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Topological Modeling and Analysis of Urban Rail Transit Safety Risk Relationship

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Abstract: Risk monitoring and risk prediction are of great significance to improve the safety of urban rail operation. Existing studies often analyze the topological characteristics of accident networks from the perspective of network theory, in order to point out the role of specific influencing factors in urban rail accidents. This article proposes a risk analysis method of urban rail operation accidents, which takes risk factors, risk points and risk events as nodes to form a network, and combines the interaction between risk points to evaluate the safety of the whole system. The existing system safety analysis methods all build models based on the accidents that have occurred. Based on the analysis of the existing urban rail transit infrastructure and operating environment, this article puts forward the risk factors and risk points that may cause risk events, and combines the mechanical connection, electrical connection and signal connection among risk points to deeply explore the interaction between risks so as to find the key risk points that cause accidents and evaluate the safety of the whole system. The results show that the proposed risk analysis method can provide effective theoretical support for risk monitoring.

Keywords: Urban rail transit; Risk analysis; Complex network

1. Introduction

Safety is an important part of urban rail transit operation that cannot be ignored, and any minor risk may cause serious accidents. The safety of urban rail operation not only reflects the level of traffic management and service quality, but also is the premise to ensure the efficient operation of urban rail system. Operational safety is the goal pursued by every rail transit company, and it is also the fundamental guarantee to meet the needs of passengers and obtain good social and economic benefits. In order to ensure the safety of urban rail operation, it is essential to understand the hidden risks caused by accidents. There are many different types of factors that generate risks, such as human risk, equipment and infrastructure risk, environmental risk and management and organizational risk. Extracting important risks and risk types can help us to improve the security of the system pertinently and efficiently.

Accidents are ubiquitous in daily life. There have made a lot of research and thinking on the causes of accidents, and ways to prevent and predict accidents, and many causal accident models have been proposed. The first accident causality model in history can be traced back to the accident prone tendency proposed by Greenwood and Woods in 1919 [1]. In the past hundred years, new causal accident models have been continuously put forward with improvements, and the famous one is domino theory, which holds that the occurrence of casualty accidents is not an isolated event, but the result of a series of events [2]. According to the Swiss cheese model proposed by James reason, organizational activities can be divided into different levels with loopholes, and accidents will occur when unsafe factors pass through these loopholes [3]. Jens Rasmussen proposed the accimap analysis method, using cause-result diagram is easy to use analysis. The hfacs analysis method proposed by Shappell, SA and Wiegmann, DA solves the long-term separation of human error theory and practical application, and analyzes accidents from the perspective of human and management reasons [4]. These models analyze the process from cause to accident in detail. However, because one event may affect many other events, the common accident model lacks the ability to analyze the interaction between the causes.

Another commonly used analysis method is statistical analysis of accidents that have occurred. By counting the causes of accidents, the frequency of certain accidents, the distribution of accidents and other indicators, it reveals the danger of accidents. Evans investigated the frequency of accidents at different types of railway intersections from 1946 to 2009 [5]. Zhou and Lei divided 407 accidents into different types, and the frequency statistics of each type were carried out; it was concluded that human error was the main cause of accidents [6]. However, for urban rail system, the number of accidents is small, and there are potential risks that have not caused accidents due to correct prevention and control, so this method is not suitable for studying urban rail accidents.

Complex network theory has been used in accident analysis constantly, and its ability to analyze the interaction between causes has been widely praised. Complex networks can be traced back to the Konigsberg Seven Bridges Problem proposed by mathematician Euler, which is represented by the graph of node and line connection for the first time [7]. In 1960s, Erods and Renyi established the random graph theory, which initiated the systematic study of complex network theory. Subsequently, Milgrarm put forward the small-world theory and the "small-world" characteristics of interpersonal relationship. After that, the characteristics of the network have been constantly proposed through experiments. Until the end of the 20th century, Watts and Strogatz published Collective Dynamics of 'small-world 'networks, which can calculate the average shortest path and clustering coefficient, and put forward a model with smaller average shortest path and larger clustering coefficient [8]. These two articles initiated a new era of complex network research. After that, various attributes of networks have been constantly explored [9, 10], which was no longer limited to mathematical theory, but widely used in accident analysis, medicine and other fields to study various large-scale complex systems in the real world.

In the research of railway operation accidents, it’s realized that it is usually a variety of dangers that lead to an accident through the analysis of existing railway accidents [11]. In railway system, dangers may exist in multiple subsystems or components. Due to the complex interaction among railway system components, dangers existing among components will also interact. The interaction among dangers and the causal relationship between dangers and accidents constitute the accident cause network [12]. The topology analysis of complex network can meet the demand of railway cause network analysis. Zhou et al established a directional weighted accident causal network (DWACN) to discover the potential laws and propagation characteristics of accidents [13], and Klockner and Toft developed a safety and fault event network (SAFE-Net) to sort the influencing factors of accidents [14]; Liu et al. put forward the method of constructing accident causal network, customized specific topological indicators and revealed the potential laws of railway operation accidents [15]; Lam and Tai extracted Japanese railway accident reports to build a network model, and studied the influence of each factor on accidents from three angles of local view analysis, global view analysis and context view analysis [16]. Compared with railway system, subway system has more complex subsystems and more complex interactions among their components. Considering that there are few subway accidents and it is difficult to build a network, this article puts forward customized indicators for the risk classification of subway system to find key risk points.

The main contributions of this article are as follows:

(1) Taking risk factors, risk points and risk events as nodes, combined with the interaction between risk points, the urban rail transit accident risk analysis network is constructed.

(2) It proposes a topological indicator-based accident risk analysis method for urban rail operation to evaluate the key risk points of the whole system.

The remaining structure of this article is as follows. The second section introduces different indicators classified by node, type and overall system and constructs the specific construction process of URORN; the third section analyzes and compares the results of URORN according to the risk data, draws conclusions and puts forward suggestions for improvement; the fourth section is discussion, which analyzes the systems of different parts of the whole and puts forward suggestions for improvements; the fifth section is a summary, which summarizes the whole article.

2. Network Modeling of Accident Risk Analysis in Urban Rail Transit

In order to use complex network theory to study urban rail operation accidents, this article constructs the urban rail operation risk network (URORN). In order to better analyze accidents, this article proposes the following modeling process.

2.1 Define Risk Points Based on Incident Reports

Because URORN is a network based on risk points, which could present risk propagation and accidents, the very important step is to collect potential risk points causing accidents. In order to ensure the reliability and accuracy of URORN, some methods are selected to study URORN, and the results are compared to explore the risk points more comprehensively.

There are many factors that cause risks, such as human factors and equipment factors. In URORN, we regard the factors that cause risks as risk factors. In order to facilitate the subsequent URORN analysis, all risk factors are classified as follows: human hazard (H), facilities hazard (F), environmental hazard (E), and each risk is numbered, such as welding operation error (H03), substandard component quality (F01), and foreign object impact (E01). At the same time, different positions or structures of urban rail will produce certain risk points. In this article, the risk points are numbered as R, such as car body (R01). The states with different risk points are indicated by lowercase letters. For example, if the battery has two states: deformation and leakage, the battery deformation is numbered as R42a and the battery leakage is numbered as R42b. The final risk event is numbered as A, such as train derailment (A04).

2.2 Accident Chain

Complex networks are mainly composed of nodes and edges. Most of the complex networks studying railway accidents consider risk and accident nodes and causality edges. However, in urban rail or railway system, except causality edges, mechanical connection, electrical connection and signal connection between risk points should also be considered. Therefore, in URORN, nodes are divided into three categories: risk factors, risk points and risk events. However, no matter how risks affect each other (such as mechanical connection, electrical connection and signal connection), these influences will eventually turn into causal factors in URORN. Therefore, the causal factors between risks are defined as edges. Risk factors will have an impact on the state of risk points, and the changed risk points may lead to risk events. For the convenience of analysis, the states of risk points below are all states that can lead to risk events. For events where two or more nodes cause the next node, by default each node can cause the next node directly, because these nodes are risky and need to be dealt with. Finally, the accident chain of URORN is risk factor-risk point-risk event, and the edge is causality. That’s, risk factors lead to risk points, and risk points lead to risk events.

2.3 Analysis

After determining the nodes and edges of URORN, URORN is analyzed as follows. $P_{mn} = 1$ is defined when node *m* can directly cause the occurrence of node *n*, that’s, there is only one edge connection between nodes *m* and *n*. When node *i* can indirectly cause node *j* to occur, that’s, there are multiple edges between nodes *i* and *j* to connect them, the shortest path is defined as:

$$URSP_{ij}=\sum_{m,n\in V} P_{mn} \tag{1}$$

where, *V* represents the node set of the shortest path from nodes *i* and *j*.

When the shortest path $URSP_{ij}>0$, the reachability $URSP_{ij}=1$ is defined, indicating that node *i* can cause node *j* to occur. Otherwise, $URSP_{ij}=0$, indicating that node *i* will not cause node *j* to occur.

Using URORN, we evaluate the safety of urban rail operation accidents based on risk points, risk propagation and the resulting risk events, so it is particularly important to intercept some customized topological indicator analysis systems. Using appropriate indicators to analyze the network can better help us find key risk points, evaluate the security of the whole system and customize effective security measures. We analyze the network from the point of view of nodes, types and the whole system, and makes use of community algorithm to supplement URORN.

2.3.1 Analysis of a single node

An accident may be composed of multiple nodes and multiple accident chains. Extracting key risk points from multiple risks can make safety measures more efficiently and pertinently. URORN uses three indicators to find key nodes.

For a given risk point, define the following indicators:

$$L_i = \sum_{i\in FC, a\in AC} URSP_{ia} / \sum_{i\in FC, a\in AC} URR_{ia} \tag{2}$$

where, *i* represents the specified risk factor, *a* represents the risk event caused, *AC* represents the risk event set, *FC* represents the risk factor set, and L_i represents the average shortest path of the risk event caused by the risk factor. The indicator can reflect the risk degree of the risk factor to a certain extent. The lower the value is, the shorter the path from the risk factor to the risk event is, the easier it is to cause accidents and the greater the risk degree is.

$$NC_i = \sum_{\substack{a\in AC,\ i\neq j \\ i\in IC, j\in IC}} URR_{ji} * URR_{ia} \tag{3}$$

where, *i* represents the specified risk factor or risk point, *a* represents the risk event caused, *AC* represents the risk event set, *IC* represents the risk point set and risk factor set, and NC_i represents the node center, that's, the number of paths passing through the risk and linking other risks with accidents. The higher the indicator is, the more nodes appear in the shortest path are, and the more dangerous they are. This indicator can help identify key risks.

2.3.2 Analysis of risk types

Risks are divided into four categories, and the degree of risk caused by different risk types may be different, and types will also influence each other. Through the analysis of risk types, URORN identifies the hazards caused by different types, and should pay more attention to those risk types in an urban rail system.

For the specified risk type, define the following indicators:

$$L_h = \sum_{\substack{a\in AC \\ i\in he}} URSP_{ia} / \sum_{a\in AC} URR_{ia} \tag{4}$$

where, *i* represents the risk factor, *he* represents the specified risk type, *a* represents the risk event caused, *AC* represents the set of risk events, and L_h represents the average shortest path of risk events caused by a certain risk factor type. To a certain extent, it can reflect the relationship between risk types and accidents.

$$N_{ef} = \sum\nolimits_{\substack{i\in e \\ j\in f}} P_{ij} \tag{5}$$

where, *i* and *j* represent risk factors, *e* and *f* represent two different risk types respectively, and N_{ef} represents the number of direct edges between the two risk types, that's, the local connectivity between the two risk types, which is helpful to find the correlation between the risk types.

2.3.3 Analysis of the Entire Risk System

$$Rea = \sum_{i\in FC, j\in AC} URR_{ij} / (N_{AC} * N_{FC}) \tag{6}$$

where, *i* represents risk factors, *j* represents accidents, N_{FC} represents the number of nodes of risk factors, *AC* represents risk event set, *FC* represents risk factor set, and *Rea* represents accessibility density, which indicates the global connectivity between risk factor nodes and risk event nodes and reflects the closeness of causal relationship between risks and accidents. When this value is 1, it means that any accident can be caused by any danger, and the system is more dangerous.

$$L = \sum_{i\in FC} L_i / N_{FC} \tag{7}$$

where, L_i represents the average shortest path of risk *i*, N_{FC} represents the number of nodes of risk factors, *FC* represents the set of risk factors, and *L* represents the average shortest path of risk of the whole system, which is used to judge the risk degree of the system. When *L* is lower, the risk in the system is more likely to lead to accidents, and the system is more dangerous.

3. Data Analysis

After the establishment of URORN, the author analyzes the data to find risk factors, and according to the network of risk factors-risk points-risk events, calculates the indicators proposed above to evaluate the security of the whole system.

3.1 Collection of Data

In order to study the influence of potential risk factors and the interaction between risk points on the safety of urban rail transit operation, the data of this study comes from the main risks of urban rail transit operation safety summarized by workers in urban rail transit industry and experts in related fields. Table 1 shows some data for each type of risk points.

Table 1. Part of risk factors and number of risk points

Risk description	Node No.	Risk points	Risk point No.
Leakage or breakage occurs at the thread connection	F04	Brake pipe	R28
Poor quality or processing quality of connecting pipe	H06		
The rubber gasket between the valve and the seat is aged and deformed	F25	Main valve, emergency valve and valve seat interface	R29
Wrong installation of main valve or intermediate	H01		
Bolts are not tightened or tightened evenly	F03		
No raw material belt is used for assembly after the air cylinder block is disassembled for dust removal	H02	Air reservoir	R30
Air cylinder cracks	F27		

3.2 Build a Model

From the collected data, 67 risk factors, 56 risk points (R) and 21 accidents are sorted out. Among them, there are 8 human risk factors (H), 49 facilities risk factors (F) and 10 environmental risk factors (E). The URORN diagram drawn is as follows in Figure 1:

Figure 1. URORN based on collected data

3.3 Analysis Results

After finishing the arrangement of nodes and edges of URORN and forming a network, the author analyzes its indicators.

3.3.1 Analysis of a single node

The average shortest path is an indicator that can directly reflect the risk degree of nodes in complex networks. The lower the value is, the shorter the path from risk to accident is, the easier it is to cause accidents and the greater the risk degree is. Figure 2 and Figure 3 show the average shortest path length of risk events caused by a single node of environmental risk factors and human risk factors respectively.

It can be seen from Figure 2 that among the average shortest paths of Class E risk factors, the average shortest path of E10 (freezing and hanging ice) is the shortest, which shows that when freezing and hanging ice occurs, it is easy to cause changes in some risk points and then cause risk events. However, due to the uncontrollable environmental factors, only some protection work can be made for the risk points affected by icing and hanging ice. For example, in the data collected in this article, the catenary will break due to freezing and hanging ice, so it's necessary to pay attention to the protection of catenary in cold weather. It can be seen from Figure 3 that among the average shortest paths of Class H risk factors, H01 (wrong installation of main valve or wrong installation of intermediate) and H02 (No raw material belt is used or unfastened for assembly after the air cylinder block is disassembled for dust removal) have the shortest average shortest paths. When the relevant staff make such mistakes, it is easy to directly affect the main valve and air cylinder, and then affect the braking system to cause risk events. Therefore, strict training should be carried out for relevant staff to ensure that the work is correct.

As shown in Figure 4 and Figure 5, among the average shortest paths of Class F risk factors, the average shortest path of up to 22 nodes is 2.0, that's, these risk factors can directly lead to the change of risk point state, and then cause risk events, which indicates that most risk factors have greater risks. This is because the facilities risk factors in the accident chain are detailed and rarely overlapped, which also shows that the facilities risk factors are numerous and complex, so more attention should be paid in risk prevention and control.

It is worth noting that the node with larger average shortest path does not mean lower risk degree. For example, the average shortest path of E03 is 3.5455, but it can indirectly lead to accidents A06, A18, A19 and A20, while the average shortest path of F02 is 2, which can only indirectly lead to accident A02. Obviously E03 is more risky. Therefore, only relying on the average shortest path is not conducive to helping us find key nodes, so the indicator node centrality is introduced.

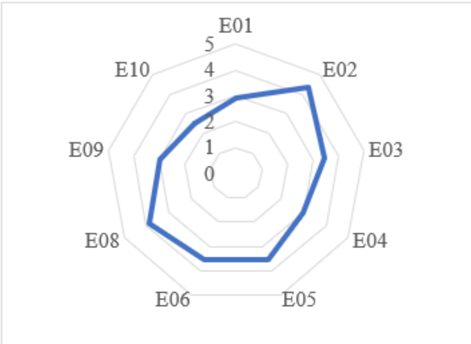

Figure 2. Average shortest path of Class E risk factors

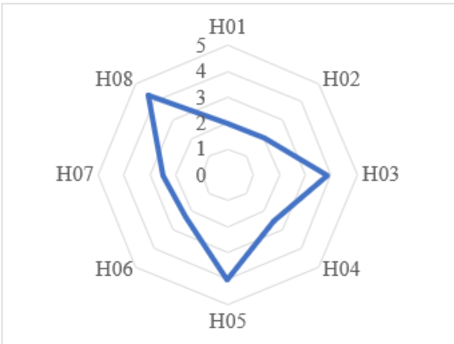

Figure 3. Average shortest path of Class H risk factors

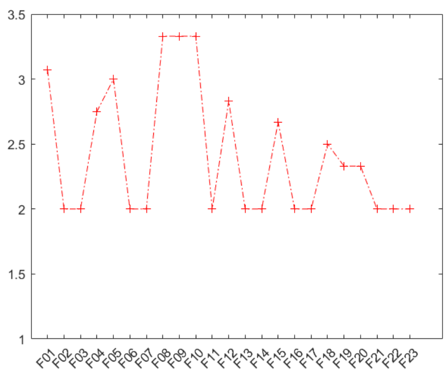

Figure 4. Average shortest factors of risk factors F01-F23

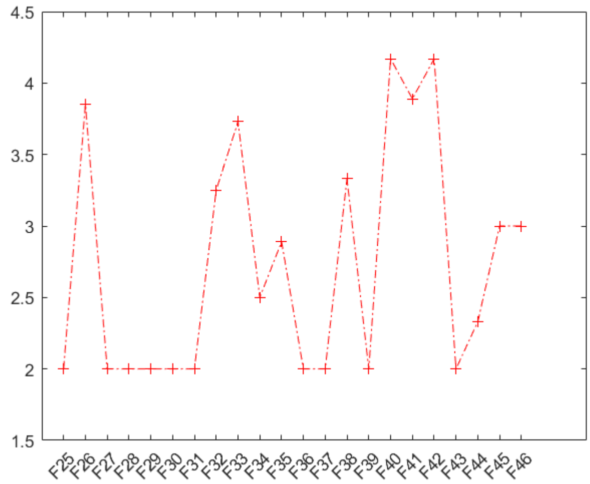

Figure 5. Average shortest factors of risk factors F25-F47

Table 2. Node centrality of some nodes

Node	F03	F11	R08	R09	R13a	R16	R42	R43	R55	R56
Centrality	36	78	58	54	51	36	81	60	70	96

Node centrality indicates the ability of a node to connect other nodes with accidents, and the higher it is, the more important role the node occupies in the network. For risk factors, some risk factor nodes are the beginning of the accident chain and will not cause other risk factors, and the node centrality is 0. Only some risk factors can combine the node centrality indicator to judge the risk degree, so the node centrality is only a supplement to the average shortest path to identify the risk degree. For risk points, they are generally connected after risk factors and before risk events, and the node centrality of most risk points is not zero. Therefore, node centrality is an important indicator to identify the risk degree of risk points. Ignore the nodes with a node center of 0, and the nodes with node centrality of top ten are shown in Table 2.

Among the risk points, R56 (CCU) has the highest node centrality, which is in line with reality, because the whole train system needs CCU signal control. If CCU is damaged, it will bring a series of chain reactions and affect many systems. It's followed by R55 (brake control device) and R42 (battery), which are also in line with reality as failure of brake control device will affect the whole control system, and failure of battery may lose power to the whole vehicle system. This means that the change of R56, R55 and R42 is more likely to lead to accidents and other risks. It is necessary to pay more attention to these nodes and focus on protecting these risk points. Among the risk factors, F11 (frame fracture) and F03 (firmware looseness) have higher node centrality. Frame fracture will have a great influence on primary and secondary springs, gearboxes, bogies and couplers, while firmware looseness will affect multiple risk points. Other high-risk risk points refer to primary and secondary springs (R08), broken gearbox boom (R09), failure of doors to open and close normally (R13a), failure of smoke alarm system (R16) and pantograph (R43), all of which are risk points needing attention. To sum up, in the vehicle system, it's necessary to pay attention to the protection of frame and firmware, and focus on the protection of CCU, brake control device and battery.

3.3.2 Analysis of risk types

The average shortest path of accidents caused by specified risk types can be calculated from the formula: $L_{h=} \sum_{\substack{a\in AC \\ i\in h}} URSP_{ia} / \sum_{a\in AC} URR_{ia}$, where, the average shortest path of accidents caused by environmental risk factors is 3.4242; the average shortest path of accidents caused by facilities risk factors is 3.0287; and the average shortest path of accidents caused by human risk factors is 3.5758. This indicates that human risk factors are more likely to directly lead to accidents. Table 3 shows the average shortest path of different types of risk events caused by different types of risk factors. It can be seen from Table 4 that environmental risk factors easily lead to fire (A06), and speed information and train occupancy information cannot be transmitted normally (A13); facilities risk factors easily lead to equipment damage (A14), and single vehicle without high voltage (A17); human risk factors easily lead to abnormal braking (A15). These data are helpful to understand the difficulty of risk events caused by different types of risk factors from the perspective of risk propagation path.

Calculating the number of edges between different types of risk factors can make clear the relationship between different risk factors.

Table 3. Average shortest path of different risk types and each risk event

TYPE	A01	A02	A03	A04	A05	A06	A07	A08	A09	A10
E	3.5	4	2.625	3.5		2.5		6.4	4	3
F	3	3.3571	2.3225	3.5294	2.6	3.0833	2.5	4.8333	3.1176	2.6363
H	4	4	3	3.75	5	2.6667	4	4.6667	4	5

Table 4. Average shortest path of risk types and risk events

TYPE	A13	A14	A15	A16	A17	A18	A19	A20	A21	ALL
E	2.5		3.6			2.6	2.6	3	4.3333	3.4242
F	2.6667	2	2.8571	3	2	2.6	2.6	2.7	3.8571	3.0827
H	4		2.25	5				3	5	3.5758

3.3.3 Analysis of the whole risk system

According to $N_{ijef} = \sum_{\substack{i\in e \\ j\in f}} P_{ij}$, the number of edges from environmental risk factors to facilities risk factors is 10; the number of edges from human risk factors to facilities risk factors is 3; the number of edges between other risk factors is 0. It can be seen that facilities risk factors are easily caused by other two types of risk factors, which shows that in the management and prevention of facilities risk factors, attention should be paid to the impact of environmental and human risk factors on them.

The accessibility density of the system is 0.3241 according to $Rea = \sum_{i\in FC, j\in AC} URR_{ij}/(N_{AC} * N_{FC})$, which means that the risk points are closely related, and the failure of one risk point may lead to the failure of other risk points, and there is a complex causal path from risk factors to risk events; the average shortest path is 2.7310, which shows that each node reaches the accident through 2.7 edges on average, that's, although the risk points of this system are not easy to directly lead to associated accidents, they may lead to problems at other risk points, and then lead to accidents in other propagation chains.

4. Discussion

In order to prove that the customized topology indicator proposed by URORN can identify key risk points more effectively than the traditional topology indicator, PageRank algorithm is selected to compare with URORN. The method used is to remove the key nodes identified in the network one by one according to the risk degree order of nodes, and observe the reachability density of the whole network after removal to verify the risk prevention and control effect.

According to the average shortest path and importance of risk factors in URORN, five most risky risk factors are selected: F11 (frame crack), F03 (fastener looseness), F36 (pillar tilt), E01 (foreign object impact) and F04 (component damage), and the highest risk factors in PageRank algorithm are selected: F11 (frame crack), F36 (pillar tilt), F01 (component quality is not up to standard), F06 (coupler buffer deformation) and F12 (poor fusion between welding layers). In the same way, five most risky risk points of URORN are selected: R56 (CCU), R42 (battery), R55 (brake control device), R13 (door) and R43 (pantograph), and five most risky risk points in PageRank algorithm are selected: R04 (coupler), R43 (pantograph), R49 (catenary), R13 (door) and R05 (bogie). The risk factors and risk points selected by the two algorithms are removed step by step, and the accessibility density after removal is compared to prove the effectiveness of URORN. The change of accessibility density after removing risk factors one by one is shown in Figure 6.

As can be seen in Figure 6, when a small number of risk points are removed, removing the first three risk factors selected by PageRank reduces the accessibility density of the system more, which may result from the fact that there is no reasonable quantitative formula to determine the risk factors with similar risk degree when considering the average shortest path and importance of risk factors in URORN, but URORN can also identify the key risk factors. This only shows that risk factor F36 is more risky than risk factor F03. When removing multiple risk points, it is obvious that URORN is more effective in reducing the accessibility density of the system. In actual risk prevention and control, it is realistic to prevent and control multiple risk factors at the same time. Based on the above reasons, it's shown that URORN is better in identifying risks.

It can be seen from Figure 7 that the accessibility density of URORN decreases more than that of PageRank, whether a single risk point is removed or multiple risk points are removed. This shows that URORN uses importance to remove risk points and cut off the causal path of risk propagation, and can better improve the system security.

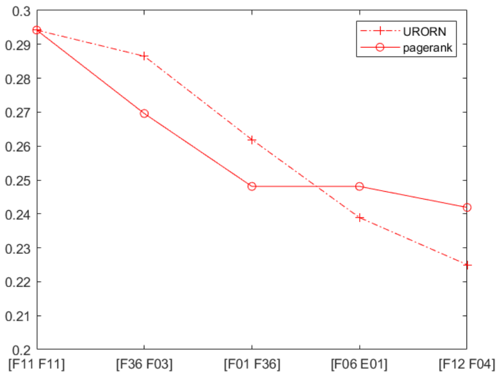

Figure 6. Comparison of selected risk factors removed by PageRank and URORN

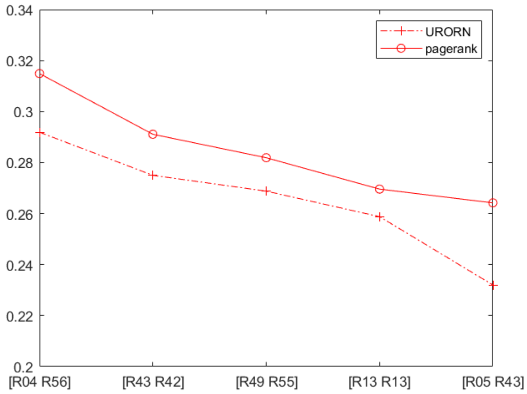

Figure 7. Comparison of selected risk points removed by PageRank and URORN

The results show that the URORN model can effectively identify the key risk factors and risk points, and the analysis results can be targeted to develop preventive measures. Using URORN needs to construct an accident chain of risk factors-risk points-risk events first, then identify key risk factors by combining the average shortest path with node centrality, and identify key risk points according to node centrality. It's essential to use customized indicators to understand the difficulty of risk events caused by different types of risk factors and the relationship between them, and finally evaluate the security of the whole system.

5. Conclusion

This article proposes a new method of urban rail accident risk analysis based on complex network, which studies the location and cause of risks separately, and adds mechanical connection, signal connection and electrical connection among risk points on the basis of traditional causal factors. According to the accident statistics of previous years, this article focuses on the vehicle system, puts forward some risk factors that may cause risk events and the minimum maintenance unit, and finally predicts the key risk factors and risk points through the accident chain of risk factors-risk points-risk events and formulates corresponding indicators. Through calculation, the average shortest path of the network is 2.7310, that's, the average step from risk propagation to accident occurrence.

The following research work should further improve the data collection of risk events and the quantitative calculation method of the relationship between risk points, so as to evaluate the risk of the whole driving system.

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Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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