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EMERGENCY DECISION SIMULATION FOR URBAN RAIL TRANSIT DURING RAINSTORM FLOODS

Xing, Y. Z.; Guo, X. Y.[#]; Si, Q. M.; Zeng, Z. & Guo, Y. Y.
School of Civil Aviation, Zhengzhou University of Aeronautics, Zhengzhou, 450046, China
E-Mail: xyguo@zua.edu.cn ([#] Corresponding author)

Abstract
Forty fundamental disaster events were extracted from 52 typical flood disaster cases in urban rail transit operations in China. The evolution network and topology of rainstorm and flood disasters were then constructed based on the complete network model. Next, the characteristic parameters of nodes and connecting edges were calculated, and the chain-type evolution laws of disasters explained. Finally, complex network efficiency *E* and average clustering coefficient *C* were taken as evaluation indexes, and a simulation experiment of random and deliberate attacks was designed aiming at the nodes and connecting edges. Eventually, the critical nodes and basic events influencing the disaster network vulnerability were revealed. Results show that deliberate attacks are better than random attacks in disrupting the network during rainstorm and flood disasters. Specifically, the network is influenced significantly by deliberate attacks on nodes with high PageRank values. In the attack on edges, obstructing basic events with high PageRank values can reduce network density by up to 30.2 %.
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Key Words: Urban Rail Transit, Rainstorm and Flood, Complex Network Analysis, Network Attack, Decision Simulation

1. INTRODUCTION

With the acceleration of global warming and urbanization, extreme rainstorms are also increasing in intensity and frequency [1]. Studies have shown that for every 1 °C increase in global temperature, the maximum daily precipitation in a 50-year return period increases by nearly 7 % [2]. As underground infrastructure, urban rail transit subway systems are designed and constructed to comply with local flood prevention regulations. To enhance resilience against flooding, engineers typically raise subway station entrances by 30–45 cm above ground level. Nevertheless, rapid urbanization, which is characterized by more impervious surfaces and higher runoff, exacerbates the risk of rainwater backflow during intense rainfall events, particularly in areas with poor drainage. Consequently, urban waterlogging disasters occur frequently due to factors such as declining water storage rates in city areas, rising runoff coefficients, and insufficient drainage system capacities. Subway systems of urban rail transit, which are located underground, are susceptible to flooding due to the underground recharging of accumulated water during urban floods. In recent years, rail transit accidents induced by flood disasters have become increasingly common across the globe. The urban rail transit flood disaster system involves many risk factors, large-scale disaster systems, and a complex evolution process. Risk events are intricately correlated and evolve with temporal variation, leading to the extreme uncertainties faced by rail transit operators when formulating disaster prevention and mitigation measures [3]. Hence, the basis for effectively preventing and controlling disaster events lies in clarifying the evolution laws of disaster events, analysing their mechanisms, and identifying their transmission route.

However, existing studies on the risk analysis of urban rail transit rainstorm and flood disasters mainly focuses on resilience analysis [4], risk assessment [5], and flood control measures [6]. The study paradigm largely focuses on analysing risk resistance and the reliability of disaster prevention and mitigation measures for urban rail transit systems in the face of rainstorm and flood disasters based on the interaction analysis of disaster scenarios. It also investigates the evolution mechanism of urban rail transit rainstorm and flood disasters by modelling disaster carriers, as well as introducing the temporal idea to analyse disaster events and discuss the causation of disaster events from the macro-level [7]. However, an interaction analysis is lacking between sub-events in the disaster system from the macro-level. Moreover, a vulnerability analysis of the disaster network and a validation of the effectiveness of disaster prevention and mitigation strategies have not been explored sufficiently. Accordingly, this study extracted basic disaster events from typical historical cases of urban rail transit rainstorm and flood disasters via data mining technology. The complexity of urban rail transit rainstorm disasters arises from the multitude of underlying events and their intricate interdependencies. By leveraging the statistical properties of network evolution in a complex network model, small-world and scale-free network models were employed to analyse text mining data and unveil the underlying mechanisms and evolution patterns of urban rail transit rainstorm flood disasters, thus providing insights into the propagation of risks within the disaster network. This study adopts a novel approach of network vulnerability analysis to evaluate the effectiveness of disaster prevention and mitigation strategies. By simulating attacks on critical nodes and links within the complex disaster network, the aim is to provide a scientific foundation for urban rail transit operators to develop tailored risk management strategies that enhance resilience to rainstorm flood disasters.

2. STATE OF THE ART

Owing to technological advancements, study methods for analysing rainstorm flood disasters in urban rail transit primarily focus on causal factors, including data collection, model development, and analysis techniques [8]. Eduardo and Forero-Ortiz built a 1D/2D hydrodynamic model to analyse the risk of flood disasters in subway stations, taking Barcelona Metro Line 3 as a case study. Their study was conducted within the framework of the European project RESCCUE, named "The ability of urban areas to cope with climate change: A multi-sectoral collaborative approach focusing on floods". Sui et al. [9] put forward a subway flood risk assessment model based on improved AHP and entropy weight method aiming at the excess subjectivity of traditional AHP and performed model verification for Heshan Street Subway Station in Harbin, Heilongjiang Province, China. The advent of Industry 4.0 has spurred the development of increasingly sophisticated models for urban rail transit rainstorm flood disasters. These models, which incorporate computational techniques such as numerical simulation, computational fluid dynamics, and complex systems analysis, enable more accurate and detailed simulations of disaster processes. Xiahou et al. [10] constructed an FDA cause model of subway train flooding accident analysis, which consisted of three modules: individual, self-organization, and other organizations. Growing recognition of the complex and multifaceted nature of rainstorm flood disasters in urban rail transit has prompted a shift in study focus. Researchers are now delving into the interplay between natural factors, the built environment, and flood prevention measures to develop more effective strategies for mitigating rail flood risks. Li et al. [11] constructed a risk assessment model of subway flood disasters, which included 13 factors. They then analysed and predicted the possibility of subway flood disasters based on the DNN neural network method. To improve the accuracy of subway flood risk assessment, Mokhtari et al. [12] pointed out that the occurrence of subway flood disasters is determined by the frequency and scope of geotechnical engineering and air quality disasters. They found that the severity of accident consequences depends on the disaster-bearing threshold of the subway system. To sum up, from the study perspective, existing studies on urban rail transit rainstorm and flood disasters mostly focus on risk assessment, disaster conditions, and engineering and technical conditions. Although the risk of urban rail transit flood disasters has been discussed in detail from different perspectives, the dynamic disaster process and formation mechanism within the urban rail transit flood disaster system remains unclear. In terms of the severity of accident consequences, the catastrophe of the internal rail transit environment and the failure of the disaster system are the root causes of mass deaths and casualties.

In the study on disaster prevention and mitigation measures for urban rail transit operation and management enterprises facing rainstorm and flood disasters, earlier works predominantly focused on reactive measures, such as emergency response planning, static risk assessment, and public education to address rail flood disasters. However, recent studies have moved beyond these traditional approaches, exploring more proactive and holistic strategies. These newer strategies include developing flood prevention plans based on accident investigation reports from typical cases of urban rail transit flood events and proposing preventive measures before disaster occur. Xu et al. [13] quantitatively studied the flood risk assessment literature of subway systems, provided statistical data, and expounded on the general paradigm of disaster prevention and mitigation strategies and emergency actions that subway systems around the world often take in response to flood disasters. Wang et al. [14] adopted the accident cause analysis model and put forward improvement and optimization strategies for the flood control emergency plans of urban rail transit operations management enterprises. Researchers have employed remote sensing and meteorological monitoring techniques during disasters to track rainfall patterns and inform real-time monitoring and forecasting of urban rail transit flooding. Study on post-disaster assessments of rail flood damages aim to identify the underlying causes and develop strategies for mitigating future risks. The findings from these investigations can be used to inform the development of effective response and recovery plans for urban rail transit operators. Compton et al. [15] investigated the flood risk in Vienna, Austria, evaluated the flood risk of subways based on catastrophe modelling and Monte Carlo simulation, and compared the effectiveness of several disaster prevention and mitigation strategies through multidisciplinary analysis. Despite the well-defined stages in the process, it has been found that the lack of seamless transitions between each stage has hindered the efficiency of emergency response [16]. The need for a more integrated and holistic approach to emergency management for urban rail transit flood disasters is increasingly being recognized. As a result, the fragmented, stage-based measures of the past have evolved into a comprehensive system that addresses all phases of a disaster, from preparedness to recovery. Recent studies have adopted a systems-based approach to urban rail transit flood management, focusing on the interconnected aspects of flood prevention, risk assessment, emergency response, information sharing, and recovery. Although learning from accidents is an essential path for disaster prevention and mitigation work, analysing the direct causes of accidents simply through typical cases fails to satisfy the prevention and control needs of increasingly serious urban rail transit flood disasters.

Given the deficiencies of existing research, this study constructs a network topological graph of urban rail transit rainstorm and flood disasters based on the complex network model. Subsequently, the action mechanism between disaster events is analysed by identifying the vulnerability of disaster response systems to targeted attacks on key nodes and links. On the basis of the findings, this study proposes tailored disaster prevention and mitigation strategies for urban rail transit rainstorm flood disasters. This study contributes to a more comprehensive understanding of disaster risk management in urban rail transit systems.

3. METHODOLOGY

3.1 Extraction method of basic events from urban rail transit rainstorm and flood disasters

In this study, text mining technology was employed to extract basic disaster events from the historical cases of urban rail transit rainstorm and flood disasters [17]. First, the historical case data were formatted and processed to construct the corpus. Then, using Python and the Jieba Chinese word segmentation tool, custom dictionaries, stop word lists, and merged word lists were loaded to segment the disaster scenario texts. Finally, a co-word matrix was constructed through word frequency statistics, word cloud generation, and keyword extraction to analyse the action mechanisms between disaster events. Based on the word frequency analysis after text segmentation, a word cloud of basic disaster events was generated, and a correlation value between word frequency and font size was set [18]. To avoid the interference of redundant data, an improved TF-IDF algorithm was applied to evaluate the influence of feature words on the text, balancing the word frequency and weight, while normalizing the weight of feature words.

3.2 Index analysis method for the disaster network structure

Node importance: (1) Degree centrality. Degree centrality is an index that determines the importance of a node in a complex network [19]. In the degree attack, removing the node with the highest degree first means destroying the most active and critical disaster event in the disaster network.

(2) Betweenness centrality. Betweenness centrality is an index to describe the importance of a node by the number of shortest paths passing through it. Nodes with high betweenness are usually the key bridges in the network, and the greater betweenness centrality of a node represents its higher betweenness [20].

(3) Closeness centrality. Closeness centrality indicates the average distance between a node and other nodes in the network. The greater the closeness centrality of a node, the stronger the ability of the node to affect other nodes [21].

(4) PageRank parameter. In complex networks, PageRank is an index to measure the importance of nodes by indicating the number and quality of connected nodes [21]. A PageRank attack aims to destroy the most influential nodes in the network.

Vulnerability of disaster chain edges: In the topological structure of the disaster chain network, the vulnerability of a connecting edge refers to the degree of influence on the whole network structure after removing this edge. Based on Salama et al. [22], the vulnerability V_s of basic event-connecting edges in the complex network was analysed by selecting the betweenness of edges, the average path length, and the connectivity.

$$V_s = \frac{B_s L_s}{H_s} \tag{1}$$

In the equation above, s is the s^{th} edge, B_s is the betweenness of the s^{th} edge, L_s is the average path length of this network after removing the s^{th} edge, and H_s represents the connectivity of the complex network topological structure after removing the s^{th} edge.

(1) Edge betweenness. Betweenness refers to the number of shortest paths passing through a connecting edge of a network. The betweenness is expressed as below:

$$B_s = \sum_{i,j} g_{i,j(s)} \tag{2}$$

Here, $g_{i,j(s)}$ is the number of times for the shortest path between nodes i and j to pass through the connecting edge s.

(2) Average path length. The number of edges passed by the shortest path between nodes i and j expresses the shortest path between the two nodes [23]. The average path length is solved as follows:

$$L = 2\frac{1}{N(N+1)}\sum_{i=1}^{n} F_{ij} \tag{3}$$

In the above equation, L is the average path length, and F_{ij} is the shortest distance from node i to node j in the complex network.

(3) Connectivity. The connectivity of disaster events refers to the ratio of the number of nodes connected with the edge s in the disaster chain to the number of nodes in the disaster network after the edge s is removed [23]. The connectivity is expressed as follows:

$$H = \frac{N_s}{N} \tag{4}$$

3.3 Study on rainstorm and flood disaster network vulnerability of urban rail transit

Attack strategies: The attack strategies designed in this study were divided into random attack and deliberate attack. The former randomly attacked the nodes or edges in the network, and the latter attacked the nodes or edges in the network in a targeted manner according to the parameter values in the network. Deliberate attack was subdivided into different attack strategies according to the selected parameters. For deliberate attack, the next attack could be implemented only after parameter reordering. In this study, network vulnerability was investigated by selecting five attack strategies for node attack, namely random node attack, degree attack, betweenness attack, closeness attack, and PageRank attack. In the process of edge attack, the network vulnerability was studied using two attack strategies: random edge attack and deliberate edge attack.

Indexes to measure disaster network vulnerability: (1) Network efficiency E. When a node or edge in the network is disturbed, the network operation efficiency is certainly affected. In the urban rail transit rainstorm and flood disaster network, a slowdown in operational efficiency following attacks on nodes and connecting edges indicated a weakening interaction between disaster events within the network [24]. (2) Average clustering coefficient C. The clustering coefficient reflects the connection closeness between local nodes in the network [25]. As for the disaster network attack, a small change in the average clustering coefficient C manifests high network vulnerability.

4. RESULTS

4.1 Data source (case background)

A comprehensive dataset of 142 urban rail transit rainstorm flood disasters that occurred from 2015 to 2023 was compiled through a systematic review of news reports from China News Network, Baidu News, and Tencent News, as well as global disaster data platforms and official government documents. The dataset was constructed by searching for incidents using keywords such as “rail transit flood”, and “urban rail water disaster”, thus providing a solid foundation for subsequent analysis. By combining the universality analysis of cases by experts and professors, we obtained 98 study cases through simplification and sorting. The collected typical cases were then subjected to text mining and analysis.

4.2 Analytical results

Construction of urban rail transit rainstorm and flood disaster network model: First, the historical cases were numbered, and the urban rail transit rainstorm and flood disaster corpus was established according to the study cases after data formatting. Then the corpus was digitalized through word segmentation, and a co-word matrix was created for internal information mining of the corpus. Finally, keywords were identified, specifically focusing on 40 basic urban rail transit rainstorm and flood disaster events, as seen in Table I.

Table I: Basic urban rail transit rainstorm and flood disaster events.

Node no.	Disaster event	Node no.	Disaster event
V1	Rainstorm	V21	Ground traffic paralysis
V2	Increasing rainfall	V22	Selection of subway transportation by passengers
V3	Continuous rise of water level	V23	Increasing number of subway passengers
V4	Destruction of subway weather shield	V24	Rising groundwater level
V5	Train flooding	V25	Floating of subway structures
V6	Station waterlogging	V26	Reduction of tunnel waterproofness
V7	Communication system destruction	V27	Reduction of tunnel durability
V8	Illumination system fault	V28	Reduction of tunnel stability
V9	Ventilation system fault	V29	Tunnel permeation
V10	Signal system fault	V30	Tunnel deformation
V11	Elevator fault	V31	Tunnel collapse
V12	Train fault	V32	Tunnel inundation
V13	Train delay	V33	Subway operation fault
V14	Operating facilities fault	V34	Train derailment
V15	Passenger retention	V35	Train collision
V16	Congestion and stampede	V36	Trapped passengers
V17	Temperature rise	V37	Safety shield destruction
V18	Reduction of oxygen concentration	V38	Personnel casualties
V19	Passengers missing	V39	Economic losses
V20	Passengers panicking	V40	Adverse social impacts

From October to December 2023, we received a total of 45 valid responses, including 21 from researchers, 13 from management personnel, and 11 from frontline staff. Drawing from the ideas of Dong et al. [26], a mean-based integration approach was employed to quantify the direct influence between pairs of factors within the questionnaire data. The extracted basic events of urban rail transit rainstorm and flood disasters in Table I were abstracted into network nodes, and the correlations between disaster events were abstracted into connecting edges, as shown in Fig. 1.

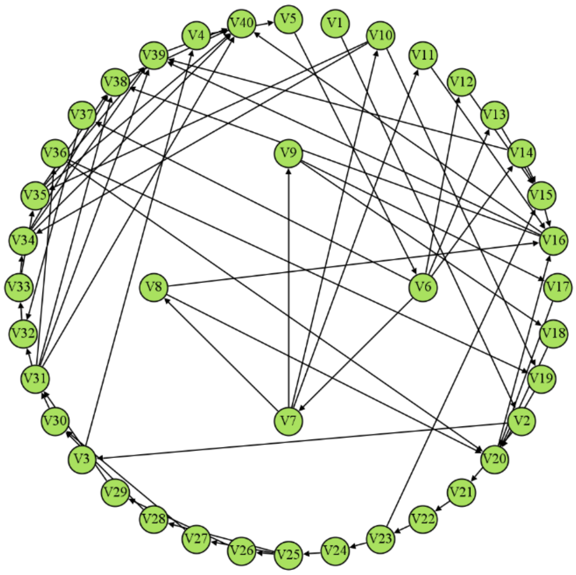


Figure 1: Complex network topological graph of urban rail transit rainstorm and flood disasters.

Risk analysis of urban rail transit rainstorm and flood disaster network: (1) Calculation of node importance. To compute the degree centrality, betweenness centrality, closeness centrality, and PageRank value of each node in the urban rail transit rainstorm and flood disaster network, as seen in Fig. 2 below.

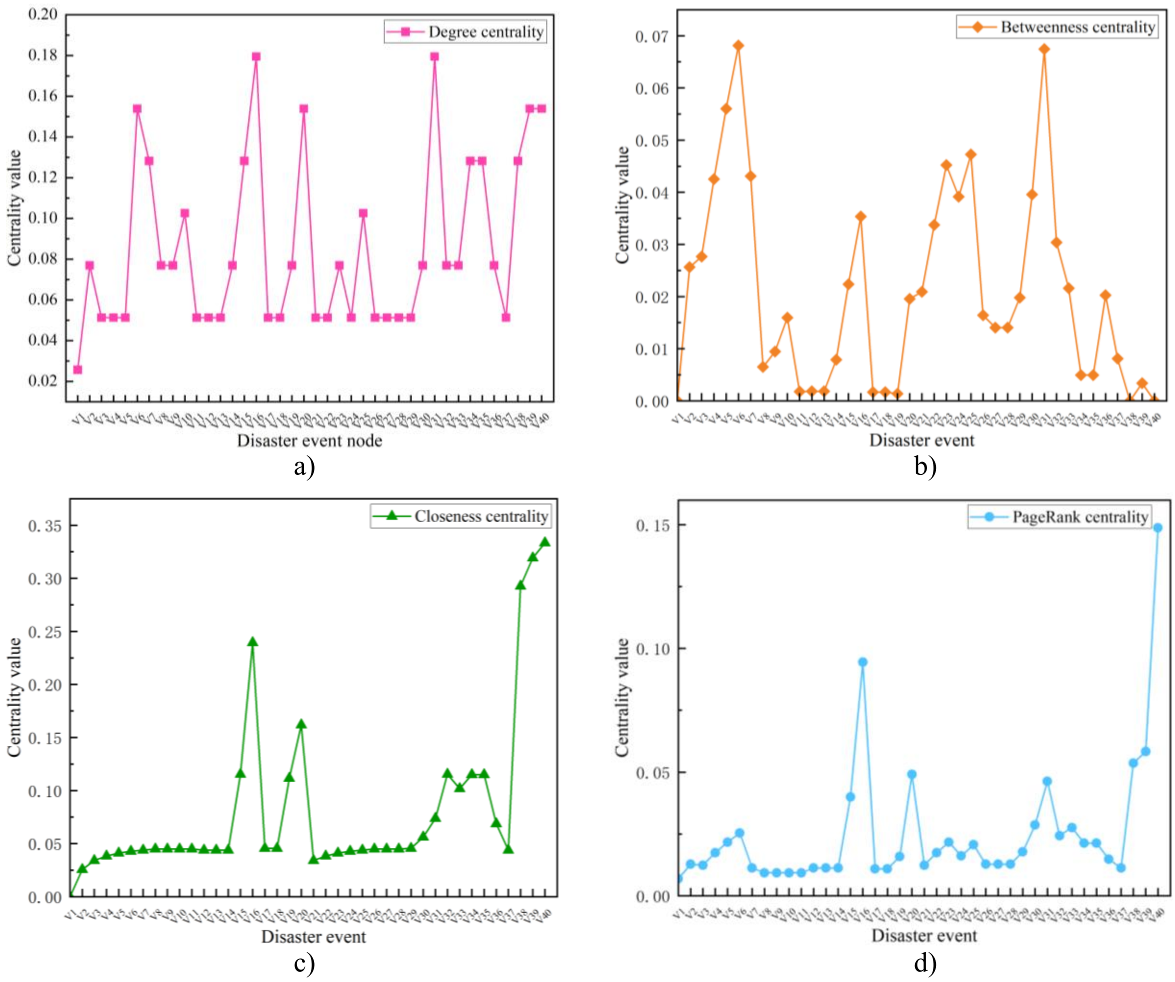


Figure 2: Parameters of disaster event nodes a) to d).

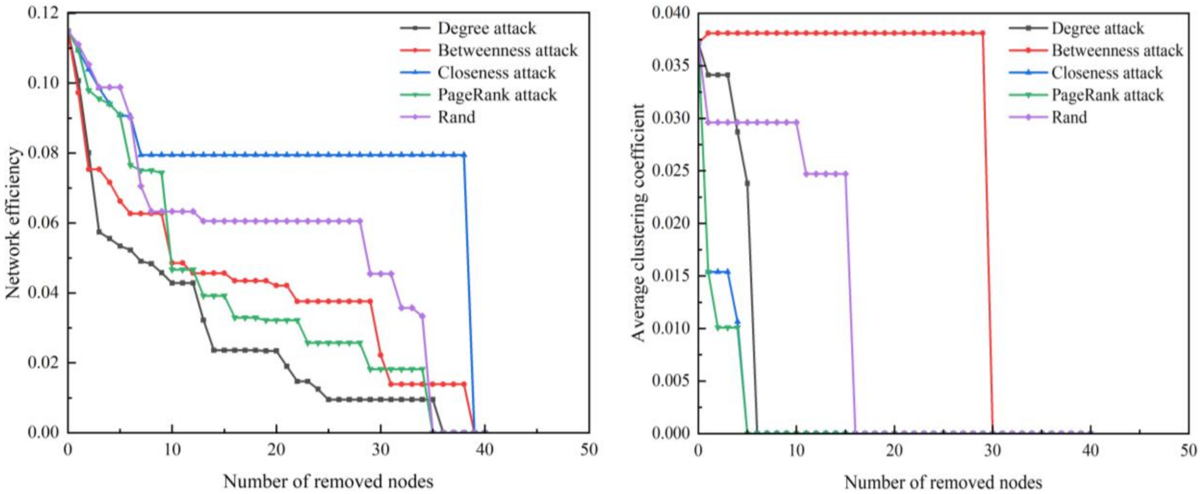
Fig. 2 a reveals that nodes V31 (tunnel collapse) and V16 (congestion and stampede) had the maximum degree centrality of 0.179, whose degree centrality was 0.154. Hence, rail transit operations management enterprises should focus on tunnel maintenance and avoid congestion and stampede events when faced with rainstorm and flood disasters. Fig. 2 b shows that nodes V6 (station waterlogging), V21 (tunnel collapse), and V5 (train flooding) presented relatively high betweenness centrality, safety departments of rail transit operations management enterprises should carry out routine inspection and maintenance of tunnel structures to reinforce their integrity. As shown in Fig. 2 c above, nodes V40 (adverse social impacts), V29 (economic losses), and V28 (personnel casualties) exhibited high closeness centrality. In the process of disaster prevention and mitigation, conspicuous signs and guide cards should be set up in subway stations, the connection closeness of this disaster network can be analysed. Fig. 2 d above reveals that nodes V40 (adverse social impacts), V16 (congestion and stampede), and V29 (economic losses) showed relatively high PageRank values. Releasing early warning information in advance, strengthening guides in the station, setting up conspicuous signs and guide cards in the subway station, and providing temporary rain shelter facilities.

(2) By performing the calculation, three edges – V5→V6 (station waterlogging due to train flooding), V4→V5 (train flooding due to the destruction of subway weather shields), and V30→V31 (tunnel collapse due to tunnel deformation) – showed relatively high vulnerability. In the process of disaster prevention and mitigation, weather shields can be reinforced or heightened. The attack on highly vulnerable edges aims to reduce the occurrence of critical paths in the urban rail transit rainstorm and flood disaster network and critical edges causing the evolution of disaster events.

Vulnerability simulation of urban rail transit rainstorm and flood disaster network:

(1) Vulnerability analysis under the attack on disaster network nodes

In the current study, deliberate attacks were conducted according to the degree centrality, betweenness centrality, closeness centrality, and PageRank of nodes in descending order. The network operation efficiency E and average clustering coefficient C were calculated to evaluate the vulnerability of the urban rail transit rainstorm and flood disaster network. The attack results are displayed in Fig. 3 below.



a) b)

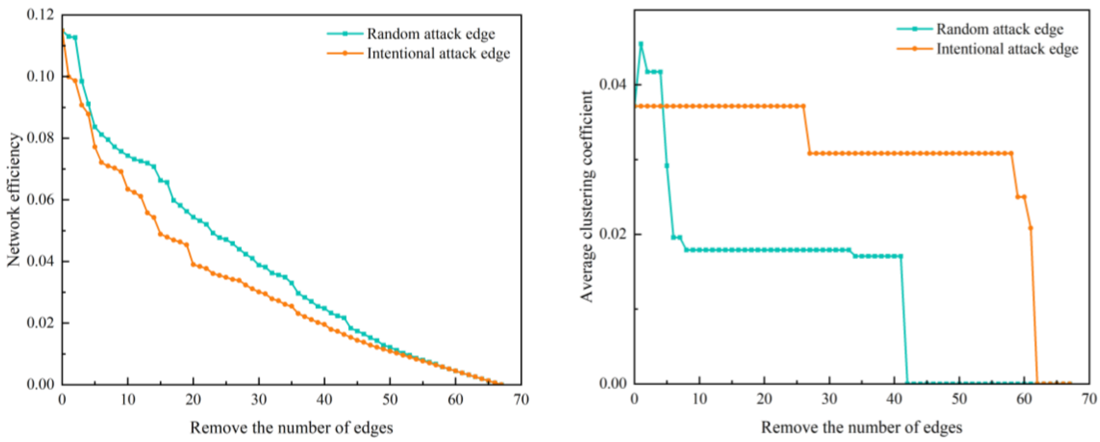
Figure 3: Network efficiency and average clustering coefficient under node attack; a) and b).

As shown in Fig. 3 a, the initial network efficiency was 0.115. In the early stages of node attacks, the network efficiency E decreased significantly. After 10 % of the nodes were attacked, the network efficiency E under degree attack was 0.056, representing a decline of approximately 50 %, indicating that degree attack had the greatest impact on the network's resilience at this point. The closeness attack initially showed a decline, followed by stabilization, and then a sharp drop. However, when 95 % of the nodes were attacked, the network efficiency E remained at 0.08, with a sharp decline occurring only when the remaining 5 % of the nodes were attacked. The network finally collapsed after 97 % of the nodes were attacked, highlighting the disaster network's strong invulnerability to closeness attack, and indicating that closeness attack had the least impact on the network. Based on this analysis, nodes with higher degree centrality exert a greater influence on the overall disaster network.

As shown in Fig. 3 b, the initial average clustering coefficient C of the network is 0.037. When 0 % to 10 % of the nodes were attacked, the average clustering coefficient C under random attack initially increased, then stabilized, and finally decreased. As the remaining nodes were attacked, the average clustering coefficient C exhibited a downward trend. In the early stages of node attacks, random attacks actually increased the network's tightness, indicating that the disaster network demonstrated a certain level of resilience against random attacks. When the average clustering coefficient C reached 0, PageRank and closeness attacks required the removal of 10 % of the nodes, while betweenness attacks required the removal of 13 %. During both the early and late stages of node attacks, the PageRank and closeness attack curves largely overlapped, but in the middle stage of node attacks, PageRank attacks showed a more pronounced destructive effect on the network. Based on this analysis, nodes with higher PageRank values have a greater influence on the overall disaster network.

(2) Vulnerability analysis of the disaster network under edge attack

Random attack meant attacking an edge randomly without considering its size, while deliberate attack was implemented in order according to the vulnerability of the edges. The attack results are shown in Fig. 4 below.



a) b)

Figure 4: Network efficiency and average clustering coefficient under edge attack; a) and b).

As shown in Fig. 4 a, when 50 % of the edges were attacked, the network efficiency E was 0.027 under deliberate attack and 0.036 under random attack. After 80 % of the edges were attacked, random attack basically coincided with deliberate attack, and the network efficiency became 0 when 100 % of the edges were attacked, under which circumstance the network collapses. Nevertheless, it was highly invulnerable under random edge attack.

As shown in Fig. 4 b, that the random attack curve first rose, tended to be stable, and then dropped sharply in the initial attack stage. Besides, the average clustering coefficient C declined after 40 % of the edges were deliberately attacked. In the initial stage of attack, this disaster network showed strong invulnerability. Moreover, the average clustering coefficient C of this disaster network was 0 only by attacking 62 % of the edges, and it would be 0 only after 92 % of the edges were attacked.

(3) Design and test of disaster mitigation strategies in the disaster chain

In this study, the connection closeness between nodes was measured by network density. The greater the network density, the closer the connection between disaster events in this disaster network, the smaller the network vulnerability, the less easily the network structure would be disrupted, and the greater the difficulty in disaster mitigation by chain scission.

Based on the vulnerability changes of this disaster network, the disaster prevention and mitigation strategies were screened, and their effects were tested. The specific strategies are listed in the Table II.

Table II: Vulnerability of urban rail transit rainstorm and flood disaster edges.

S/N	Strategy description	Strategy effect	Strategy source
Strategy 1	The nodes ranking top 10 in degree centrality are removed	Network efficiency E is reduced	Node attack result
Strategy 2	The nodes ranking top 10 in PageRank value are removed	Average network clustering coefficient C is reduced	Node attack result
Strategy 3	The edges ranking top 10 in importance are removed	Network efficiency E is reduced	Edge attack result
Strategy 4	Disaster edges are randomly removed	Average network clustering coefficient C is reduced	Edge attack result

The disaster mitigation strategies were formulated according to the effect on reducing network vulnerability after edge attack of this disaster network. The initial network density of the urban rail transit rainstorm and flood disaster network constructed in this study was 0.043. Hence, the network density was taken as the main basis for judging the effect of strategies. Through the network analysis of the above four strategies. The influencing results of the four disaster mitigation strategies on network density are exhibited in Fig. 5 below.

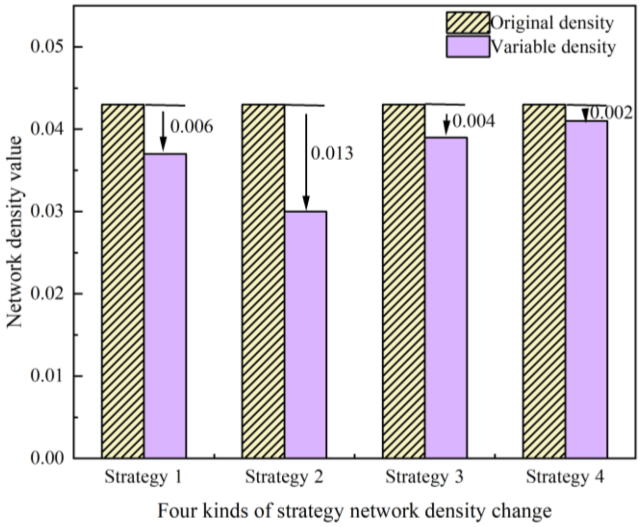


Figure 5: Network density values under different strategies.

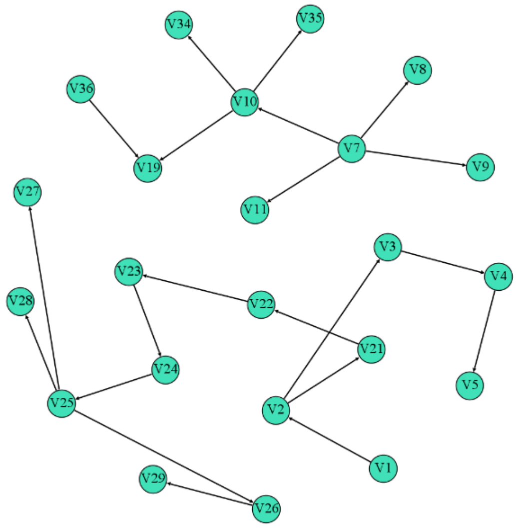


Figure 6: Complex network model after PageRank attack.

Disaster network density: The implementation of strategy 2 reduces the network density the most, strategy 2 is revealed to be the primary solution to improve the influence of the urban rail transit rainstorm and flood disaster network. The complex network graph after the nodes with high PageRank values are removed as per Strategy 2 is shown in Fig. 6. The complex network in Fig. 6 was compared with that before attack in Fig. 2. In the complex network topological graph in Fig. 6, the connecting edges between disaster events were reduced, the network density declined, and the interaction between disaster events was weakened.

6. CONCLUSIONS

This study investigated disaster prevention and mitigation strategies for rainstorm and flood disasters in urban rail transit. Based on the disaster chain mechanism and complex network theory, the study analysed interactions among disaster events, constructed a network topology model specific to such disasters in urban rail transit systems, identified critical nodes and edges within the disaster chain, and simulated the impacts of targeted attacks on these components. The following conclusions were obtained:

(1) Based on the complex network model, calculations were performed for node degree centrality, betweenness centrality, closeness centrality, and PageRank values. Additionally, edge vulnerability was assessed. The important nodes and edges that caused the evolution of urban rail transit rainstorm and flood disasters were judged as well, applying the complex network theory model to the analysis of disaster prevention and mitigation strategies for urban rail transit rainstorm and better control the risk of urban rail transit rainstorm and flood disasters.

(2) The changes in network efficiency E and average clustering coefficient C of the disaster network under attack strategies were simulated, the disaster chain scission and disaster mitigation strategies for urban rail transit rainstorm and flood disasters were deeply explored according to the attack results. The strategy experiment and analysis showed that network density could decrease from 0.043 to 0.03 (reduction of 30.2 %) by removing the nodes ranking in the top 10 in PageRank value, which could greatly reduce the occurrence of disasters.

(3) Based on the theoretical model of complex networks, the influence relationship and mechanism of action among disaster events can be deeply analysed, and the effectiveness of disaster reduction strategies can be scientifically explored, providing a theoretical reference for the disaster prevention and mitigation strategies of urban rail transit in the event of rainstorm and flood.

The urban rail transit rainstorm and flood disaster system is a complex structural system, and the disaster network structure chart established in this study is limited to real-time monitoring of time and space. In particular, disaster events in the disaster network structure still need to be subdivided and optimized. In the follow-up study, the construction, operation, and maintenance of urban rail transit will be comprehensively considered, and the disaster network structure chart will be analysed and optimized from four dimensions. The results are expected to provide urban rail transit enterprises with more accurate prevention and mitigation strategies for urban rail transit rainstorm and flood disasters.

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