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Fault Spread and Recovery Strategy of Urban Rail Transit System Based on Complex Network

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Abstract

Urban rail transit plays a pivotal role in the overall urban transportation system, serving as a preferred mode of travel for a growing number of people in recent years. However, the occurrence of station failures due to emergencies is an inevitable challenge that can significantly impact the entire transit system. This has led to an increased demand for improved operational resilience and recovery mechanisms within urban rail transit systems. Addressing how to effectively suppress fault spread and swiftly recover the system post-failure has become a pressing issue. In this research, we utilized metro network data obtained from Gaode map and employed complex network theory to establish a network topology model. The study focused on investigating the fault spread dynamics within the metro network, both in scenarios without recovery and with recovery measures in place. The goal was to understand the underlying patterns and laws governing fault propagation in urban rail transit systems. By analyzing the data and modeling recovery strategies, we aimed to contribute insights into mitigating the impact of failures and enhancing the overall reliability of urban rail transit systems. The research concludes with a simulation of four distinct recovery strategies, providing a comparative analysis of their effectiveness. These findings are crucial for urban planners, transit authorities, and policymakers in developing strategies to minimize the impact of emergencies on urban rail transit, ensuring a resilient and efficient transportation system for the growing urban population.

Keywords: Urban Rail Transit System, Complex Network Theory, Fault Spread, Recovery Strategy

1. Introduction

In recent years, China's rapid economic development, followed by people's demand for urban transportation is also growing. The emergence of urban rail transit systems such as light rail and underground lines has greatly eased the pressure on urban traffic. More and more passengers choose rail transit travel, the problem is that the rail traffic load is becoming more and more serious. Large passenger flow is the determining factor in the fault [1]. Many station nodes and rail transit networks formed by lines are characterized by complex systems. In recent years, many scholars have also combined it with complex network theory for research and analysis [2].

Complex network theory is a new theoretical method, which is generally used to analyze the structure and evolution of complex systems. It abstracts complex systems into networks of points and lines, and analyzes and studies abstract networks based on graph theory.

The station in the rail transit system is equivalent to the network node, and the connected lines are equivalent to the link between nodes [3]. Firstly, an abstract and complex network model can accurately describe the basic characteristics of urban rail transit system. Using the structural generation method of complex network, obtaining the parameter values of its characteristics, referring to the complex network model and evolution generation model. Establishing a complex network model that can comprehensively describe the characteristics of the rail transit system. Laying the foundation for the next step to study the fault spread and recovery strategy. Secondly, the law of fault spread of urban rail transit system is studied. By simulating the process of fault spreading, the relevant parameters of the system network after the fault spread can be obtained, and the fault spread law of the urban rail

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transit system can be obtained through the change of these parameters. Finally, a set of efficient post-fault recovery scheme is given. After the spread of the fault, the system machine can be recovered quickly by using reasonable and efficient recovery means.

The presented research is organized as follows. Section 2 introduced the basic methods of the simulation system. In the Section 3, the simulation system implementation and analysis are displayed. The Section 4 is given to conclude this paper and suggest some works in the future.

2. Literature Review

2.1. Urban Rail Transit Systems and Growing Passenger Demand

The surge in economic development witnessed in China over recent years has propelled an unprecedented increase in the demand for urban transportation. In response to this mounting pressure on existing infrastructures, urban rail transit systems, comprising light rail and underground lines, have emerged as pivotal contributors to the evolving transportation landscape [1]. The escalating preference among passengers for rail transit not only underscores the systemic role of these transit systems in urban mobility but also accentuates the urgency of addressing the associated challenges [2].

2.2. Complex Systems and Network Theory

Within the intricate realm of complex systems analysis, scholars have progressively gravitated toward complex network theory, an innovative and potent theoretical methodology. This approach, rooted in graph theory, proves to be a valuable tool for dissecting the multifaceted structures and dynamic evolution of complex systems. By abstracting these systems into networks characterized by interconnected nodes and links, complex network theory facilitates a nuanced understanding of the underlying patterns and relationships within such systems, contributing significantly to the theoretical foundation of the study [3].

2.3. Urban Rail Transit Systems as Complex Networks

Recognizing urban rail transit systems as quintessential examples of complex networks, researchers have drawn a parallel between the nodes and links in these systems and the stations and rail lines, respectively. This metaphorical alignment allows for the effective application of complex network theory to capture and analyze the inherent complexities of urban rail transit systems. Scholars advocate for the development of comprehensive models that transcend mere representation, accurately encapsulating the fundamental characteristics of these transit networks to enhance our understanding of their intricate dynamics [4].

2.4. Fault Management in Complex Systems

The study of fault management within the domain of complex systems has emerged as a pivotal research focus, gaining prominence due to its direct implications for the robustness and reliability of critical urban infrastructures. A comprehensive investigation into the propagation of faults through complex networks is essential for the formulation of strategies that ensure the continuous functionality of urban rail transit systems. Scholars emphasize the necessity of developing sophisticated fault management mechanisms capable of identifying, containing, and addressing faults within the intricate web of these transit systems, reflecting a crucial aspect of ensuring their reliability [5].

2.5. Simulation Methods for Complex Networks

Against the backdrop of increasing complexity, researchers have turned to simulation methods as indispensable tools for modeling the dynamic behavior of complex networks. This involves creating intricate virtual scenarios to capture the nuanced responses of urban rail transit systems to faults. The simulation process allows for the extraction of pertinent parameters governing the network's behavior post-fault, providing valuable insights into the intricate laws governing the spread of faults within these systems. This empirical approach, combining theoretical understanding with practical simulations, has proven instrumental in unraveling the vulnerabilities and dynamic behaviors of urban rail transit networks [6].

2.6. Post-Fault Recovery Strategies

Efficient post-fault recovery schemes represent a critical facet of maintaining the resilience of urban rail transit systems in the face of unforeseen disruptions. Prior research in this domain has explored a myriad of recovery strategies aimed at swiftly restoring normalcy to the system. The emphasis is on formulating rational and efficient recovery plans that can mitigate the impact of faults and expedite the restoration of full system functionality. A nuanced understanding and successful implementation of these effective recovery strategies are integral to minimizing disruptions and ensuring the seamless operation of urban rail transit systems [7].

3. Basic Method

3.1. Network Construction

The network is composed of a set of nodes {vi} and a set of edges {eij}. This paper uses the adjacency matrix[4] to further express the national railway network as the adjacency matrix of graph G= (V, A) is defined as follows,

M is a 0-1 matrix (n*n),

$$M = (m_{ij})_{nxn} \in \{0, 1\} m_{ij} = \{1 (i,j)\in A \ 0 (i,j) \notin A \quad (1)$$

Average shortest path length, cluster coefficient, degree distribution and betweenness centrality are the four characteristic parameters [5-8], which are often used to quantitatively describe the complex network are.

3.1.1. Average shortest path length.

The average path length of node i is defined as,

$$L_i = \frac{1}{n-1} \sum_{j-1, j\neq 1}^{n} L_{ij}$$

Where L_{ij} represents the number of edges that exist between the two nodes i and j, and the average path length L of the network is defined as follows,

$$L = \frac{2\sum_{i\geq} L_{ij}}{n(n-1)}$$

3.1.2. Cluster coefficient.

For a node in the network, its cluster coefficient represents the probability that any two nodes connected to this node are connected to each other. The specific definition is as follows,

$$M_i = \frac{E_i}{k_i(k_i-1)/2}$$

Among them, Mi is the cluster coefficient, ki is the number of nodes connected to the node, and Ei is the number of edges connected to the node.

The cluster coefficient of the network is defined as follows,

$$M = \frac{\sum_i M_i}{N}$$

The value range of M is [0,1]. When M=1, any two nodes in the network are connected, and the network is called a fully connected network. When M=0, the network may be a fully isolated node, or it may be a connected network where the cluster coefficient of each node is 0.

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3.1.3. Degree distribution.

The average degree of the network is defined as follows,

$$\langle k\rangle = \frac{1}{n}\sum_{i=1}^{n} k_i$$

Among them, <k> represents the average degree of the network, and n represents the number of nodes.

The probability that the degree value of a node in the network is a certain fixed value is usually used as the degree distribution function of the node in the network.

3.1.4. Betweenness centrality.

The definition of betweenness centrality is as follows,

$$B(v) = \sum_{i\neq v\neq j} \frac{\sigma_{ij}(v)}{\sigma_{ij}}$$

B(v) represents the importance of node v in the entire network, and $\sigma_{ij}(v)$ represents the number of shortest paths from node i to node j and through node v.

3.1.5. Distance distribution and characteristic length.

Referring to the definition process of the distribution function of degree distribution, we can define a distribution function P(l) to describe the distribution of length l in the network. This distribution function represents the ratio of the edge with length l in the network to the total number of edges in the network. This distribution function p(l) is the distance distribution function of the network. In complex networks, nodes are more inclined to connect nearby nodes than remote nodes. In order to characterize this characteristic, the concept of characteristic length is introduced. After research, it is found that the characteristic length and the distance distribution have an exponential distribution relationship.

3.2. The Fault Propagation Process of the Network

Complex networks typically face two types of attacks, random attack and selective attack. One for the network's own reasons, and one for deliberate destruction [9]. In complex network theory, fault propagation is defined as the process of system component faults causing a series of other faults and even spreading to the entire system is called fault propagation. That is, a small number of node faults may cause the entire network to collapse and cause catastrophic consequences.

In complex networks, the evaluation indicators are network efficiency and the relative size of the maximal connected subgraph. This paper describes fault tolerance by calculating the relative size of the maximal connected subgraph of a rail transit network [10].

3.3. Recovery Process after Network Fault

Regarding the network recovery process, because different system recovery resources are different, there are generally two situations. One situation is that there are fewer recovery resources, and only a few nodes or even one node and its adjacent nodes can be recovered at a time. One situation is that there are many recovery resources, and multiple nodes can be recovered at a time. If only a few nodes or one node can be recovered at a time, the recovery sequence is particularly important, which can directly determine the recovery ability of the recovery strategy. If considering the situation of more recovery resources, the recovery strategy is more flexible and the recovery speed is greatly accelerated. Under normal circumstances, when only a few nodes or one node can be recovered at a time, there are three common methods, random recovery, degree priority recovery, and betweenness priority recovery. When multiple nodes can be recovered at one time, the most common recovery method is edge recovery.

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The research method employed is a qualitative approach with a descriptive method. Qualitative approach with a descriptive method is a research method that utilizes qualitative data and is elaborated descriptively. The objective of qualitative descriptive research is to create a systematic description, depiction, or portrayal along with the relationships among the phenomena being investigated. The descriptive method itself is a research method used to examine the status of human groups, subjects, a thought system, or a class of events in the present with the aim of creating a systematic description, depiction, and understanding the relationships among the phenomena being investigated. Qualitative approach, on the other hand, is a research procedure that produces descriptive data in the form of written or spoken words from individuals.

Furthermore, interview and literature study methods are also employed in this research. Interviews provide a direct perspective from relevant parties and specific information about the practical experiences of CV Media Computindo, while literature studies provide a knowledge base and broader insights from previous research. The combination of these two methods can provide rich and in-depth insights into Instagram Ads optimization strategies and their effects on brand awareness at CV Media Computindo.

In this research, the Instagram platform is utilized because Instagram is a social media platform with a significantly higher number of active users compared to other social media platforms. This study focuses more on Instagram Ads to understand how to optimize Instagram post ads for more effective information delivery and to optimize marketing activities.

4. Results and Discussion

This paper takes Beijing subway network data as an example.

4.1. Simulation of the Fault Spreading Process of the Network

4.1.1. Fault spread without recovery process.

Through the Monte Carlo simulation of the urban rail transit network, the relationship between its giant component, its characteristic length and node survival rate after the occurrence of fault is calculated. Fig. 1 is the Monte Carlo fault spread simulation results of the urban rail transit network, p∞ represents the size of the giant component, ζ represents the length of the characteristic path, and P represents the survival rate of the node after the fault. It can be seen that the curve is similar to the first-order phase transition curve, and the critical threshold of network phase transition is about 78%. That is to say, when the network is attacked and the survival rate is higher than 78%, the fault spreading speed is relatively slow. When the survival rate is lower than 78%, the network collapses sharply.

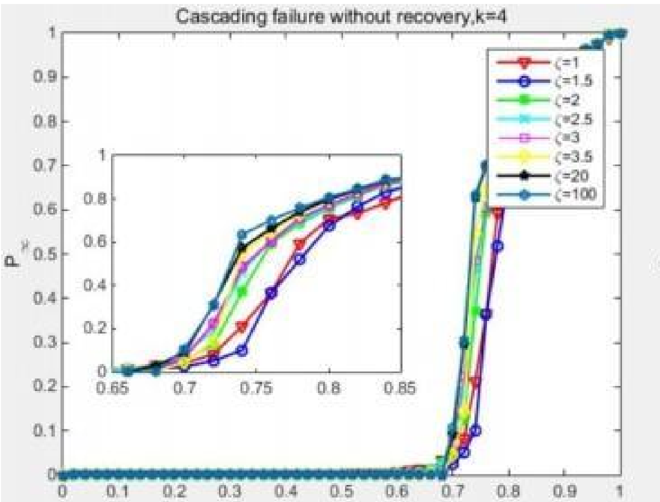

Figure 1. Simulation results of fault propagation

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4.1.2. The law of fault spread with edge recovery.

Through Monte Carlo simulation, the relationship between the recovery probability of its the giant component and its edge recovery and the node survival rate after the occurrence of fault propagation is calculated, and the relationship between iteration times of fault propagation, recovery probability of edge recovery and node survival rate is discussed.

In the Fig. 2, γ is the edge recovery probability, and NOI represents the number of iterations of fault propagation. This indicator shows that using edge recovery can reduce the critical threshold of network phase change and improve the ability of the network to resist faults. It can be seen from Fig. 2 that when the edge recovery probability γ changes from 0 to 1, the number of iterations of fault propagation at the phase transition threshold is reduced from 7 to 6, which means that the time for fault propagation is reduced. Therefore, for the network, adjusting the edge recovery probability can play a role in adjusting the range of fault spread after a fault. Through the number of iterations, it can be found that the propagation time of the fault with edge recovery increases, which has an inhibitory effect on the fault propagation.

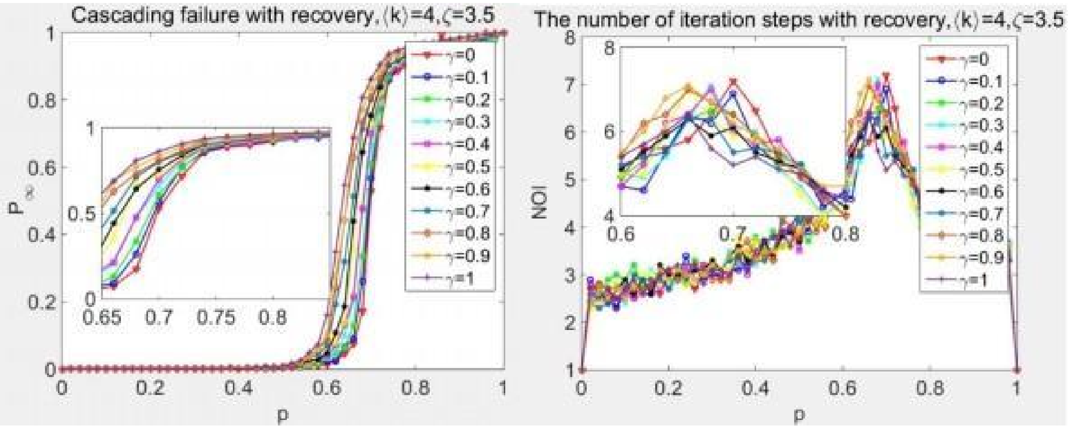

Figure 2. The relationship between the most connected subgroups and the survival rate of nodes

4.2. Simulation of Recovery Process after Network Fault

When discussing recovery, the model after fault propagation is the same.

4.2.1. Random recovery.

As can be seen in the Fig. 3, random recovery nodes sometimes recovery multiple, sometimes one, sometimes not one, but relatively speaking, when the survival rate of nodes in the network is low, the number of nodes recovered each time is relatively large, in the network node survival rate is low, basically only one node is recovered or not recovered at a time. Reflected in the functional curve, the slope of the recovery initial time curve is significantly higher than that of the end of the recovery, i.e., the recovery speed is gradually slowing down.

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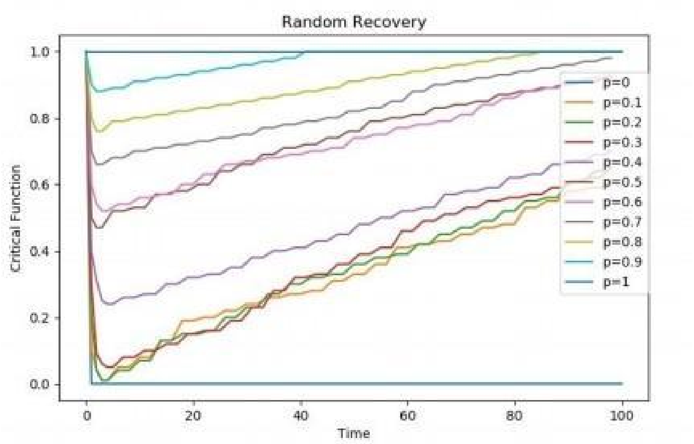

Figure 3. Random recovery network function curve

4.2.2. Degree priority recovery.

It is assumed that each iteration step takes 1 MS, and the time in the functional time variation curve of the following degree priority recovery and betweenness priority recovery is the iteration time.

As can be seen in Fig. 4, it has fewer iterative steps than random recovery, that is, the recovery time will decrease, because the number of nodes recovered during its recovery is higher than random recovery, resulting in a relatively fast pace of recovery, the recovery effect is better than random recovery. According to the network function curve of degree priority recovery, the recovery speed of degree priority recovery and random recovery are decreasing gradually.

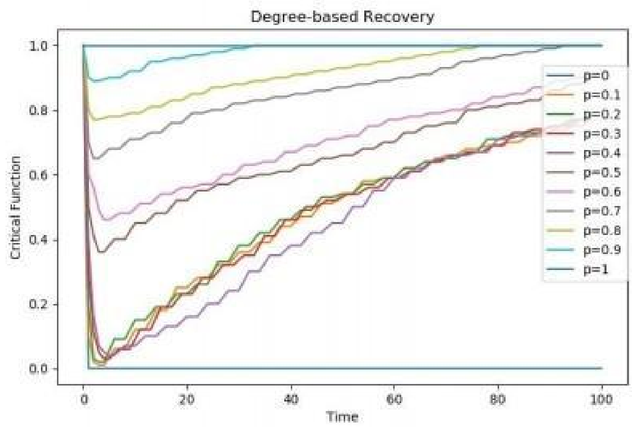

Figure 4. Degree priority recovery network function curve

4.2.3. Betweenness priority recovery.

Where p is the survival rate of nodes in the failed network. As can be seen in Fig. 5, it has the fewest iterative steps and the shortest recovery time compared to random recovery and degree priority recovery, because the initial stages of its recovery are to recover many nodes, and the number of nodes that are fixed later will be smaller, and the recovery effect is best compared to random recovery and degree priority recovery. It can be concluded that the importance of using betweenness to describe nodes in a network is better than using degree values to describe the importance of nodes in a network. However, it is worth noting that although the betweenness priority recovery is relatively good, but not so obvious, compared with the degree priority recovery, the gap can be almost ignored. According to the network function curve of betweenness priority recovery, betweenness priority recovery and random recovery and degree priority recovery have one thing in common, and the rate of recovery is gradually decreased from high to low.

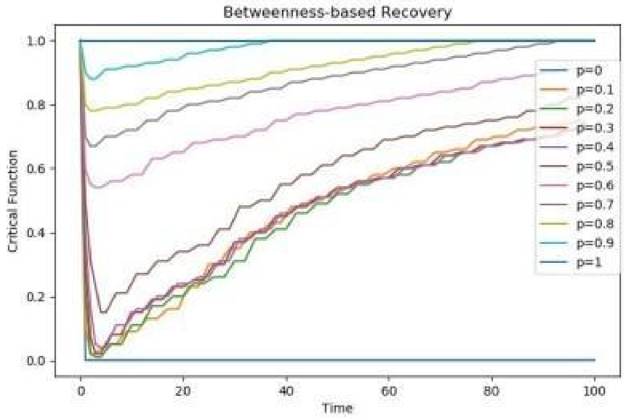

Figure 5. Betweenness priority recovery network function curve

In summary, we can draw the conclusion that when there are fewer recovery resources, the urban rail transit system in Beijing is suitable for fault recovery using the betweenness priority method, and when there are more recovery resources, the edge recovery method is chosen.

5. Conclusion

Based on the theory of complex network, this paper focuses on the fault propagation of urban rail transit networks and the recovery problems after faults. However, because the author's ability and knowledge are limited, the established model only stays at a shallow level, so the follow-up research can be carried out from several aspects,

The perfect model of urban rail transit network. In this paper, only the model of the data level of the subway network is established, and if the practical application is considered, its power supply system and subway control network should be considered comprehensively, and the recovery strategy developed by this model is more instructive.

This paper uses the existing random recovery, degree priority recovery, betweenness priority recovery and edge recovery and another recovery means to recovery network. I hope that in the future, we can study parameters that can better reflect the nature of the network, not limited to cluster coefficient, degree, betweenness and other parameters, through these parameters to propose more efficient and practical recovery methods.

6. Declarations

5.1. Author Contributions

Conceptualization: W.Y. and L.M.; Methodology: L.M.; Software: W.Y.; Validation: L.M. and W.Y.; Formal Analysis: L.M. and W.Y.; Investigation: L.M.; Resources: W.Y.; Data Curation: L.M.; Writing Original Draft Preparation: W.Y.. and L.M.; Writing Review and Editing: W.Y.; Visualization: L.M. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

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5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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