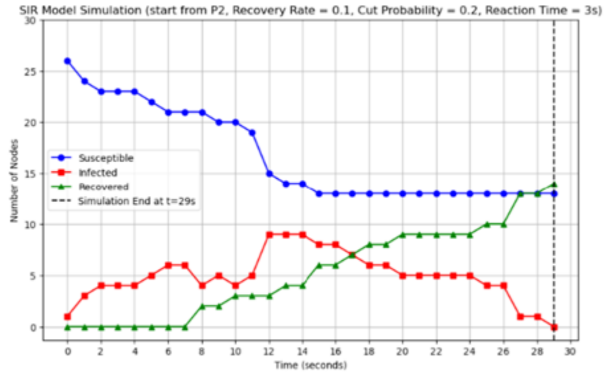

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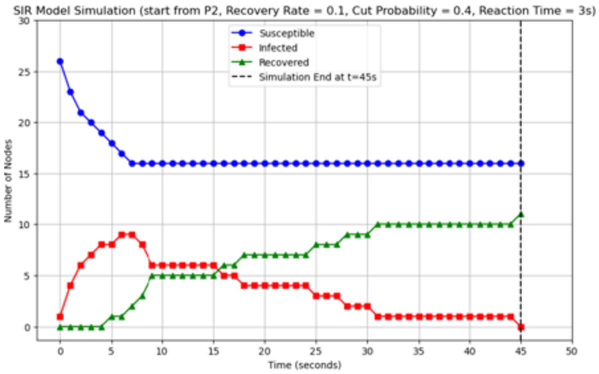

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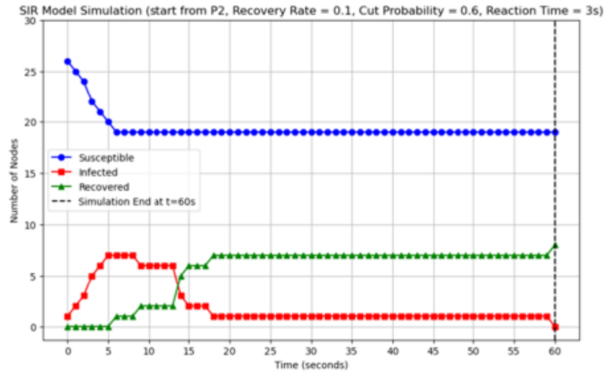
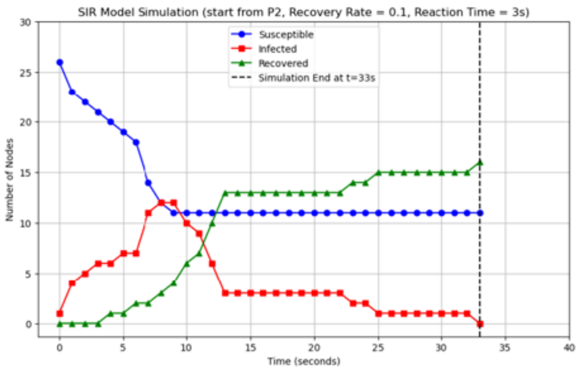
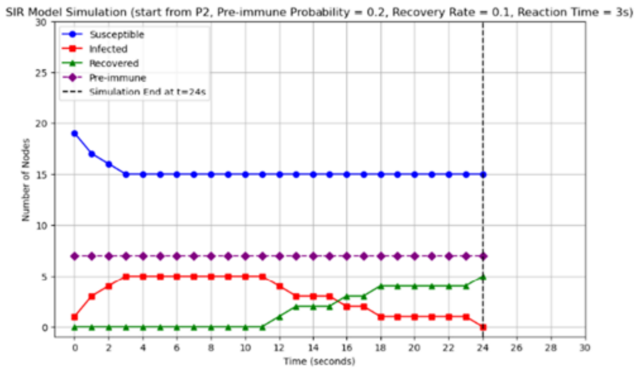


d)

Figure 5: A single simulation result diagram of the SIR model with P2 as the initial node under different edge cut probabilities: a) 0, b) 0.2, c) 0.4, d) 0.6.



a)



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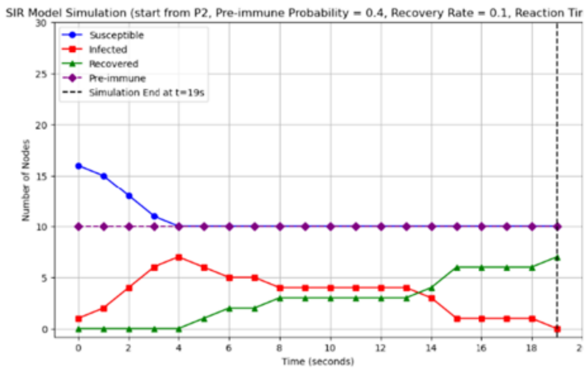

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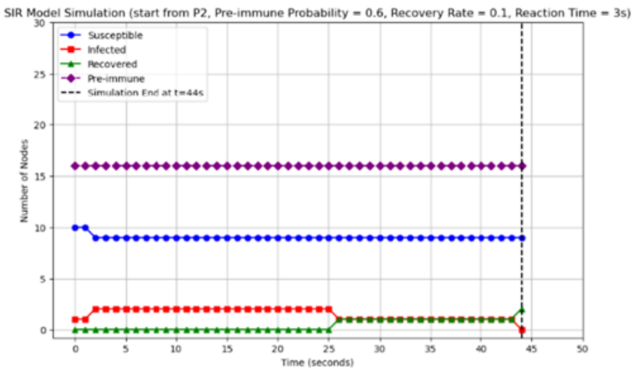

d)

Figure 6: A single simulation result diagram of the SIR model with P2 as the initial node under different pre-immunization probabilities: a) 0, b) 0.2, c) 0.4, d) 0.6.

4. DISCUSSION AND CONCLUSION

The analysis of the topological characteristics of the metro fire risk network shows that certain nodes, such as Q1 and Q3, stand out across multiple indices and are key nodes within the network. Nodes Q4 and E5 have the highest clustering coefficients, indicating stronger associations with their adjacent nodes and making it easier for risks to spread among them. In practice, it is essential to ensure that preventive and control measures for these critical causative factor nodes are effective. Although the network demonstrates strong overall connectivity, its local clustering is relatively weak, suggesting that risks can propagate more rapidly across the network and are more likely to trigger chain incidents, which calls for faster emergency responses in metro fire prevention and control.

From the simulation results of metro fire risk propagation, it is observed that increasing the recovery rate, the edge-cutting probability, and the pre-immunisation probability can, to varying degrees, reduce the spread of risk across the network. In terms of risk management theory, the following recommendations are proposed for metro fire prevention and control: (1) In metro fire prevention and control, it is necessary to place particular emphasis on monitoring the causal factors that can directly trigger metro fires, as well as those causal factors located at the later stages of the causal chain, thereby improving the efficiency of emergency response and handling. (2) Initiating risk factor nodes should be monitored and inspected, and fire safety equipment capable of interrupting risk transmission should be reasonably planned and deployed to improve the efficiency of blocking risk propagation. (3) Pre-treatment of equipment and facilities should be undertaken to enhance the capacity of relevant causal factors to resist potential metro fire risks.

This study constructed a metro fire risk complex network model and, based on this model, conducted risk propagation simulations using an improved SIR model to investigate the patterns of risk propagation, thereby providing support for ensuring the safe operation of metro systems. The conclusions of this study are summarized as follows:

(1) By constructing the metro fire risk complex network and analysing its topological characteristics, it was found that vehicle equipment failure and electromechanical equipment failure are key nodes in the network and require focused attention.

(2) Through establishing the improved SIR model and simulating metro fire risk propagation, the results indicate that increasing the recovery rate, the edge-cutting probability, and the pre-immunization probability can all reduce the number of infected nodes at different levels and limit the spread of risk within the network.

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