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Analysis of Urban Road Network Robustness under Different Attack Conditions

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Abstract

In preventing large-scale congestion caused by urban road traffic attacks, both random and deliberate attack methods were employed, with the robustness of the traffic system analyzed using a cascading failure model. The details of the proposed methods are, firstly, a road network model is constructed based on Geographic Information System (GIS), and the traffic flow data of a provincial city during peak traffic hours is obtained by Python. Then, the flow data of Origin-Destination (OD) pairs for the road network under normal operation is obtained using OD estimation module in TransCAD, the urban transportation network is modeled based on the actual traffic flow distribution. Subsequently, random attacks and deliberate attacks based on traffic volume were conducted on the road network. The traffic flow of the attacked segments was reallocated according to a cascading failure model, with the robustness of the urban road network assessed using topological and traffic flow indicators. The results indicate that, in the robustness analysis considering cascading failures, deliberate attacks have a more significant impact on high-traffic segments compared to random attacks with the same number of attack steps. Therefore, future urban traffic management should focus on ensuring the efficiency of high-traffic road segments, and prevent it from becoming ineffective due to excessive traffic flow.

Keywords

Robustness, road traffic network, random attacks, deliberate attack, cascading failure.

1. Introduction

As a critical infrastructure in modern cities, the functionality of the transportation network directly impacts economic development, social activities, and emergency response capabilities. With the acceleration of urbanization and increased transportation demand, the frequency of traffic accidents and congestion is rising. Particularly in the face of emergencies and human disruptions, For example, Houston was hit by Hurricane "Rita", several major roads out of the city were congested for hundreds of kilometers, and Beijing was paralyzed by heavy rain caused by a large area of traffic, the robustness of the transportation network largely determines its overall performance. Therefore, evaluating and enhancing the robustness of the transportation network is of significant research importance for urban traffic management.

Gao and Shi (2007) researched the system's anti-destruction reliability in urban rail transit. They conducted a comprehensive evaluation of urban rail transit network topology and passenger flow distribution, providing a significant theoretical basis for improving the structure of urban rail transit. Wang and Yang (2009) investigated the complex network characteristics of Shanghai's rail transit using network features such as degree and clustering coefficient. Duan (2010) proposed a network robustness analysis method based on a bipartite graph model, studying the robustness differences between Beijing's bus network and random networks under various attack conditions.Gao Peng and Hu Jianbo (2013) researched the robustness of Beijing's urban rail transit network under different weights, calculating and optimizing the robustness by weighting different traffic nodes. Li (2016) studied the anti-destruction capabilities of rail transit networks based on their topological characteristics and identified key nodes for city management. Wang (2016) examined Wuhan's public transportation network using node degree and clustering coefficient, finding that nodes with high degree values and clustering coefficients have excellent connectivity, though they are not necessarily the busiest in actual bus routes. Based on this, relevant recommendations were proposed to address traffic congestion issues.

In recent years,Lu and Guo (2018) researched the robustness of Shanghai's bus network and found that random attacks are more robust than deliberate attacks. Tran (2019) studied the robustness of Vietnam's road network using topological metrics such as average path length and global efficiency, considering both random and deliberate attacks. Qiang and Zhao (2019) established a multimodal transport network topology based on complex network principles, comparing network characteristics through network feature metrics. Jin and Wang (2022) built an enhanced network to study the robustness of Nanjing's bus-rail mixed network, finding that initial node capacity has a significant impact on cascading failures. Li (2024) considers the impact of geological hazards, evaluates the robustness of the network in terms of structure and performance, and identifies key road sections.Gao (2024) Combined with the accessibility index of subway stations, the node importance evaluation system of the rail transit network was constructed, and the robustness of Hangzhou metro network was studied by taking the global efficiency of the network and the maximum connectivity subgraph as the evaluation indexes. From the perspective of the current research status at home and abroad, the robustness of the complex transportation network is mainly focused on the bus network and rail transit network, while the research on the urban road traffic network is rare. In terms of robustness research methods, most of the studies focus on the robustness of the road network after removing the failed nodes through the analysis of network topological characteristics, and the traffic flow evaluation index is rarely used. In addition, the real road traffic flow analysis cascade failure process is not used in the analysis process, and the research lacks a certain degree of authenticity.

This paper first introduces the use of the existing topology index and traffic flow index to evaluate the traffic network and explains the mechanism of the cascading failure model adopted in this paper. The real urban traffic network model is built through online traffic data, and the robustness of the urban transportation network is studied by using two attack methods: random attack and deliberate attack.

2. Method

2.1. Cascading failure model of urban roads

The cascading failure process refers to a scenario where a key or a small number of nodes (or edges) in a network fail due to external or internal factors. This failure causes the traffic or load already assigned in the network to be redistributed based on optimal paths. This redistribution can lead to other nodes (or edges) collapsing due to overload, triggering a chain reaction that results in the failure of a large number of nodes (or edges) within the network, and potentially even leading to network paralysis.

In the study of cascading failures in urban transportation complex networks, the capacity load cascading failure model is generally used (Zuo 2008). The specific steps are as follows:

Step 1: Assign the maximum capacity C_i to each segment (Newman 1999).

$$C_i = \left(1+\rho\right) \times n \times \omega \tag{1}$$

In the formula: ρ is the capacity parameter, which determines the allowable capacity of the network segment; n is the number of lanes on the road; ω is the traffic capacity per lane segment, referring to the general speed-flow model parameter table for different road levels (Wang 2001). The traffic capacities for expressways, arterial roads, and secondary arterial roads are set at 1950, 1650, and 900 pcu/h, respectively.

Step 2: Use both random and deliberate attacks. For deliberate attacks, three different strategies are employed: targeting edges with the maximum flow, edges with the highest betweenness centrality, and edges with both the maximum flow and the highest betweenness centrality.

Step 3: Distribute the load of the failed segments evenly to the adjacent segments.

Step 4: After the initial distribution, calculate whether the load on adjacent edges exceeds the maximum capacity of those segments. If it does, consider the segment as failed and repeat Step 3 until the load on all segments in the network is less than their maximum capacity. If the load is below the maximum capacity, the segment does not fail, and the distribution process stops.

2.2. Robustness Analysis of Road Networks Based on Topological Metrics and Traffic Flow Indicators

The robustness of a transportation network refers to its ability to maintain its initial state in the face of disturbances, typically measured by the system's performance after a disaster. Here, urban network robustness is defined as the ability of the urban road network to remain connected under random or deliberate attacks. Random failures (attacks) can be understood as natural disasters (e.g., earthquakes, floods), while deliberate attacks can be seen as traffic congestion, road control, and accidents caused by human factors. This paper evaluates the robustness of the transportation network using both topological indicators and traffic flow methods.

2.2.1 Topological Metrics.

Topological indicators for assessing the robustness of transportation networks include global efficiency, average path length, connectivity, relative size of the largest connected subgraph, and betweenness. Historically, average shortest path length has been a common evaluation metric. However, research shows that as network damage from attacks increases, average path length initially grows and then decreases, making it less meaningful for research purposes. Thus, using average path length as an evaluation metric is unsuitable. Betweenness accounts for changes in nodes and edges but does not consider overall network size changes. For analyzing urban road network robustness, the clustering coefficient measures local connectivity and is of limited significance for assessing the overall network's robustness. Therefore, this paper selects the relative size of the largest connected subgraph and global efficiency as the two indicators for analyzing urban transportation network robustness, providing a more comprehensive assessment of the network's robustness.

（1） Relative size of the largest connected subgraph

In a network, the largest connected subgraph refers to the subgraph with the fewest edges connecting all the nodes. The relative size of the largest connected subgraph is the ratio of the number of nodes in this subgraph to the number of nodes in the network that have been attacked. Initially, the relative size of the largest connected subgraph is 1. When the network is attacked or experiences an incident, its topology changes and is divided into several subgraphs, causing the relative size of the largest connected subgraph to vary.

The formula for calculating the relative size of the largest connected subgraph is as follows (Dunn 2016):

$$F = \frac{|V|}{N} \quad (2)$$

In the formula, N represents the number of nodes, and V is the number of nodes in the largest connected subgraph after the network is attacked. Before any attacks, V and N are equal. However, when the network undergoes targeted or random attacks, the network topology changes, and V gradually decreases as more nodes are attacked. Thus, observing the relative size of the largest connected subgraph can indicate the extent of damage to the network.

（2） Network global efficiency

Paolo and Vito (2004) proposed a measure for network connectivity called global efficiency. The efficiency E_{ij} between nodes i and j in the network can be expressed as the reciprocal of the shortest distance d_{ij} between these two nodes, $E_{ij} = \frac{1}{d_{ij}}$

When nodes i and j are not connected, d_{ij} is infinite, and thus E_{ij} is 0. From the perspective of the entire network, the global efficiency is defined as the average of the efficiencies between all pairs of nodes, and is denoted by E_{glob}, The formula is as follows (Zhang 2018):

$$E_{glob} = \frac{1}{|V|(|V|-1)} \sum \frac{1}{d_{ij}} \quad (3)$$

In the formula, $|V|$ represents the number of nodes, and d_{ij} is the path length between nodes. The range of E_{glob} is (0, 1], where $E_{glob} = 1$ indicates that any two nodes in the network are directly connected, reflecting the best connectivity of the network.

2.2.2 Traffic Flow Indicators

Traffic flow indicators are based on principles of traffic engineering to allocate traffic demand across various segments of a network, quantifying changes in system functionality through traffic delay. The traffic flow method calculates congestion and travel time for each road segment and can account for the degradation of the service capacity of basic traffic components and its impact on system functionality. Typically, total travel time or total travel distance are used to describe the overall traffic cost of the system (Donovan 2017, Joongmin and YoungJoo 2021). In post-disaster studies, scholars often measure traffic network functionality loss by the increase in total travel time or total travel distance. The calculation formula is as follows (Donovan 2017):

$$Q_{TTT} = \frac{\sum_{i \in I} \sum_{j \in J} F_{ij} T_{ij}}{\sum_{i \in I} \sum_{j \in J} f_{ij} t_{ij}} \quad (4)$$

In the formula, Q_{TTT} represents the traffic network robustness evaluation index; F_{ij} and f_{ij} are the traffic flow on road segment after and before an attack; T_{ij} and t_{ij} are the travel times on road segment d_{ij} after and before an attack. Figure 1 presents the detailed flowchart explained in the next subsections and section 3.

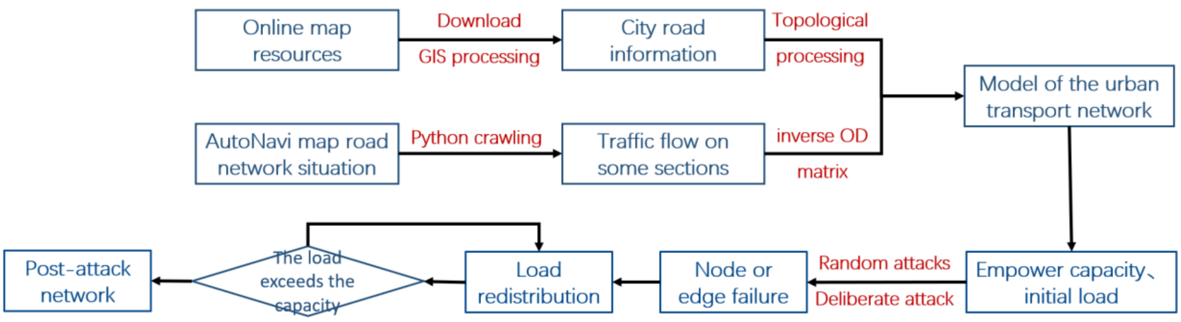

Figure 1: The robustness evaluation process of urban roads (source: by authors)

3. Study area model construction

3.1 Study area

Hefei is located on the western wing of the Yangtze River Delta and is part of the "Yangtze River Delta" urban agglomeration. It is one of China's 19 megacities. The study area in this paper includes the main urban districts of Luyang, Shushan, Yaohai, and Baohe, covering an area of 154.59 square kilometers with a residential population of approximately 1.9 million and a total of 339 roads. In 2023, Hefei's commuting peak traffic congestion index was 1.597, ranking 15th among megacities.

3.2 Collection of Road Traffic System Data

First, the Gaode traffic network layer data (figure 2 (a)) for the study area was downloaded, and the information on expressways, main roads, and secondary roads was extracted using ArcGIS software. This resulted in the major road distribution map of the urban center shown in Figure 2 (c). The map includes 198 nodes and 339 segments, with each network node representing a traffic zone. The regions were then divided into traffic zones using Voronoi polygons.

Figure 2(a) Traffic distribution o

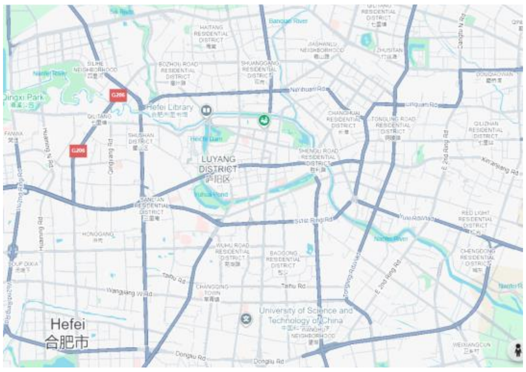

Figure 2(b) Hefei road map from Google Earth

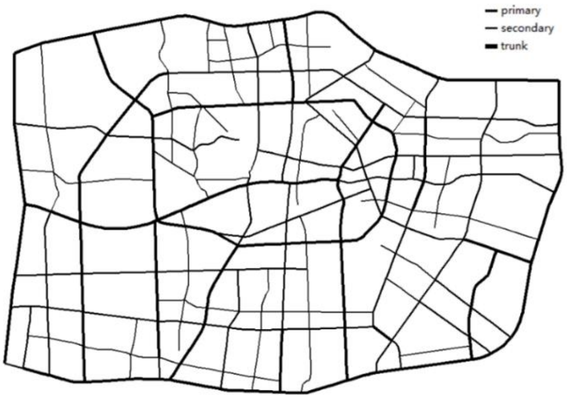

Figure 2(c) Hefei distribution of main roads in the central area of the city

3.3 Acquisition and Integration of Traffic Situation Information

This study uses feedback information provided by the traffic status interface of the Gaode Map’s API and processes it using Python for reading and regional network segmentation, ultimately obtaining traffic status information for certain roads during the evening peak period. The traffic status is provided by an HTTP interface from Gaode Map, which reports attributes such as road speed and congestion within a given area. The approach involves using Python’s `requests` module to retrieve traffic status data from the Gaode Map’s API, and then parsing the returned JSON data to store it in a CSV file. Subsequently, the TransCAD OD (Origin-Destination) matrix estimation module was used to obtain the traffic flow and OD data for all segments of the road network during the evening peak period, as shown in Figure 3. The OD matrix estimation function in TransCAD is based on the method proposed for estimating traffic demand from traffic flow. This method includes single-path estimation (SPME) and multi-path estimation (MPME), where the OD matrix is estimated based on input traffic flows. The estimated OD matrix generates traffic flow as a random variable, which is compared with the actual traffic flow. This process is iterative: starting from an initial OD matrix, the traffic flows produced by the estimated OD matrices are compared with the actual traffic flows. If the error is large, the estimation is refined until convergence is achieved, producing the final output results.

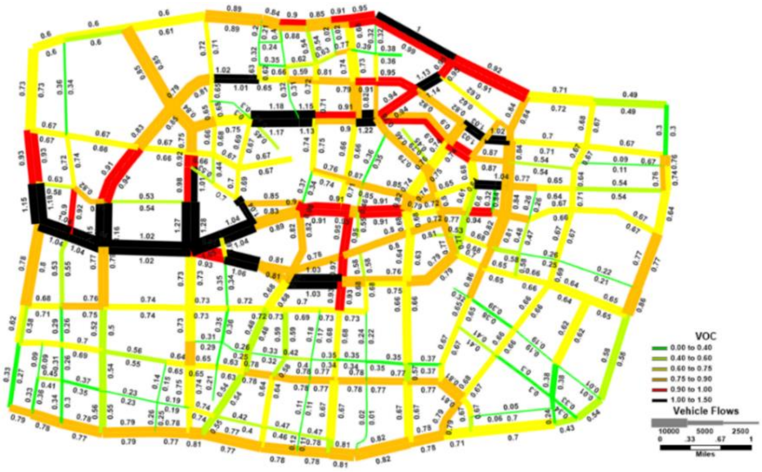

Figure 3 Traffic distribution of the road network during peak hours

4. Rsults

Based on the traffic network cascading failure model, this study investigates the robustness of urban road networks using two attack strategies: deliberate attacks based on segment traffic flow and random attacks. The analysis employs functional indicators such as total travel time, the relative size of the largest connected subgraph, and global network efficiency. The study uses the urban road traffic network within the second ring road of Hefei as a case example.

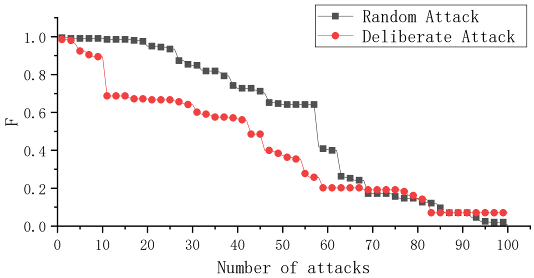

Figure 4 (a) Relative size of the largest connected subgraph

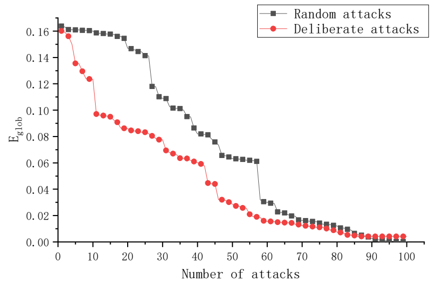

Figure 4 (b) Network global efficiency

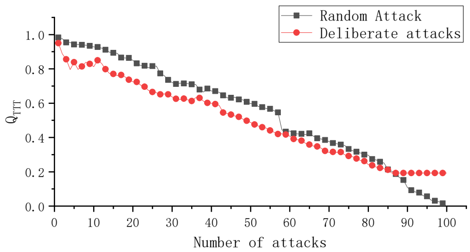

Figure 4 (c) total travel time

Figure 3 Relationship between the number of attacks and different functional indicators

According to Figures 4 (a) and (b), under the same number of attacks, the Hefei urban road network experiences a more significant decline in functionality under deliberate attacks based on edge traffic flow compared to random attacks. Particularly, after approximately 10 key segments are deliberately attacked, the network functionality shows a noticeable decline, whereas random attacks result in a relatively constant rate of functionality decrease. As the number of attacks increases, the gap between the two attack strategies gradually narrows, at which point network functionality is mainly influenced by node connectivity.

According to Figure 4 (c), when using traffic flow indicators, deliberate attacks lead to a more significant decline in network functionality compared to random attacks, and the declining trends for both are essentially consistent. This is because traffic flow indicators measure vehicle travel time. After deliberate attacks destroy key segments, traffic is redirected to other adjacent segments, increasing overall traffic flow and travel time.

5. Conclusions

By analyzing traffic flow distribution during peak hours, the Hefei urban road network was constructed and simulated. Under two different road network attack strategies, the maximum connectivity subgraph, global network efficiency and total system travel time were used as evaluation indicators, the random attack strategy causes relatively less damage to the network, indicating that the Hefei road network has strong robustness against random sudden events. However, under the deliberate attack strategy based on segment traffic flow, there is a sharp decline in network functionality, showing that the Hefei road network has weaker robustness against deliberate attacks. After attacking the top 4% of the most trafficked segments, there is a rapid decline in network efficiency. Segments with higher traffic have a greater impact on network robustness. According to the results, the topology index with the maximum connectivity subgraph and global network efficiency can better reflect the stepwise decline of the traffic network function after multiple attacks, while the traffic flow index with the total travel time does not reflect this characteristic.

During the road planning and design phase, it is advisable to increase the road capacity of segments with high anticipated traffic and their adjacent segments. In the traffic management phase, when high-traffic segments fail, it is important to quickly redirect vehicles while strictly controlling the number and nodes of redirected vehicles to prevent large-scale cascading failures.

In the future research on the robustness of the transportation network, the network modeling of the road sections that often occur in the actual city can be carried out, and the traffic distribution during the morning and evening peak hours can be simulated, so as to strengthen the traffic capacity of the congested road sections to improve the robustness.

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Ethics Approval.

Not applicable.

Conflict of Interest.

The authors declare there is no conflict.

References

Brian Donovan & Daniel B. Work. (2017). Empirically quantifying city-scale transportation system resilience to extreme events.*Transportation Research Part C*333-346. http://dx.doi.org/10.1016/j.trc.2017.03.002

Cho Joongmin, Lee YoungJoo, Lee Seongkwan Mark, Song Ki Han & Suh Wonho. (2021). Analysis of Macroscopic Traffic Network Impacted by Structural Damage to Bridges from Earthquakes. *Applied Sciences* (7),3226-3226. https://doi.org/ 10.3390/app11073226

Crucitti Paolo, Latora Vito & Marchiori Massimo. (2004). Model for cascading failures in complex networks .*Physical review. E, Statistical, nonlinear, and soft matter physics* (4 Pt 2),045104.

Duan Houli, Li Zhiheng & Zhang Yi. (2010). Robustness Analysis Model of Urban Transit Networks. *Journal of South China University of Technology (Natural Science Edition)* (03),70-75+81. DOI:10.3969/jissn.1000-565X.2010.03.013.

DUNN S & WILKINSON S. (2016). Increasing the resilience of air traffic networks using a network graph theory approach[J]. Transportation research, Part E. Logistics and transportation review,2016,90E(Jun.):39-50. DOI:10.1016/j.tre.2015.09.011.

Gao Jie & Shi Qizhou. (2007). Definition and Evaluation Modeling of Metro Network Invulnerability. *Journal of the China Railway Society* (03),29-33. DOI: 10.3321/j.issn:1001-8360.2007.03.006

Gao Peng, Hu Jianbo & Wei Gaole. (2013). Robustness Analysis of Urban Transit Network Based on Complex Network with Varied Weight. *Computer Simulation* (09),153-156. DOI: 10.3969/j.issn.1006-9348.2013.09.035

GAO Lei & LI Shubin. (2024). Importance Evaluation and Robustness Analysis of Urban Rail Transit Stations[J]. *Logistics Sci-Tech*,2024,47(15):70-74+84.DOI:10.13714/j.cnki.1002-3100.2024.15.018.

Jin Kun, Wang Wei, Li Xinran, Hua Xuedong & Qin Shaoyang. (2022). Exploring the robustness of public transportation system on augmented network: A case from Nanjing China. *Physica A: Statistical Mechanics and its Applications(P1)*, https://doi.org/10.1016/j.physa.2022.128252

Li Jie & Zhang Xinyu. (2024). Robustness Analysis of Expressway Network under the Influence of Landslide Disasters[J]. Journal of Hunan University (Natural Sciences),2024,1-11[2024-11-26].http://kns.cnki.net/kcms/detail/43.1061.N.20240902.1643.002.html.

Li Fan. (2016). Research on the structural characteristics of urban rail transit network based on complex network theory(Master's thesis, DaLian JiaoTong University).

Lu Ruimin & Guo Jinli. (2018). Topological Characteristics and Robustness Analysis of Shanghai Bus Hypernetwork. *Mathematics in Practice and Theory* (20),129-137.

NEWMAN MEJ & WATTS DJ. (1999). Scaling and percolation in the small-world network model[J]. Physical review.E.Statistical physics, plasmas, fluids, and related interdisciplinary topics,1999,60(6 Pt.b):7332-7342.

Qiang Tiangang, Zhao Mingming & Pei Yulong. (2019). An Analysis of Characteristics of Complex Network and Robustness in Harbin Multi-mode Traffic Network. *Journal of Transport Information and Safety* (01),65-71. DOI: 10.3963/j.issn.1674-4861.2019.01.009

TRAN Vu Hieu, CHEONG Siew Ann & BUI Ngoc Dung. (2019). Complex Network Analysis of the Robustness of the Hanoi, Vietnam Bus Network .*Journal of Systems Science & Complexity*(05),1251-1263. DOI:10.1007/s11424-019-7431-x.

Wang Haiping. (2016). Numerical characteristics analysis of the complex traffic network in Wuchang urban area . *The Guide of Science & Education* (10):190-190. DOI:10.3969/jissn.1674-6813(s).2016.10.144.

Wang Yi and Yang Chao. (2009). Study on the Complex Network Characteristics of Shanghai's Metro Network. *Urban Mass Transit* (02),33-36+55.DOI: 10.16037/j.1007-869x.2009.02.005

Wei Wang, Wei Deng, & Qi Yang. (2001). Methods for planning, construction and management of highway networks. *Science Press.*

ZHANG & DONG. (2018) Resiliency assessment of urban rail transit networks: Shanghai metro as an example[J]. Safety science,106230-243. DOI:10.1016/j.ssci.2018.03.023.

Zuo Jiwei. (2008).Research for Scale-free Network Model and Cascading Failure (Master's thesis, Jiangsu University). DOI: 10.7666/dy1262074