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Sustainable Development of Urban Rail Transit Networks: A Vulnerability Perspective

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Abstract: Urban rail transit (URT) systems are critical to modern public transportation services. Unfortunately, disruptions in URT systems can lead to dysfunction and threaten sustainable development. This study analyses URT network sustainability from a vulnerability perspective. Two network attack scenarios, including random attacks and intentional attacks, are designed to assess different kinds of disruptions to URT networks. Under random attacks, nodes are randomly removed from the network. In contrast, under intentional attacks, key nodes are identified and removed based on topological metrics and passenger flow volume. Then, URT network vulnerability is evaluated by quantifying the changes in network efficiency and structural integrity under the network attacks from a spatio-temporal point of view. The real-world case of the Shanghai URT system from 1993 to 2020 is used to illustrate the vulnerability in the evolution of the URT system. The results indicate that the URT network is increasingly fault-tolerant and structurally robust over time. The URT network is more vulnerable to intentional attacks than to random failures. Additionally, there are significant spatial differences in the vulnerability of Shanghai URT network. Stations in the central activity zone (CAZ) are more fault-tolerant and robust than stations located outside of the CAZ. Furthermore, stations with large centrality and greater passenger flow volumes and lines with many key nodes and greater passenger flow volumes, are vulnerable to disruptions in the URT networks. This study provides a new index to comprehensively quantify node centrality; it also fills a research gap by analysing the vulnerability of URT networks based on both longitudinal and spatial patterns. Finally, this paper highlights significant practical implications for the sustainable development of URT networks, as well as the sustainable development of public transportation services.

Keywords: urban rail transit; public transportation; sustainability; complex network; vulnerability; robustness

1. Introduction

Urban rail transit (URT) systems play a significant role in modern transportation services. URT systems are attractive to the public because of their advantages of speed, capacity and comfort. For example, the Shanghai URT system accommodates approximately 9.7 million passengers daily, which accounted for more than 59% of the total volume of public transport passengers in 2017 [1]. However, URT trains are operated with short departing time interval and consistently approach their capacity, especially during peak periods. This renders URT systems sensitive to different threats and disruptions, such as technical failures, accidental failures from human error and natural disasters. Unfortunately, URT systems have already been the targets of sabotages and terrorist attacks, due to their important role in modern society. These events can cause significantly negative consequences.

For example, approximately 50 people were injured, with 15 deaths, in the 2017 Saint Petersburg Metro bombing and all lines were closed down on 3 April 2017 [2]. Both accidental failures and terrorist attacks negatively impact the sustainable development of URT systems. Therefore, it is important to identify the vulnerable stations in URT systems and make them more robust to avoid serious consequences.

The vulnerability of public transport systems has attracted considerable attention from researchers and practitioners in recent decades (e.g., [3–5]). However, most studies have applied a static method to analyse URT network vulnerability (e.g., [6,7]); the evolution of vulnerability under network attacks from a longitudinal point of view remains unclear. In addition, there are spatial differences in the vulnerability of URT networks. As such, it is important to analyse the vulnerability along with the urban spatial layout. To fill these research gaps, this study analyses the sustainability of URT networks from both longitudinal and spatial perspectives.

Using the Shanghai URT system as an empirical case study, this research dynamically analyses the sustainable development of URT networks from a vulnerability perspective. Since the first line opened in 1993 with five stations and 6.5 kilometres, the Shanghai URT system has rapidly expanded its size and service range; there are expected to be 20 lines, with 409 stations and 831.4 kilometres in 2020 [8]. Using the theory of complex network, this paper investigates the evolution in vulnerability of the Shanghai URT network from 1993 to 2020, from longitudinal and spatial points of view. The objectives of this study are to:

i. Construct undirected but weighted networks for URT systems;
ii. Design network attack scenarios in terms of random attacks and intentional attacks, based on different patterns of threats to URT networks and provide three kinds of attack objects, including a single node, multiple nodes and a single line;
iii. Identify the key nodes by quantifying node degree, betweenness centrality and passenger flow volume, as well as a new comprehensive index termed C_Hub;
iv. Evaluate the vulnerability, by calculating the damages to network efficiency and structural integrity under different network attack scenarios, present the distribution of the vulnerable stations and dynamically analyse the sustainable development of URT networks;
v. Apply the vulnerability analysis framework to the Shanghai URT system from 1993 to 2020, investigate the evolution in vulnerability and analyse the vulnerability of the Shanghai URT network in 2020 from a spatial point of view.

This study provides significant theoretical and practical insights into the sustainable development of URT systems. URT network sustainability is analysed using both longitudinal and spatial perspectives. The dynamic and spatial differences analysis from a vulnerability perspective fills a current research gap, that few studies have analysed the vulnerability of URT networks using longitudinal and spatial patterns. The study also provides a new indicator to identify key nodes in simulating URT network attacks from a topological point of view; this indicator could be an integrated centrality measure for quantifying node centrality. Furthermore, this study can serve as an aid for proactive planning and improving URT systems by providing recommendations for enhancing the robustness of URT networks in terms of topological structure. In addition, the consequences of threats and disruptions may be reduced by strengthening operational and risk management of URT systems, especially for the most vulnerable stations.

2. Literature Review

2.1. Sustainable Development of Public Transport System

A widely accepted definition of "sustainable development" is described as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [9]. Based on this definition, sustainable transport is defined as "satisfying current transport and mobility needs without compromising the ability of future generations to meet these needs" [10]. Transport systems face significant challenges with respect to sustainable development [11]. A sustainable transport system should be affordable, efficient and support a competitive economy in the economic dimension; it should provide equitable and safe access for the public in the social dimension; and it should limit emissions, waste, noise and the land use in the environmental dimension [12–14].

When considering the social dimension of sustainable development, the service provided by a sustainable transport system balances accessibility to city facilities and services with safety needs [15,16]. One of the critical elements of sustainable transport is sustainable accessibility [17]. The transport system should provide access to facilities and services in an efficient and effective way. Safety is the other essential element of sustainable transport services. A safe environment is vital for passengers. However, undesired events can occur in a transportation system, leading to an unbalanced system [18,19]. When responding to undesired events, a sustainable transport system should tolerate disruptions and rapidly return to original equilibrium after threats. The overall objective of most transportation policies is to provide a long-term sustainable transport function [20]. In general, improving accessibility and safety are focal topics in public transport planning.

There is a set of indicators used to evaluate the sustainable development of a public transport system. Accessibility [21–23] is a crucial measurement to assess the access to facilities and services and is introduced to analyse social inequities [24]. Other concepts, vulnerability and resilience, can be used to analyse the sustainability of public transport systems with respect to responses to disruptions. Vulnerability and resilience are two sides of the same coin. Vulnerability is susceptibility to disruptions [25], while resilience is the speed at which a network returns to its original equilibrium after disruptions [26]. Recent studies have also described resilience as reliability [27–29], recovery rapidity [6] and survivability [30,31].

Empirical studies have been carried out in the analysis of sustainability of public transport system from different perspectives. The accessibility and reliability in the evolution of the Seoul subway system are examined and it is found that the subway system turns more and more accessible and reliable over time [27]. The resilience of the passenger transportation system is quantified, using the 2005 London subway and bus bombings as a case study [32]. Another study used the Singapore public transit system as an example, finding that the resilience of the metro system could be enhanced by leveraging bus services [33]. The network resilience of URT systems, with respect to impacts on travel time, is measured under operational incidents [34]. To promote the sustainability of public transport systems, the high-risk nodes are identified in a station of URT system on a micro level [35]. Moreover, the resilience of the United States air transportation network is evaluated under a single attack and sustained attack scenarios [36].

2.2. Vulnerability of Public Transport System

The vulnerability is analysed by various studies from different research domains; however, there is no uniform definition of vulnerability. Adger [37] defined vulnerability as the susceptibility to stresses with respect to the harmful effects of environment and society. Turner et al. [38] proposed that vulnerability was the degree of loss in a system exposed to a threat. Seeliger and Turok [39] suggested that vulnerability was the constituent to harmful effects. Reggiani et al. [18] and Perrings [26] pointed out that vulnerability reflected reductions in quality for a network under strain. The vulnerability of transportation networks was first defined as: a susceptibility to incidents that can result in considerable reductions in the serviceability of transportation systems [20]. This study defines the vulnerability of URT systems as the degree of tolerance and robustness against different disruptions that could result in considerable damages in network efficiency and structural integrity. The disruptions include accidental failures and intentional interferences.

There are different disruptions and threats to public transport systems, such as accidental failures and intentional attacks. The most common accidental failures are technical failures. The most vulnerable equipment in a subway system include the train door and the system of train control and management [40]. Terrorist attacks cannot be predicted and can bring serious consequences [41]. To make public transport systems more robust and avoid heavy losses, studies on the vulnerability of public transport systems have grown rapidly in recent years. These studies have presented a set of vulnerability measurements in terms of topological characteristics, travel demand and passenger travel behaviours.

Public transport systems are constructed as complex networks in a topological vulnerability analysis. Some of the constructed networks are directed or weighted [3,42,43], while others are undirected and unweighted [6]. To identify critical nodes, topological measurements have been introduced in terms of node degree, betweenness centrality and node clustering [44]. From a global network perspective, most metro networks are scale-free [45] and scale-free networks are found to be tolerant under random failures [46]. Small-world networks are presented to be the most robust networks, compared to geometric random networks and scale-free networks [47]. Pairwise connectivity is proposed to assess vulnerability in order to optimize a graph-theoretical problem [48] and the connectivity is sometimes indicated by network efficiency [6]. From a local network perspective, the impact area is quantified under a link failure to evaluate the vulnerability of road transport networks, considering travel demand and the risk-taking behaviour of travellers [49]. Network-based accessibility measures are introduced to evaluate the vulnerability of transport systems and changes in travel time and travel cost under link failures are quantified in network-based accessibility measures [50]. Similarly, traffic demands and travel time are introduced to investigate the vulnerability of congested networks [51] and the vulnerability of road networks is analysed in terms of travel cost [52]. From a passenger perspective, the vulnerability of links in public transport networks is quantified and crowded links in the metro network are found to be vulnerable [4].

Different studies have applied different attack scenarios to analyse network vulnerability. The most common attack scenarios are node attacks [53] and edge attacks [54]. Different empirical studies have been conducted under different network attacks. The Greater Philadelphia road network in the United States is used as a case study to investigate the vulnerability of road networks to disruptions by quantifying the connectivity [3]. Accessibility is introduced as an index to analyse the vulnerability of regional road networks under node attacks, taking a rural region in south east Australia as an example [53]. The Swedish road network is used as an empirical study to evaluate the vulnerability of road network under area-covering disruptions and single link failures are introduced as a comparison attack scenario with the area-covering disruptions [55]. Using the Shanghai metro network in 2015 as an example, the vulnerability and recovery rapidity are analysed and the results show that the network is robust under random disruptions but vulnerable under intentional disruptions [6]. The vulnerability of Shanghai metro network in 2013 is evaluated under line attack [56]. A topological vulnerability analysis is applied to investigate the Beijing metro network with respect to travel time and passenger flow and network efficiency is introduced to evaluate the vulnerability [57].

Previous studies have presented a set of frameworks to support the sustainability analysis of public transport networks and different measurements have been presented to assess accessibility and safety. Vulnerability is used to evaluate the susceptibility to disruptions that can threaten the safety of public transport system. However, most of the recent studies have used a static method and few studies have dynamically analysed vulnerability. Furthermore, there are spatial differences in the vulnerability of a transport system; however, few studies have accounted for spatial differences.

3. Methodology

3.1. URT Network Topology

A URT system can be considered to be a complex network. A URT system can be represented in a straightforward way when the stations are represented by nodes and the edges correspond to the physical connections between stations. It is possible to construct different networks, such as L-space, B-space, P-space and C-space networks [58]; however, L-space and P-space [59,60] networks are more common for analysing transportation networks.

This study introduces a simple URT map with two lines (see Figure 1a). Stations A-G are serviced by Line 1 (blue) and Line 2 (purple). Passengers can travel from Line 1 to Line 2 by station B or station C. Similarly, passengers in Line 2 can arrive at Line 1 by station F or station C. There is one station serving different lines in one transfer point in most of the URT systems in the world. For example, station C serves both Line 1 and Line 2 in one transfer point. However, in the Moscow metro system, there are two or more separated stations in one transfer point. There are pedestrian connections between these separated stations. As shown in Figure 1a, stations B and F are separated stations with pedestrian connections between platforms in one transfer point. Actually, stations B and F could be considered to be a single stop. Therefore, stations B and F are merged into one station (represented by station B) in this study. Figure 1b is structured using the L-space. The L-space network represents each stop by a node and a link connects the nodes if they are consecutive stations on a specific line. Figure 1c is structured using the P-space. In the P-space, nodes are connected only if they can be reached without a transfer.

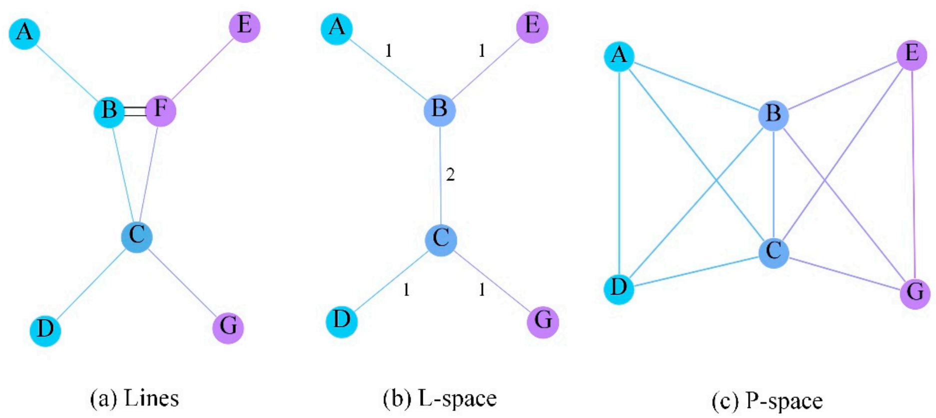

Figure 1. (**a**) A simple urban rail transit (URT) map with two lines. Stations A-G are serviced by Line 1 (blue) and Line 2 (purple), while B and F are separate stations with pedestrian connections between platforms; (**b**) L-space network; (**c**) P-space network.

Figure 1 shows that the L-space network visually reflects the geographic structure, while the P-space network focuses on transfer information. The L-space topology allows the study to focus on the physical tracks [61] and provides insights about the physical structure and vulnerability in the URT network [7]. Additionally, the L-space is an appropriate method for analysing the consequences of threats and disruptions in URT networks. Using the simple URT map in Figure 1 as an example, if station C is attacked, then node C is removed in the network and the link between node B and node D is broken. Consequently, there is no edge between node B and node D and it conforms to the L-space network after the node attack. However, the edge between node B and node D remains in the P-space network if node C is removed. Therefore, this study applies the L-space as a way to construct networks.

This study does not consider the direction of URT networks. The URT system is converted into a weighted network $G(N, E, W)$ with L-space, where N is the node set, E is the edge set and W represents the weight set. The network can be described as an adjacency matrix $A = (a_{ij})_{N\times N}$, where $a_{ij} = 1$ if there is an edge between node i and node j and $a_{ij} = 0$ if there is no direct edge [62]. For example, the L-space network in Figure 1b is described as:

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix}, \quad (1)$$

3.2. Network Properties

3.2.1. Degree and Node Strength

Degree, denoted by k_i, is the most fundamental character of a network. In an undirected and unweighted network, the degree of node i is defined as the number of edges connected to it. The variable k_i could be described as:

$$k_i = \sum_{j=1}^{N} a_{ij}, \quad (2)$$

In an undirected but weighted network, a weight is placed at a node, referred to as node strength [63]. The node strength considers the number of connections and the weights of the edges. Node strength is defined as follows:

$$S_i = \sum_{j=1}^{N} a_{ij} w_{ij}, \quad (3)$$

If all $w_{ij} = 1$, the network becomes an unweighted network and $S_i = k_i$. Using the L-space network in Figure 1b as an example, $k_A = k_D = k_E = k_G = 1$ and $k_B = k_C = 3$, while $S_A = S_D = S_E = S_G = 1$ and $S_B = S_C = 4$.

Both the degree and the node strength reflect the node centrality or connectivity in URT networks. Generally, stations with greater k_i and S_i have more adjacent connections and hold more important positions in URT systems.

3.2.2. Centrality Measures

Typically, certain nodes play crucial roles in a network and these nodes are central within the network structure. Centrality is a fundamental concept of network topological properties and represents the significance of a node in a network. Betweenness centrality is a common indicator of concern in recent public transport system studies [64].

Betweenness centrality, first defined by Freeman [65], describes the correlation and interaction between nodes. Based on betweenness centrality, the importance of a node depends on whether it is on the shortest path between any two other nodes. In weighted networks, betweenness centrality is denoted as:

$$BC_i = \sum_{s \neq i \neq t} \frac{n_{st}^{w}(i)}{n_{st}^{w}}, \quad (4)$$

In this equation, nodes s and t represent any pairs of all nodes, except node i; $n_{st}^{w}(i)$ is the number of weighted shortest paths between s and t travelling through i and n_{st}^{w} is the number of all weighted shortest paths between s and t [66]. The betweenness centrality of terminal vertexes is zero. In weighted URT networks, stations with higher BC_i have more weighted shortest paths travelling through them and play more critical roles in URT systems.

Node centrality is quantified using different measures. Besides betweenness, the basic centrality measures contain degree centrality (DC), closeness centrality (CC) and eigenvector centrality (EC) [67]. Different centrality measures have different focuses. For example, degree centrality counts direct connections; closeness centrality considers the distance from one node to the others; betweenness centrality considers the shortest paths; and eigenvector centrality counts important links [68].

Degree centrality is an immediate measure to centrality. It depends on the strength (S_i) and the largest possible degree ($N-1$) of a node, which can be defined as the form:

$$DC_i = \frac{S_i}{N-1}, \tag{5}$$

Closeness centrality represents whether or not a node is close to all other nodes. This depends on the average of the weighted shortest path length between node i and all other nodes, which is described as:

$$CC_i = \frac{N}{\sum\limits_{j=1}^{N} d_{ij}}, \tag{6}$$

In this equation, d_{ij} is the weighted shortest path length between i and j.

Eigenvector centrality reflects that the importance of a node relies on both the degree and the importance of its neighbour node. It is calculated using an adjacency matrix, A, where $A = (a_{ij})$. If node i is linked to node j, then $a_{ij} = 1$; otherwise, $a_{ij} = 0$. The relative centrality score of node i can be defined as:

$$x_i = \frac{1}{\lambda'} \sum_{j=1}^{N} a_{ij} x_j, \tag{7}$$

In this equation, λ' is a constant.

Different centrality measures quantify node centrality from different perspectives [68]. This makes it difficult to identify central nodes by only evaluating a single centrality measure. To evaluate the traffic hubs more comprehensively, this study introduces a new concept, called *C_Hub*, which applies a centrality perspective. *C_Hub* is described as:

$$C\_Hub_i = \lambda_1 BC_i + \lambda_2 CC_i + \lambda_3 DC_i + \lambda_4 EC_i, \tag{8}$$

In this equation, C_Hub_i represents the *C_Hub* of node i. It is quantified using the sum of four centrality measures (betweenness centrality, closeness centrality, degree centrality and eigenvector centrality), multiplied by their weighting coefficients λ_1, λ_2, λ_3 and λ_4. Entropy method is adopted to evaluate the weighting coefficients.

3.3. Vulnerability Model

3.3.1. Threats and Disruptions

Different threats and disruptions occur in URT systems. Based on different kinds of causes, this study classifies the common threats and disruptions into two categories: accidental failure and intentional interference (Table 1).

Table 1. Causes and consequences of threats to urban rail transit (URT) network.

Cause	Event	Consequence
Accidental failure	Door fault Vehicle fault Line fault Signal failure Power failure Foreign bodies on the line Natural disaster	Speed limit Longer interval time Temporary stop Train exit Line shutdown Close down Injuries and deaths
Intentional interference	Sabotage Terrorist attack	Line shutdown Close down Injuries and deaths

Accidental failures originate from accidents caused by technical failures or from human error. Technical failures are the most common threats to URT systems. For example, staff cannot close or open the door; the train breaks down; the signals are interrupted; or the power supply system fails. In addition, passenger mistakes can cause accidental failures, such as balloons or banners falling on the line. Natural disasters, including floods and earthquakes, can cause accidental failure as well. For example, several stations in the Guangzhou metro system were inundated by a flood on May 10, 2016 [69].

Intentional interference, such as sabotage and terrorist attack, is a relatively rare kind of threats. However, they come with grave consequences and the time and place cannot be predicted. Unfortunately, URT systems have already been deliberately targeted, because society is dependent on URT systems.

3.3.2. Network Attack Strategies

Network events and attacks are simulated to analyse the vulnerability of URT networks. Different kinds of disruptions and threats show different characteristics and require different network attack patterns. This study applies two approaches to simulate URT network attacks (Table 2). The first is random attack, corresponding to accidental failure. Accidental failures happen randomly, therefore, nodes will be randomly selected to simulate random attacks. In random attack pattern, multiple nodes will be randomly selected and removed one by one from URT networks. The second one is intentional attack, corresponding to intentional interference. Sabotage and terrorist actions are premeditated. Terrorists will select one or several stations before their acts. Generally, the selected stations are crucial in the URT systems, to create significant negative consequences. These stations may have higher betweenness centrality, degree, *C_Hub* or have greater passenger flow volumes. Therefore, key nodes are selected to simulate intentional attacks. Nodes are ranked based on betweenness centrality, degree and *C_Hub* and are removed one by one from URT networks at all stages until there are only isolated nodes or lines. Additionally, to analyse and project the sustainability of URT network in 2020, this study introduces a single node attack by random selection and based on *C_Hub*, passenger flow volume and transfer passenger flow volume. Meanwhile, each line is removed to analyse the vulnerability of URT network in 2020.

Table 2. Network attack strategies in the simulation of the Shanghai URT network.

Network Attack	Object	Basis	Stage
Random attack	A single node	Random	2020
	Multiple nodes	Random	1993–2020
Intentional attack	A single node	C_Hub, passenger flow volume transfer passenger flow	2020
	Multiple nodes	Betweenness, degree, C_Hub	1993–2020
	A single line	Line	2020

Figure 2 compares the consequences of random attack and intentional attack. A small world network with 30 nodes is created as an example. It is shown in Figure 2a1,b1. The network in Figure 2a is simulated by random attack and Figure 2b is simulated by intentional attack. The negative consequences caused by intentional attack are much more significant.

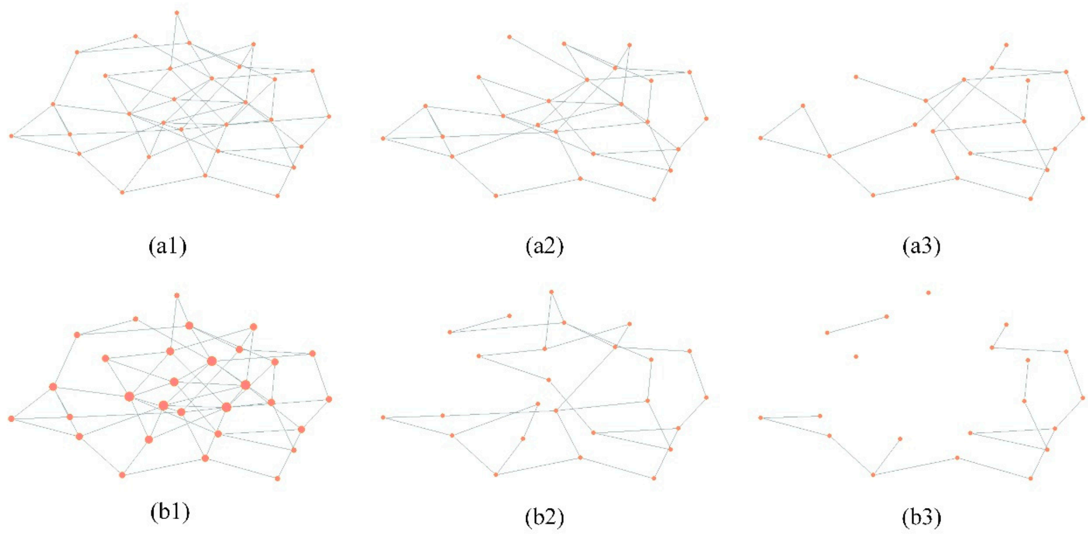

Figure 2. Comparison between the consequences of random attack and intentional attack: (**a1**) a small world network with 30 nodes and 60 edges; (**a2**) effects on connectivity of the network under random attack with 5 nodes removed; (**a3**) the network under random attack with 10 nodes removed; (**b1**) a small world network with 30 nodes and 60 edges (node sizes are ranked according to degree, node with greater degree has larger node size); (**b2**) the network under intentional attack with top five nodes removed; (**b3**) the network under intentional attack with top 10 nodes removed.

3.3.3. Vulnerability Measurement

After network attacks, some stations are out of operation and some links are break down in URT systems. Consequently, the efficiency and the topological structure of URT networks change. Network vulnerability is introduced to investigate these changes. This study evaluates the vulnerability of the URT network by quantifying the damages to network efficiency and structural integrity.

Network efficiency is defined by Latora and Marchiori (2001) [70]. It is expressed as:

$$NE(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}}, \tag{9}$$

In this expression, d_{ij} is the weighted shortest path length between i and j, if i and j are not connected, $d_{ij} = \infty$ and $1/d_{ij} = 0$.

The size of the largest connected component is useful for quantifying changes in network topological structure [71]. The largest component size is introduced to quantify the network structural integrity. This study normalizes the largest component size as follows:

$$LCN = \frac{N_l}{N}, \tag{10}$$

In this expression, N_l is the largest component size and N is the size of the original network. In the weighted network, the weight value should be considered. Therefore, the normalized largest component strength in a weighted network is described as:

$$LCS = \frac{\sum_{i=1}^{N_l} S_i}{\sum_{i=1}^{N} S_i}, \tag{11}$$

In this expression, S_i is the strength of node i. Both LCN and LCS reflect the topological integrity of the network after attacks.

4. The Case Study Context

This study empirically estimates the sustainability of URT systems from a vulnerability perspective. Shanghai is used as a case study. Located in the west coast of the Pacific Ocean and the mouth area of the Yangtze River and the Huangpu River, Shanghai has the world's busiest container port based on container traffic. In other words, Shanghai has geographical conditions that are similar to other international metropolises. Meanwhile, with more than 24 million inhabitants and an area about 6340.5 square kilometres in 2017 [72], Shanghai is the centre of international economy, finance, trade, shipping and technological innovation in China. These conditions make Shanghai a good case study, because of its geographical environment and historical development. This paper, therefore, provides a reference for the sustainable development of public transport networks in metropolises with a similar geographical environment as Shanghai.

Based on Shanghai urban master planning (2017–2035) [73], three circles are drawn within the boundary of the main urban area (MUA). The first circle is the central activity zone (CAZ). The CAZ has an area of approximately 75 square kilometres and is the core centre of the urban functions of Shanghai. The second circle lies outside the CAZ and extends to the central area (CA), with an area of approximately 589 square kilometres. There are five sub-centres of the city located in the second circle. The third circle is the main urban area (MUA), which consists of approximately 466 square kilometres; there are four city sub-centres located in the third circle.

The Shanghai URT system includes different types of rail systems, for example, tram, metro and maglev. Trams mainly run along streets, at lower speeds compared to other types of URT. In this study, the Shanghai URT system contains metro and maglev, excluding the tram. The first line in the Shanghai URT system opened in 1993, with five stations and 6.5 kilometres. Some of the recent new lines under construction are expected to open before 2020. There are projected to be 20 lines with 409 stations and 831.4 kilometres in 2020 [8]. Therefore, Shanghai URT systems from 1993 to 2020 are assessed in this study and they are divided into four stages: stage 1 (2005), stage 2 (2010), stage 3 (2015) and stage 4 (2020). Figure 3 shows the evolution of the Shanghai URT system from 1993 to 2020. In stage 1 (2005), there are only six lines, however, it is projected that there will be 20 lines in stage 4 (2020). Meanwhile, the coverage area of Shanghai URT system is visibly enlarged between stage 1 (2005) to stage 4 (2020). The supply service of the Shanghai URT system covers the main urban area (MUA) and extends to the peripheral urban area.

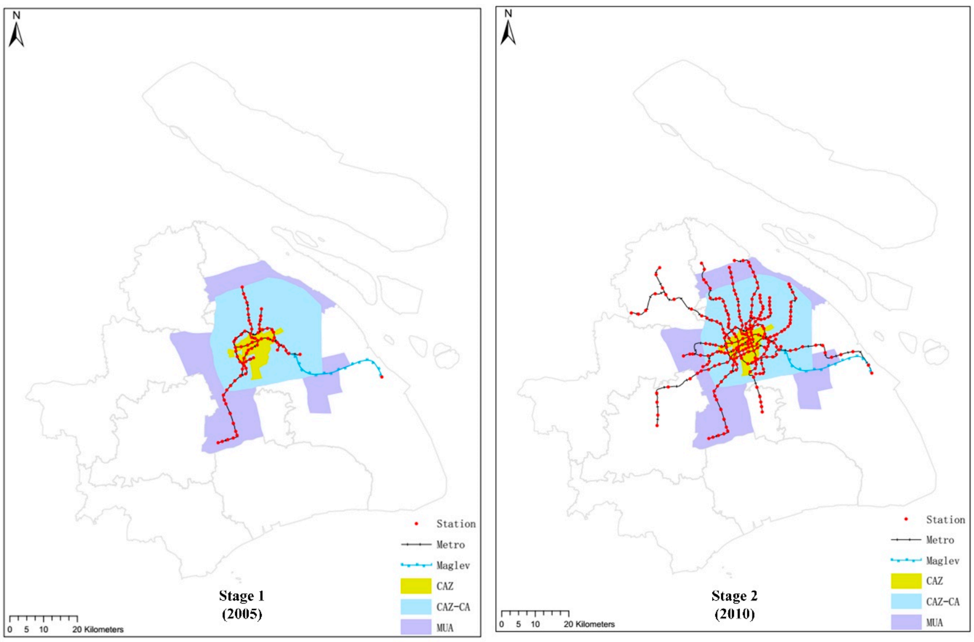

Figure 3. *Cont.*

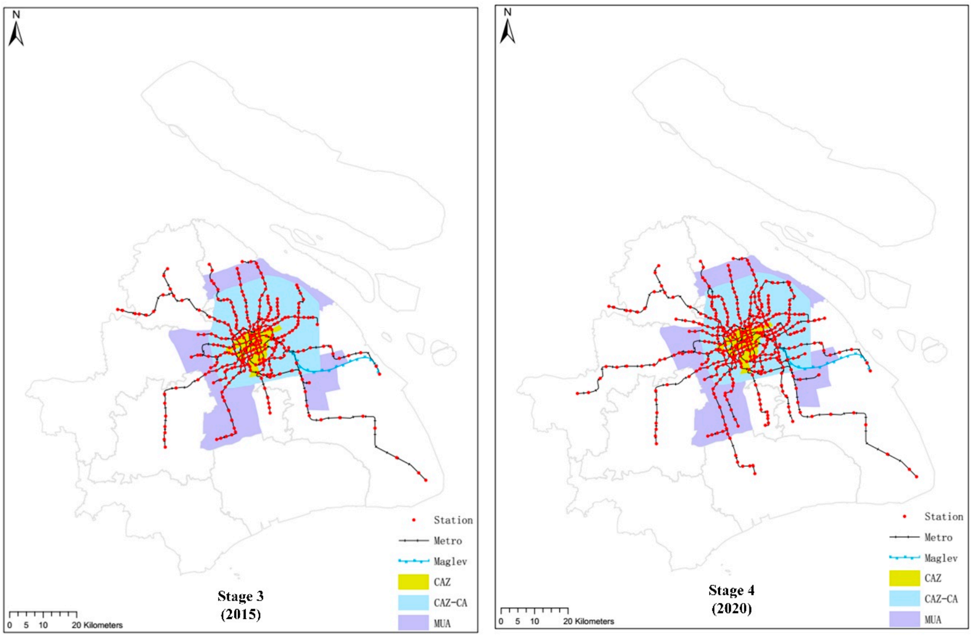

Figure 3. Evolution of the Shanghai URT network.

Using Shanghai metro network maps at the end of each stage, this study constructs four weighted URT networks using the L_space. Positional information about the stations and lines is digitized in a Geographic Information System (GIS) environment. Then, the Pajek program is used for the network analysis. The graphs are drawn in GIS and R.

5. Results

5.1. Four Periods in the Evolution of Shanghai URT Network

Table 3 summarizes the network properties for the final years of each stage. The network properties include the population (Pop.), the number of nodes (N), edges (E) and lines (L), the average degree ($\langle k \rangle$), average strength ($\langle S \rangle$), average weighted shortest path length ($\langle d \rangle$) and the diameter (D) (the maximum of the weighted shortest path length).

Table 3. Summary of network indicators for the final years of each stage.

Year	Pop. [million]	N	E	L	$\langle k \rangle$	$\langle S \rangle$	$\langle d \rangle$	D
2005	17.784	73	76	6	2.082	2.329	11.051	34
2010	23.027	244	268	12	2.197	2.279	14.925	41
2015	24.153	303	350	15	2.310	2.376	14.872	41
2020	$\leq$25	409	487	20	2.381	2.435	15.603	44

Table 3 shows that the numbers of nodes (N), edges (E) and lines (L) increase from stage 1 (2005) to stage 4 (2020), along with the average degree ($\langle k \rangle$) and the diameter (D). In particular, there is a rapid construction of new lines in stage 2 (2010). The 41st World Expo was held in Shanghai in 2010; as such, the government invested huge sums of resources to construct the public infrastructure in stage 2. As a result, the scale of the URT network extends rapidly from this period. By 2020, it is projected that there will be 409 stations and 20 lines in the Shanghai URT network.

5.2. Evolution in Vulnerability

Dynamic vulnerability is measured using network efficiency (NE), the normalized largest component size (LCN) and the normalized largest component strength in a weighted network (LCS).

Damages to *NE*, *LCS* and *LCN* are evaluated under random attacks and intentional attacks over the four studied stages. Following the strategies of multiple nodes attacks, the original networks are attacked by removing nodes one by one continuously. In random attacks, the nodes are randomly selected and removed. However, in intentional attacks, nodes are ranked from largest to smallest, using different centrality measures in terms of betweenness centrality (*BC*), degree (*D*) and *C_Hub*. Then, multiple nodes are removed one by one continuously, until the original network is broken into small fragments, such as isolated nodes or lines without a transfer node.

5.2.1. Network Efficiency

This study compares the damages caused by different attack patterns horizontally and longitudinally. In the longitudinal analysis, Figure 4 shows the changes in the network efficiency under different attack patterns in the evolution of Shanghai URT network. It shows that the network efficiency decreases as more nodes are removed from the original network; the degree of the decrease is mitigated between stage 1 (2005) to stage 4 (2020). In other words, the network vulnerability of the Shanghai URT network is projected to decline as the network extends from stage 1 (2005) to stage 4 (2020). Meanwhile, the Shanghai URT network is projected to become increasingly robust as time passes.

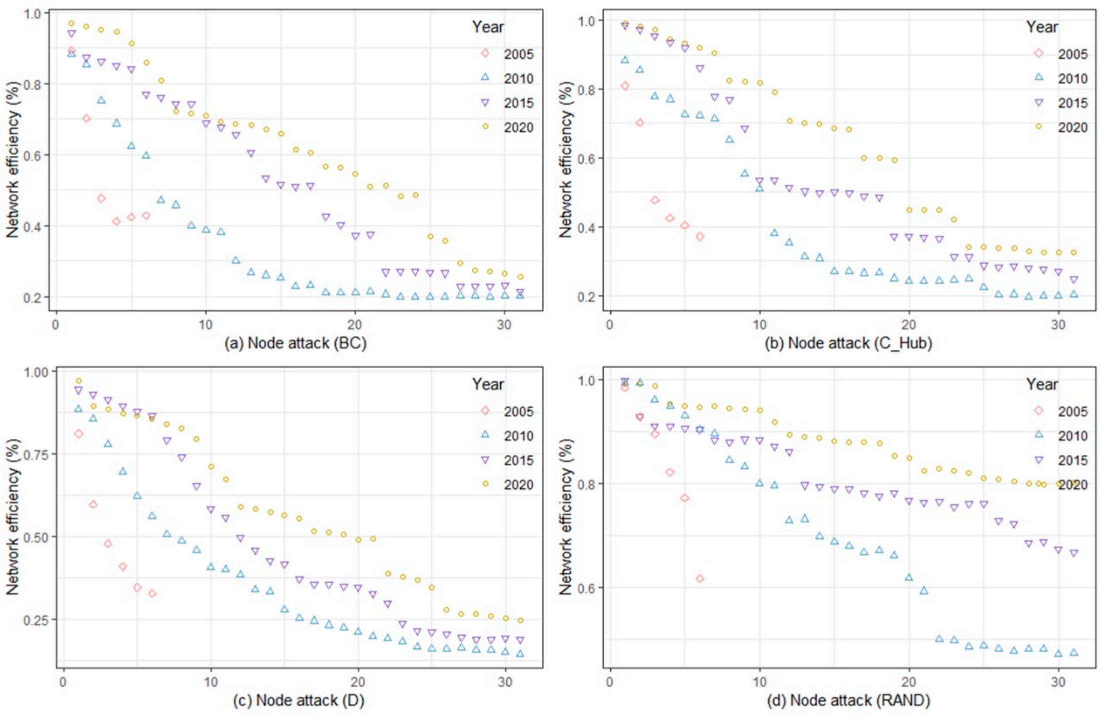

Figure 4. Changes of the network efficiency in the evolution of URT networks: (**a**) intentional attacks following *BC* rank; (**b**) intentional attacks following *C_Hub* rank; (**c**) intentional attacks following *D* rank; (**d**) random attacks.

In the horizontal comparison, Figure 5 shows the damages of network efficiency under multiple nodes attacks according to different strategies of nodes selection. Compared with the results in the environment of random attacks, the network efficiency decreases faster under the intentional attack strategies. This indicates that the network is expected to become more vulnerable under intentional attacks in each stage. The shapes of the curves based on *BC*, *D* and *C_Hub* are similar, although the changes of network efficiency upon removal of nodes identified by *D* decrease faster than the other two. In particular, *C_Hub* appropriately represents node centrality in the simulation of intentional attacks. In the simulation of intentional attacks based on *BC*, *D* and *C_Hub*, the values of network efficiency drop to less than 50% of the original network with the top five percent of nodes removed. The network efficiency falls to even less than 25% of the original network in stage 2 (2010) under intentional attacks, when the top five percent of nodes are removed. In other words, the damages of network efficiency experience a significant decline after multiple key nodes (especially nodes on top five percent) being removed from the original network.

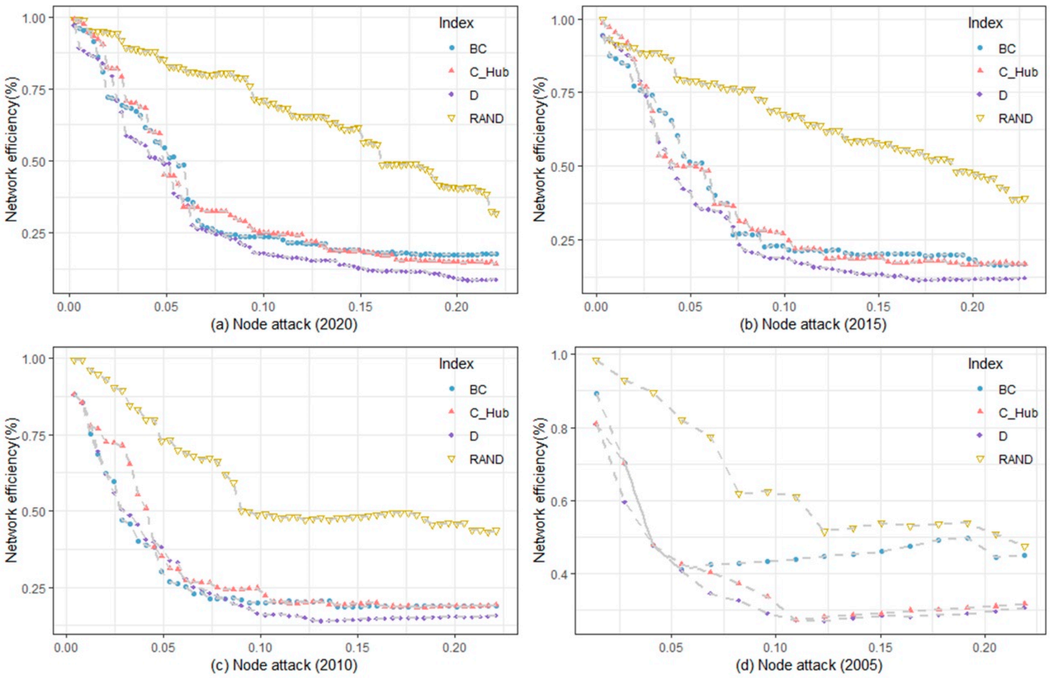

Figure 5. Damages of network efficiency under multiple nodes attacks in four stages.

5.2.2. Network Structural Integrity

Network structural integrity is quantified based on the size of the largest component. Two indicators are introduced: the normalized largest component size (*LCN*) and the normalized largest component strength in a weighted network (*LCS*).

Based on the horizontal and longitudinal perspectives, Figures 6 and 7 describe the changes of *LCN* under different attack strategies in the evolution of Shanghai URT network. Figures 8 and 9 demonstrate the damages of *LCS*. The results indicate that the changes of *LCN* under network attacks are similar to the damages of *LCS*. This is because, for most of the multiple nodes' attacks in the Shanghai URT network, the values of *LCS* under two adjacent continuous attacks are equal, if the largest component sizes do not vary.

Figures 6 and 8 demonstrate that both of the *LCN* and *LCS* decline when more nodes are removed. The degree of decrease is mitigated between stage 1 (2005) to stage 4 (2020). In other words, the structure of the Shanghai URT network appears to become increasingly robust from stage 1 (2005) to stage 4 (2020) when multiple nodes are attacked. Compared Figures 6 and 8 with Figure 4, the changes of *NE*, *LCS* and *LCN* under random attacks decrease slowly. In stage 4 (2020), the values of *NE*, *LCS* and *LCN* remain in about 80% of the original values with 30 nodes removed from the network randomly. The loss distributions of *NE*, *LCS* and *LCN* under intentional attacks are similar. However, the loss distributions of *NE* decrease a little faster than the damages of *LCS* and *LCN*.

Figures 7 and 9 show that, compared with the changes under random attacks, both of the size and strength of the largest component decrease more quickly under intentional attacks based on *BC*, *D* and *C_Hub*. The curves based on *BC*, *D* and *C_Hub* have similar shapes; however, the damages associated with *LCN* and *LCS* under intentional attacks following *D* rank decrease a little faster than the other two. In the simulation of intentional attacks based on *BC*, *D* and *C_Hub*, both of the *LCN* and *LCS* drop to less than 50% from the original network, some even less than 25% with the top five percent of nodes removed. This means that the structural integrity of the Shanghai URT network will be heavily destroyed with the removal of multiple key nodes (especially nodes on top five percent) under intentional attacks. However, the degree of the damages is relatively slight under random attacks.

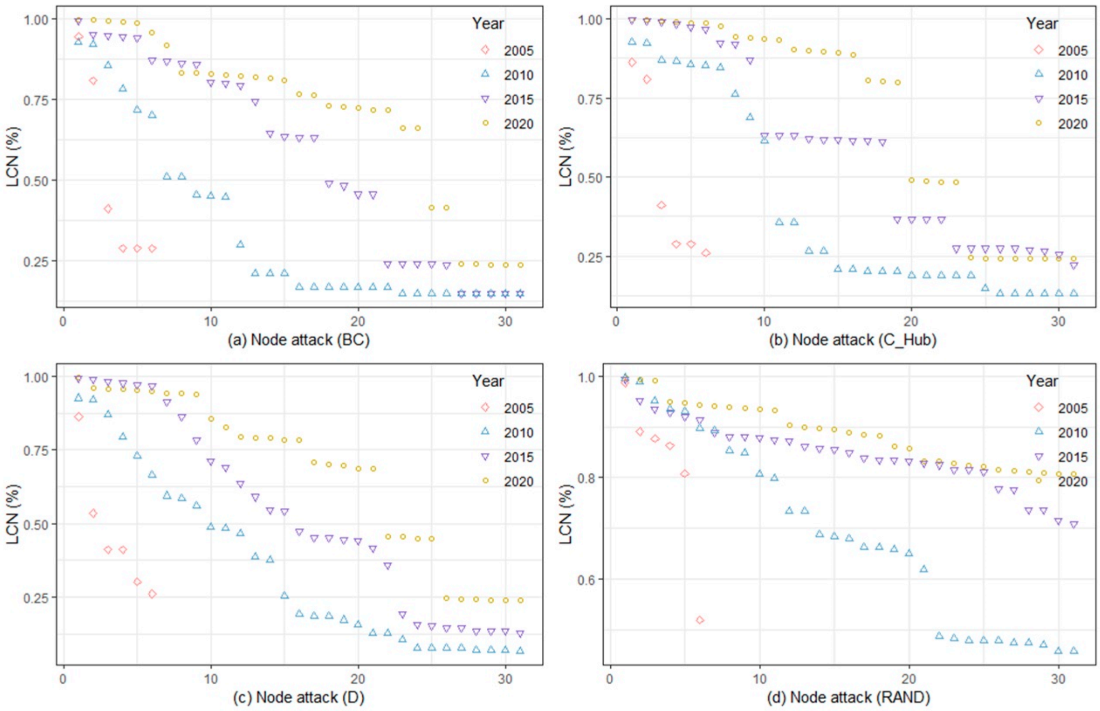

Figure 6. Changes of LCN under different attack patterns in the evolution of URT networks: (**a**) intentional attacks following BC rank; (**b**) intentional attacks following C_Hub rank; (**c**) intentional attacks following D rank; (**d**) random attacks.

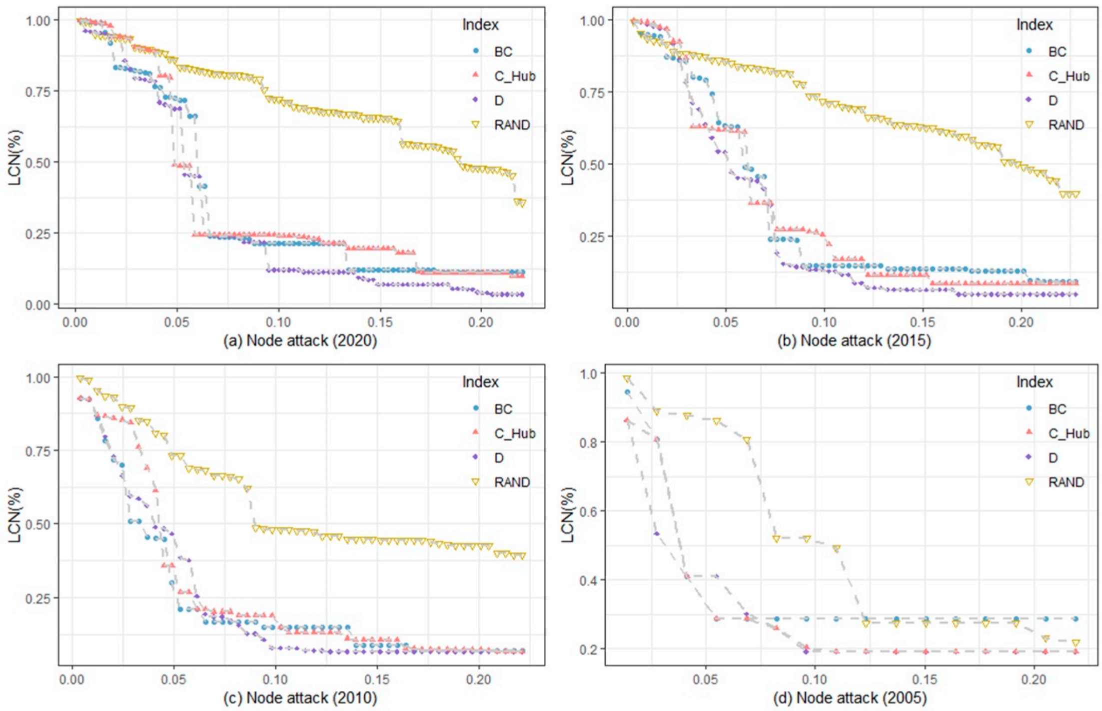

Figure 7. Damages of LCN under multiple nodes attacks in four stages.

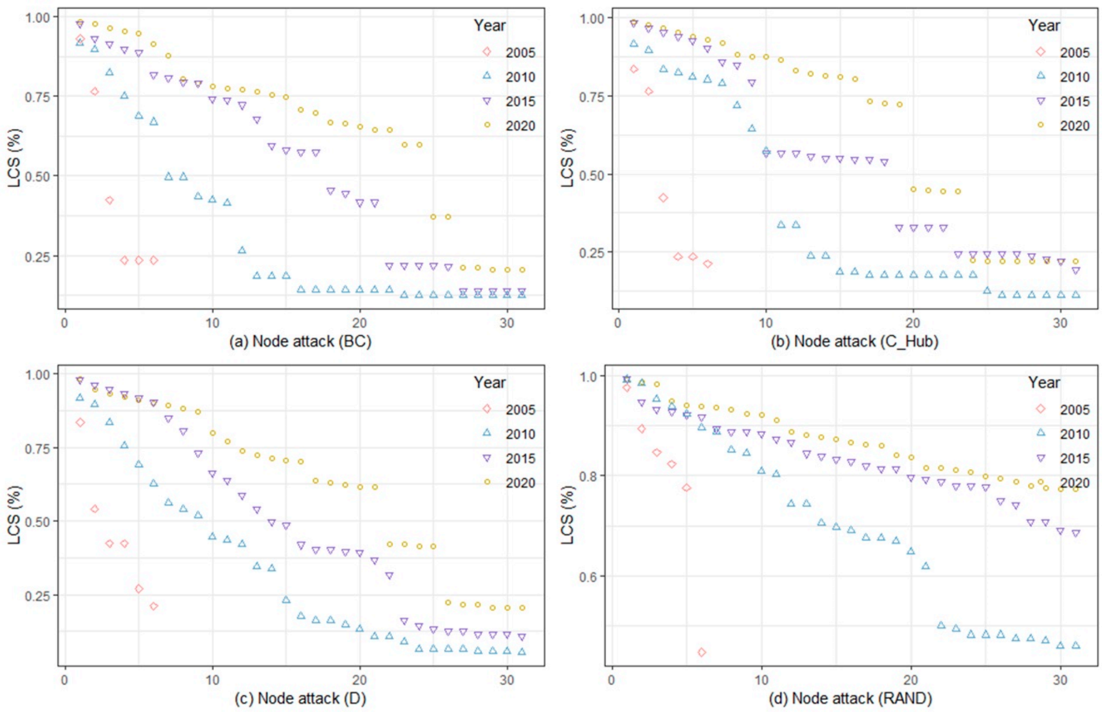

Figure 8. Changes of *LCS* under different attack patterns in the evolution of URT networks: (**a**) intentional attacks following *BC* rank; (**b**) intentional attacks following *C_Hub* rank; (**c**) intentional attacks following *D* rank; (**d**) random attacks.

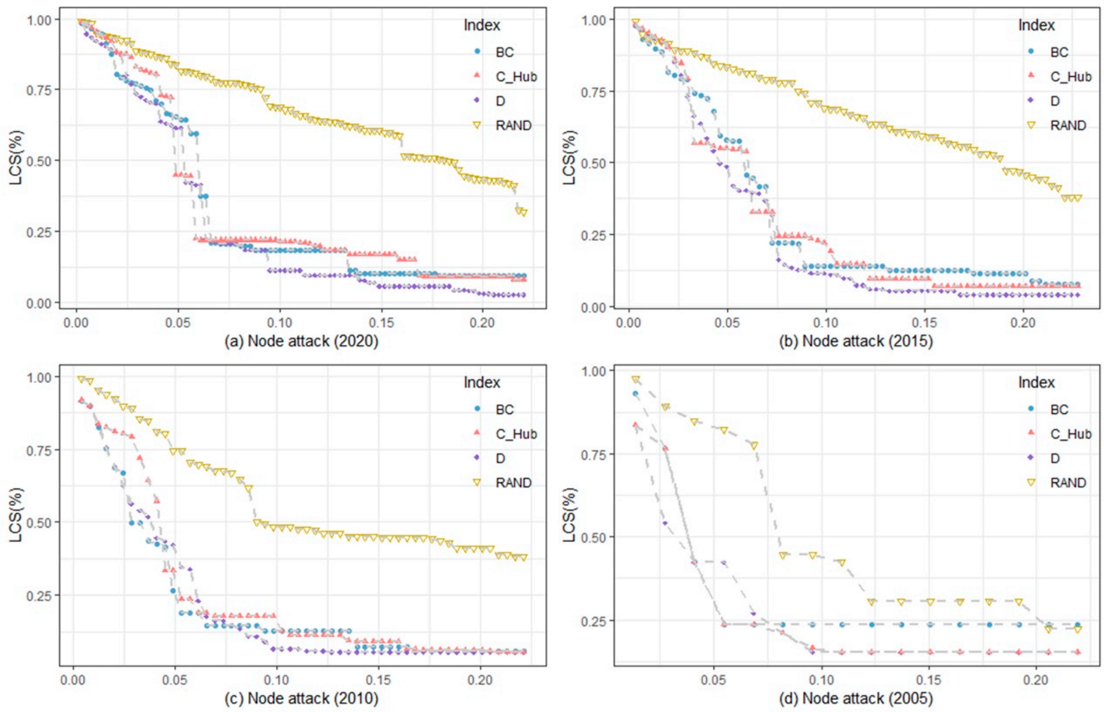

Figure 9. Damages of *LCS* under multiple nodes attacks in four stages.

5.3. Vulnerability of Shanghai URT Network in 2020

To thoroughly evaluate the projected vulnerability of the Shanghai URT network in 2020 under intentional attack, this study analyses the simulations of a single node attack and a single line attack. Each node and each line in the Shanghai URT network in 2020 are assessed in separate attacks.

The decline in the rates of NE, LCS and LCN are quantified to evaluate the vulnerability of the Shanghai URT network in 2020. To enhance readability, NE', LCS' and LCN' are introduced to describe the declining rates of NE, LCS and LCN, where:

$$NE' = \frac{NE(G) - NE(G')}{NE(G)} \times 100, \tag{12}$$

$$LCS' = \frac{LCS(G) - LCS(G')}{LCS(G)} \times 100, \tag{13}$$

$$LCN' = \frac{LCN(G) - LCN(G')}{LCN(G)} \times 100, \tag{14}$$

In these equations, G is the original network and G' is the surviving network under an attack.

5.3.1. A Single Node

The simulated results under a single node attack of the Shanghai URT network in 2020 are demonstrated on the environment of Geographic Information System (GIS), which contains three circles within the boundary of the main urban area (MUA) in Shanghai. As demonstrated in Section 5.2, C_Hub represents node centrality in the simulation of intentional attacks appropriately. Therefore, Figure 10 compares the C_Hub of each node. Along with the C_Hub, the decline rates in terms of NE', LCS' and LCN' are also demonstrated in Figure 10. The node size changes according to the value of each node. The larger the value is, the bigger the node is.

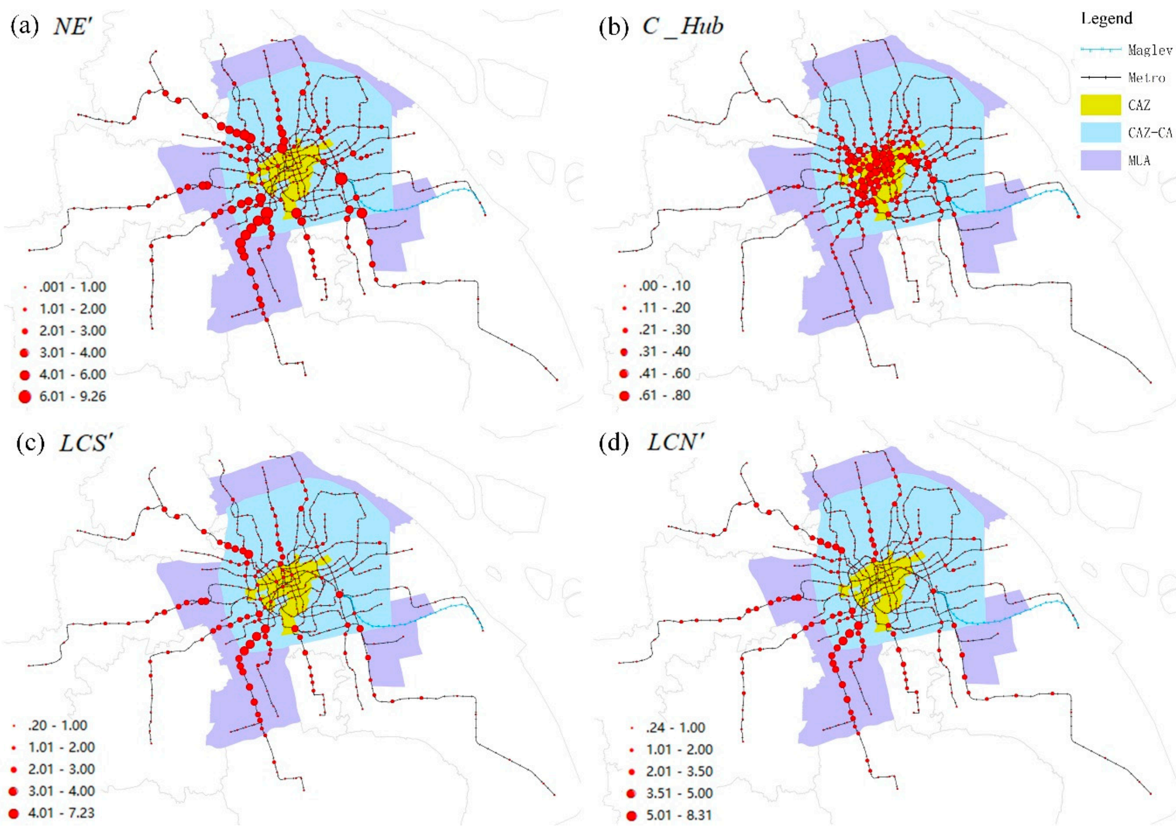

Figure 10. Vulnerability in terms of NE', LCS' and LCN' under a single node attack, compared with the C_Hub of each node in the Shanghai URT network in 2020.

Figure 10a shows that most of the nodes with the largest values of NE' are distributed in CAZ-CA and MUA; however, nodes in CAZ have much smaller NE' values. Figure 10c,d show that the results of LCS' and LCN' are similar. Nodes in CAZ are relatively smaller than nodes in CAZ-CA and MUA. However, as shown in Figure 10b, almost all the key nodes (identified by C_Hub) are distributed among CA, especially in CAZ. That is to say, network efficiency is in a small decline and the structural integrity of network is not easily damaged in CAZ. In other words, nodes in CAZ are less vulnerable than those in CAZ-CA and MUA, although nodes in CAZ have larger C_Hub values. As shown in Figure 10, the distributions of NE', LCS' and LCN' are similar. Nodes with higher values of NE', LCS' and LCN' are located outside of the CAZ. However, the network efficiency decreases more significantly than the network structural integrity, because the maximum values of NE', LCS' and LCN' are 9.26, 7.23 and 8.31.Top 10 stations in terms of NE', LCS' and LCN' are provided in Table 4. The node with the largest value of NE', LCS' and LCN' is Shanghai South Railway Station. It means that Shanghai South Railway Station is projected to be the most vulnerable in the Shanghai URT network in 2020. As shown in Table 4, most of the top 10 NE' stations are in CAZ-CA, except Shanghai Railway Station and Oriental Sports Centre. Meanwhile, all the top 10 stations in terms of LCS' and LCN' are in CAZ-CA and MUA. In other words, most of the top 10 stations in terms of NE', LCS' and LCN' are distributed outside the CAZ. The nodes in CAZ are more robust than those in CAZ-CA and MUA.

Table 4. Top 10 stations in terms of NE', LCS' and LCN'.

Sta. (NE')	**Cir. (NE')**	**Sta. (LCS')**	**Cir. (LCS')**	**Sta. (LCN')**	**Cir. (LCN')**
Shanghai South Railway Station	CAZ-CA	Shanghai South Railway Station	CAZ-CA	Shanghai South Railway Station	CAZ-CA
Longyang Road	CAZ-CA	Jinjiang Park	CAZ-CA	Jinjiang Park	CAZ-CA
West Shanghai Railway Station	CAZ-CA	Lianhua Road	CAZ-CA	Lianhua Road	CAZ-CA
Jinjiang Park	CAZ-CA	West Shanghai Railway Station	CAZ-CA	Waihuanlu	CAZ-CA
Shanghai Railway Station	CAZ	Waihuanlu	CAZ-CA	Xinzhuang	MUA
Guilin Road	CAZ-CA	Xinzhuang	MUA	West Shanghai Railway Station	CAZ-CA
Lianhua Road	CAZ-CA	Longyang Road	CAZ-CA	Chunshen Road	MUA
Oriental Sports Centre	CAZ	Chunshen Road	MUA	Liziyuan	CAZ-CA
Luoshan Road	CAZ-CA	Guilin Road	CAZ-CA	Yindu Road	MUA
Waihuanlu	CAZ-CA	Liziyuan	CAZ-CA	Qilianshan Road	CAZ-CA

In intentional attack, the targets are not only the central nodes but also the nodes with greater passenger flow volumes. Table 5 lists the top 10 stations in terms of C_Hub, passenger flow and transfer passenger flow. For most stations within the top 10 C_Hub, passenger flow and transfer passenger flow, the declining rates of network efficiency and the size and strength of the largest component are below 2%. The exceptions are Century Avenue and Longyang Road, which have large C_Hub values and great volume of transfer passenger flow; Hongqiao Railway Station, Shanghai Railway Station and Shanghai South Railway Station, which have great volume of passenger flow; and the Oriental Sports Centre, which has great volume of transfer passenger flow. Therefore, these six stations are projected to be more vulnerable in the Shanghai URT network in 2020.

Table 5. Top 10 stations in terms of C_Hub, passenger flow and transfer passenger flow.

Index	Rank	Station	Cir.	NE'	LCS'	LCN'
C_Hub	1	West Nanjing Road	CAZ	0.801	1.205	0.244
	2	Jing'an Temple	CAZ	1.097	1.205	0.244
	3	People's Square	CAZ	0.445	1.205	0.244
	4	Century Avenue	CAZ	2.940	1.606	0.244
	5	Xujiahui	CAZ	0.908	1.205	0.244
	6	South Shanxi Road	CAZ	0.567	1.205	0.244
	7	Hanzhong Road	CAZ	0.882	1.205	0.244
	8	Longyang Road	CAZ-CA	7.296	3.614	3.178
	9	Jiangsu Road	CAZ	1.078	0.803	0.244
	10	South Huangpi Road	CAZ	0.382	0.803	0.244
Passenger flow	1	People's Square	CAZ	0.445	1.205	0.244
	2	Hongqiao Railway Station	MUA	3.315	3.012	3.423
	3	East Nanjing Road	CAZ	0.459	0.803	0.244
	4	Shanghai Railway Station	CAZ	5.226	2.610	3.178
	5	Xujiahui	CAZ	0.908	1.205	0.244
	6	Jing'an Temple	CAZ	1.097	1.205	0.244
	7	Lujiazui	CAZ	0.867	0.803	0.244
	8	West Nanjing Road	CAZ	0.801	1.205	0.244
	9	Zhongshan Park	CAZ	1.501	1.205	0.244
	10	Shanghai South Railway Station	CAZ-CA	9.263	7.229	8.313
Transfer passenger flow	1	Century Avenue	CAZ	2.940	1.606	0.244
	2	People's Square	CAZ	0.445	1.205	0.244
	3	Xujiahui	CAZ	0.908	1.205	0.244
	4	Hanzhong Road	CAZ	0.882	1.205	0.244
	5	Longyang Road	CAZ-CA	7.296	3.614	3.178
	6	Laoximen	CAZ	0.453	0.803	0.244
	7	Lujiabang Road	CAZ	0.809	0.803	0.244
	8	East Nanjing Road	CAZ	0.459	0.803	0.244
	9	Oriental Sports Centre	CAZ	4.640	3.012	2.934
	10	Jiangsu Road	CAZ	1.078	0.803	0.244

5.3.2. A Single Line

It is projected that there will be 20 lines in the Shanghai URT network in 2020. Each line is simulated under a single line attack and the decline in the rates of NE, LCS and LCN are evaluated. Figure 11 shows the top five lines in terms of NE', LCS' and LCN'. Figure 11 shows that the declining rate of network efficiency is smaller than that of the size and strength of the largest component under a single line attack. In other words, the structural integrity of the network is destroyed more easily than the network efficiency under a single line attack. In particular, Line 1 (L1) has the largest values of NE', LCS' and LCN'. It means that if Line 1 is removed from the Shanghai URT network in 2020, the damages of the network efficiency and the structural integrity of the network will be the largest among all of the 20 lines. Therefore, Line 1 is projected to be the most vulnerable line in the Shanghai URT network in 2020.

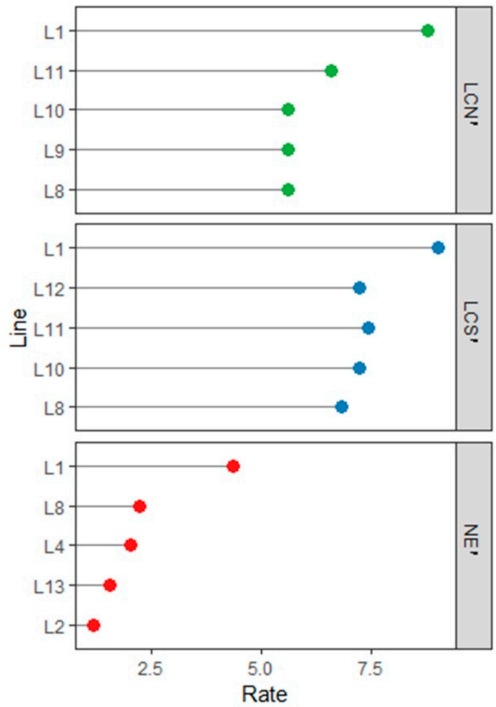

Figure 11. Top five lines in terms of NE', LCS' and LCN'.

6. Discussion

Using complex network theory, weighted networks are constructed to analyse the sustainable development of URT networks from a vulnerability perspective dynamically. Vulnerability is evaluated based on the changes in network efficiency and structural integrity under different network attacks. From a longitudinal perspective, the Shanghai URT network is more and more fault-tolerant and structurally robust to threats as the network extends from stage 1 (2005) to stage 4 (2020).

From a horizontal perspective, the Shanghai URT network is more vulnerable under intentional attacks in each stage, compared with random attacks. A similar result is found in other vulnerability analyses of URT systems [7,74,75]. Most of the URT networks constructed by L-space, have been found to be scale-free [45,75]. Generally, a small number of nodes play a significant role in a scale-free network [46]. These vital nodes always have high degree (D) and could be potential targets of intentional attacks. This study indicates that damages to network efficiency and structural integrity significantly decline after removing multiple key nodes (especially nodes on top five percent) under intentional attack strategies, following the ranks by BC, D and C_Hub.

In particular, this study proposes a new centrality measure, called C_Hub. Because the four centrality measures have different focuses, C_Hub is defined by a complex weighted sum of betweenness centrality (BC), degree centrality (DC), closeness centrality (CC) and eigenvector centrality (EC). It is verified that the shapes of the curves, demonstrating the damages of NE, LCS and LCN under intentional attack strategies, are similar. The C_Hub index can comprehensively and appropriately evaluate node centrality in the simulation of intentional attacks.

In addition, from a spatial perspective, stations in CAZ are more fault-tolerant and robust to disruptions than stations in CAZ-CA and MUA, although nodes in CAZ have larger C_Hub. This is because stations in CAZ have many alternatives, so if stations in CAZ are attacked, passengers can choose alternative routes to reach their destinations. However, some stations in CAZ-CA play significant roles in maintaining connectivity between stations in CAZ and MUA and stations at the periphery of the central areas. If these stations are attacked, there may not be alternative routes from stations in CAZ to stations at the periphery of the URT network. As discussed in Derrible and Kennedy

(2010) [45], the robustness of metro networks can be increased by creating additional transfers at the peripheries of central areas.

In addition to central nodes, the nodes with greater passenger flow volumes are consistent targets of intentional interference. In particular, Century Avenue and Longyang Road with large C_Hub and great volume of transfer passenger flow; Hongqiao Railway Station, Shanghai Railway Station and Shanghai South Railway Station with great volume of passenger flow; and the Oriental Sports Centre with great volume of transfer passenger flow are projected to be more vulnerable to disruptions in the Shanghai URT network in 2020. Moreover, Line 1 is projected to be the most vulnerable line to disruptions. This is because there are five stations in the top 10 stations in terms of NE', LCS' and LCN' in Line 1 and seven stations in the top 10 stations in terms of C_Hub, passenger flow and transfer passenger flow. It indicates that lines that have more key nodes and with greater volume of passenger flow are more vulnerable in URT networks.

7. Conclusions and Implications

7.1. Conclusions

This study investigates the sustainability of URT networks from a spatio-temporal point of view, using an empirical study of the Shanghai URT system from 1993 to 2020. Vulnerability is introduced to evaluate sustainability, which is quantified by the changes of network efficiency and structural integrity under different network attacks. Since the first line opened in 1993, the Shanghai URT network has been extended rapidly over the past decade. The URT system turns more and more robust and fault-tolerant to disruptions as time goes on. Compared with random attacks, URT networks are more vulnerable under intentional attacks. The intentional attacks are simulated based on both of the nodes with higher centrality and greater volume of passenger flow.

In particular, C_Hub is validated as an appropriate index to identify the central nodes in the simulation of intentional attacks. Additionally, there is projected to be spatial variance in the vulnerability of the Shanghai URT network in 2020. Stations in CAZ are projected to be less vulnerable than stations in CAZ-CA and MUA. Meanwhile, stations with large C_Hub values and great volume of passenger flow are vulnerable to disruptions and threats. These vulnerable stations include Century Avenue, Longyang Road, Oriental Sports Centre, Hongqiao Railway Station, Shanghai Railway Station and Shanghai South Railway Station. Moreover, Line 1 is projected to be the most vulnerable of the 20 lines of the Shanghai URT network in 2020. This is because many key nodes are located on Line 1 and it has greater volume of passenger flow.

7.2. Implications

This study contributes to the literature in several ways. On one hand, this study analyses the sustainability of URT networks from both longitudinal and spatial points of view. The evolution of the Shanghai URT network from 1993 to 2020 is used as a case study to investigate the sustainable development of URT networks dynamically. This approach fills a research gap, as few studies have assessed the vulnerability of URT networks using both of the longitudinal and spatial patterns. On the other hand, a complex centrality measure, called C_Hub, is proposed in this paper. This measure serves as a proper index to identify the central nodes of URT networks and the integrated centrality measure could appropriately evaluate node centrality in the simulation of intentional attacks.

Meanwhile, this paper has significant practical implications. Some recommendations are provided here. As demonstrated in this study, URT networks are more vulnerable to intentional interferences, compared to accidental failures. Nodes with high centrality and great volume of passenger flow are targets of intentional attacks. To enhance the robustness of URT networks in terms of topological structure, vulnerable stations should be identified from URT networks. In particular, stations with high centrality or great volume of passenger flow are the most insecure and vulnerable stations in URT networks. Alternative routes should be constructed for the most insecure stations, especially those connecting the city centre to the periphery of urban area, when proactively planning or improving URT systems. Moreover, operational management should be strengthened and emergency program should be made in the most insecure stations to avoid serious consequences.

7.3. Limitations and Future Work

The vulnerability analysis in this study considers the changes in network efficiency and structural integrity under network attacks; however, losses in passenger flow and travel time are not considered. Future research should dynamically evaluate the impacts of network attacks on passenger travel. Furthermore, URT and bus transport systems are interconnected and interdependent with each other. An integrated network, combining both the URT and bus transport networks, should be constructed to investigate the vulnerability of the public transport network.

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References

1. Report on Annual Statistical Analysis of China's Urban Rail Transit Systems in 2017. Available online: http://www.camet.org.cn/index.php?m=content&c=index&a=show&catid=18&id=13532 (accessed on 8 April 2018).
2. 2017 Saint Petersburg Metro Bombing. Available online: https://en.wikipedia.org/wiki/2017_Saint_Petersburg_Metro_bombing (accessed on 17 November 2018).
3. Nourzad, S.H.H.; Pradhan, A. Vulnerability of infrastructure systems: Macroscopic analysis of critical disruptions on road networks. *J. Infrastruct. Syst.* **2016**, *22*, 04015014. [CrossRef]
4. Yap, M.D.; van Oort, N.; van Nes, R.; van Arem, B. Identification and quantification of link vulnerability in multi-level public transport networks: A passenger perspective. *Transportation* **2018**, *45*, 1161–1180. [CrossRef]
5. De Oliveira, E.L.; Portugal, L.D.S.; Porto Junior, W. Indicators of reliability and vulnerability: Similarities and differences in ranking links of a complex road system. *Transp. Res. Part A Policy Pract.* **2016**, *88*, 195–208. [CrossRef]
6. Zhang, D.-M.; Du, F.; Huang, H.; Zhang, F.; Ayyub, B.M.; Beer, M. Resiliency assessment of urban rail transit networks: Shanghai metro as an example. *Saf. Sci.* **2018**, *106*, 230–243. [CrossRef]
7. Chopra, S.S.; Dillon, T.; Bilec, M.M.; Khanna, V. A network-based framework for assessing infrastructure resilience: A case study of the London metro system. *J. R. Soc. Interface* **2016**, *13*, 1–11. [CrossRef] [PubMed]
8. Shanghai Metro. Available online: http://www.shmetro.com/node55/node57/index.htm (accessed on 22 December 2018).
9. Chatterjee, D.K. World Commission on Environment and Development. *Environ. Policy Law* **1987**, *14*, 26–30.
10. Black, W.R. Sustainable transportation: A US perspective. *J. Transp. Geogr.* **1996**, *4*, 151–159. [CrossRef]
11. Gudmundsson, H.; Hojer, M. Sustainable development principles and their implications for transport. *Ecol. Econ.* **1996**, *19*, 269–282. [CrossRef]
12. Duncan, B.; Hartman, J. Sustainable Urban Transportation Initiatives in Canada. In Proceedings of the APEC Forum on Urban Transportation, Seoul, Korea, 20–22 November 1996.
13. Alonso, A.; Monzon, A.; Cascajo, R. Comparative analysis of passenger transport sustainability in European cities. *Ecol. Indic.* **2015**, *48*, 578–592. [CrossRef]
14. De Gruyter, C.; Currie, G.; Rose, G. Sustainability Measures of Urban Public Transport in Cities: A World Review and Focus on the Asia/Middle East Region. *Sustainability* **2017**, *9*, 43. [CrossRef]
15. Jabareen, Y.R. Sustainable urban forms—Their typologies, models, and concepts. *J. Plan. Educ. Res.* **2006**, *26*, 38–52. [CrossRef]

16. Wu, C.; Li, N.; Fang, D. Leadership improvement and its impact on workplace safety in construction projects: A conceptual model and action research. *Int. J. Proj. Manag.* **2017**, *35*, 1495–1511. [CrossRef]
17. Black, J.A.; Paez, A.; Suthanaya, P.A. Sustainable urban transportation: Performance indicators and some analytical approaches. *J. Urban Plan. Dev. ASCE* **2002**, *128*, 184–209. [CrossRef]
18. Reggiani, A.; Nijkamp, P.; Lanzi, D. Transport resilience and vulnerability: The role of connectivity. *Transp. Res. Part A Policy Pract.* **2015**, *81*, 4–15. [CrossRef]
19. Zhao, X.; Hwang, B.-G.; Yu, G.S. Identifying the critical risks in underground rail international construction joint ventures: Case study of Singapore. *Int. J. Proj. Manag.* **2013**, *31*, 554–566. [CrossRef]
20. Berdica, K. An introduction to road vulnerability: What has been done, is done and should be done. *Transp. Policy* **2002**, *9*, 117–127. [CrossRef]
21. Farber, S.; Fu, L. Dynamic public transit accessibility using travel time cubes: Comparing the effects of infrastructure (dis)investments over time. *Comput. Environ. Urban Syst.* **2017**, *62*, 30–40. [CrossRef]
22. Diao, M. Selectivity, spatial autocorrelation and the valuation of transit accessibility. *Urban Stud.* **2015**, *52*, 159–177. [CrossRef]
23. Glensor, K. Development of an index of transport-user vulnerability, and its application in Enschede, The Netherlands. *Sustainability (Switzerland)* **2018**, *10*, 2388. [CrossRef]
24. Bocarejo, S.J.P.; Oviedo, H.D.R. Transport accessibility and social inequities: A tool for identification of mobility needs and evaluation of transport investments. *J. Transp. Geogr.* **2012**, *24*, 142–154. [CrossRef]
25. Wan, C.; Yang, Z.; Zhang, D.; Yan, X.; Fan, S. Resilience in transportation systems: A systematic review and future directions. *Transp. Rev.* **2018**, *38*, 479–498. [CrossRef]
26. Perrings, C. Resilience in the dynamics of economy-environment systems. *Environ. Resour. Econ.* **1998**, *11*, 503–520. [CrossRef]
27. Kim, H.; Song, Y. Examining Accessibility and Reliability in the Evolution of Subway Systems. *J. Public Transp.* **2015**, *18*, 89–106. [CrossRef]
28. Jamous, W.; Balijepalli, C. Assessing travel time reliability implications due to roadworks on private vehicles and public transport services in urban road networks. *J. Traffic Transp. Eng. Engl. Ed.* **2018**, *5*, 296–308. [CrossRef]
29. Kim, H.; Song, Y. An integrated measure of accessibility and reliability of mass transit systems. *Transportation* **2018**, *45*, 1075–1100. [CrossRef]
30. Manchester, J.; Bonenfant, P.; Newton, C. The evolution of transport network survivability. *IEEE Commun. Mag.* **1999**, *37*, 44–51. [CrossRef]
31. Hua, W.; Ong, G.P. Network survivability and recoverability in urban rail transit systems under disruption. *IET Intell. Transp. Syst.* **2017**, *11*, 641–648. [CrossRef]
32. Cox, A.; Prager, F.; Rose, A. Transportation security and the role of resilience: A foundation for operational metrics. *Transp. Policy* **2011**, *18*, 307–317. [CrossRef]
33. Jin, J.G.; Tang, L.C.; Sun, L.; Lee, D.-H. Enhancing metro network resilience via localized integration with bus services. *Transp. Res. Part E Logist. Transp. Rev.* **2014**, *63*, 17–30. [CrossRef]
34. Lu, Q.-C. Modeling network resilience of rail transit under operational incidents. *Transp. Res. Part A Policy Pract.* **2018**, *117*, 227–237. [CrossRef]
35. Xu, H.; Jiao, L.; Chen, S.; Deng, M.; Shen, N. An Innovative Approach to Determining High-Risk Nodes in a Complex Urban Rail Transit Station: A Perspective of Promoting Urban Sustainability. *Sustainability* **2018**, *10*, 2456. [CrossRef]
36. Yoo, S.; Yeo, H. Evaluation of the resilience of air transportation network with adaptive capacity. *Int. J. Urban Sci.* **2016**, *20*, 38–49. [CrossRef]
37. Adger, W.N. Vulnerability. *Glob. Environ. Chang. Hum. Policy Dimens.* **2006**, *16*, 268–281. [CrossRef]
38. Turner, B.L.; Kasperson, R.E.; Matson, P.A.; McCarthy, J.J.; Corell, R.W.; Christensen, L.; Eckley, N.; Kasperson, J.X.; Luers, A.; Martello, M.L.; et al. A framework for vulnerability analysis in sustainability science. *Proc. Natl. Acad. Sci. USA* **2003**, *100*, 8074–8079. [CrossRef] [PubMed]
39. Seeliger, L.; Turok, I. Towards Sustainable Cities: Extending Resilience with Insights from Vulnerability and Transition Theory. *Sustainability* **2013**, *5*, 2108–2128. [CrossRef]
40. Deng, Y.; Song, L.; Zhou, J.; Wang, J. Evaluation and reduction of vulnerability of subway equipment: An integrated framework. *Saf. Sci.* **2018**, *103*, 172–182. [CrossRef]

41. Avci, O.; Ozbulut, O. Threat and vulnerability risk assessment for existing subway stations: A simplified approach. *Case Stud. Transp. Policy* **2018**, *6*, 663–673. [CrossRef]
42. Cats, O.; Koppenol, G.J.; Warnier, M. Robustness assessment of link capacity reduction for complex networks: Application for public transport systems. *Reliab. Eng. Syst. Saf.* **2017**, *167*, 544–553. [CrossRef]
43. Bell, M.G.H.; Kurauchi, F.; Perera, S.; Wong, W. Investigating transport network vulnerability by capacity weighted spectral analysis. *Transp. Res. Part B Methodol.* **2017**, *99*, 251–266. [CrossRef]
44. Lopez, F.A.; Paez, A.; Carrasco, J.A.; Ruminot, N.A. Vulnerability of nodes under controlled network topology and flow autocorrelation conditions. *J. Transp. Geogr.* **2017**, *59*, 77–87. [CrossRef]
45. Derrible, S.; Kennedy, C. The complexity and robustness of metro networks. *Phys. Stat. Mech. Its Appl.* **2010**, *389*, 3678–3691. [CrossRef]
46. Albert, R.; Jeong, H.; Barabasi, A.L. Error and attack tolerance of complex networks. *Nature* **2000**, *406*, 378–382. [CrossRef] [PubMed]
47. Mishkovski, I.; Biey, M.; Kocarev, L. Vulnerability of complex networks. *Commun. Nonlinear Sci. Numer. Simul.* **2011**, *16*, 341–349. [CrossRef]
48. Dinh, T.N.; Xuan, Y.; Thai, M.T.; Pardalos, P.M.; Znati, T. On New Approaches of Assessing Network Vulnerability: Hardness and Approximation. *IEEE-ACM Trans. Netw.* **2012**, *20*, 609–619. [CrossRef]
49. Chen, B.Y.; Lam, W.H.K.; Sumalee, A.; Li, Q.; Li, Z.-C. Vulnerability analysis for large-scale and congested road networks with demand uncertainty. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 501–516. [CrossRef]
50. Chen, A.; Yang, C.; Kongsomsaksakul, S.; Lee, M. Network-based accessibility measures for vulnerability analysis of degradable transportation networks. *Netw. Spat. Econ.* **2007**, *7*, 241–256. [CrossRef]
51. Jadamba, B.; Pappalardo, M.; Raciti, F. Efficiency and Vulnerability Analysis for Congested Networks with Random Data. *J. Optim. Theory Appl.* **2018**, *177*, 563–583. [CrossRef]
52. Leng, J.-Q.; Zhai, J.; Li, Q.-W.; Zhao, L. Construction of road network vulnerability evaluation index based on general travel cost. *Phys. Stat. Mech. Its Appl.* **2018**, *493*, 421–429. [CrossRef]
53. Taylor, M.A.P.; Susilawati. Remoteness and accessibility in the vulnerability analysis of regional road networks. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 761–771. [CrossRef]
54. Wang, S.; Hong, L.; Ouyang, M.; Zhang, J.; Chen, X. Vulnerability analysis of interdependent infrastructure systems under edge attack strategies. *Saf. Sci.* **2013**, *51*, 328–337. [CrossRef]
55. Jenelius, E.; Mattsson, L.-G. Road network vulnerability analysis of area-covering disruptions: A grid-based approach with case study. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 746–760. [CrossRef]
56. Sun, D.J.; Guan, S. Measuring vulnerability of urban metro network from line operation perspective. *Transp. Res. Part A Policy Pract.* **2016**, *94*, 348–359. [CrossRef]
57. Cai, H.; Zhu, J.; Yang, C.; Fan, W.; Xu, T. Vulnerability analysis of metro network incorporating flow impact and capacity constraint after a disaster. *J. Urban Plan. Dev.* **2017**, *143*, 04016031. [CrossRef]
58. Von Ferber, C.; Holovatch, T.; Holovatch, Y.; Palchykov, V. Public transport networks: Empirical analysis and modeling. *Eur. Phys. J. B* **2009**, *68*, 261–275. [CrossRef]
59. De Bona, A.A.; Fonseca, K.V.O.; Rosa, M.O.; Lueders, R.; Delgado, M.R.B.S. Analysis of Public Bus Transportation of a Brazilian City Based on the Theory of Complex Networks Using the P-Space. *Math. Probl. Eng.* **2016**, *2016*, 1–12. [CrossRef]
60. Sen, P.; Dasgupta, S.; Chatterjee, A.; Sreeram, P.A.; Mukherjee, G.; Manna, S.S. Small-world properties of the Indian railway network. *Phys. Rev. E Stat. Nonlinear Soft Matter Phys.* **2003**, *67*, 036106. [CrossRef] [PubMed]
61. Cats, O. Topological evolution of a metropolitan rail transport network: The case of Stockholm. *J. Transp. Geogr.* **2017**, *62*, 172–183. [CrossRef]
62. Newman, M.E.J. Analysis of weighted networks. *Phys. Rev. E* **2004**, *70*, 056131. [CrossRef] [PubMed]
63. Chen, G.; Wang, X.; Li, X. *Introduction to Complex Networks: Models, Structures and Dynamics*; Higher Education Press: Beijing, China, 2015.
64. Derrible, S. Network centrality of metro systems. *PLoS ONE* **2012**, *7*, e40575. [CrossRef] [PubMed]
65. Freeman, L.C. A Set of Measures of Centrality Based on Betweenness. *Sociometry* **1977**, *40*, 35–41. [CrossRef]
66. Dall'Asta, L.; Barrat, A.; Barthelemy, M.; Vespignani, A. Vulnerability of weighted networks. *J. Stat. Mech. Theory Exp.* **2006**, *25*, 04006. [CrossRef]
67. Bonacich, P.; Lloyd, P. Eigenvector-like measures of centrality for asymmetric relations. *Soc. Netw.* **2001**, *23*, 191–201. [CrossRef]

68. Das, K.; Samanta, S.; Pal, M. Study on centrality measures in social networks: A survey. *Soc. Netw. Anal. Min.* **2018**, *8*, 13. [CrossRef]
69. Lyu, H.M.; Sun, W.J.; Shen, S.L.; Arulrajah, A. Flood risk assessment in metro systems of mega-cities using a GIS-based modeling approach. *Sci. Total Environ.* **2018**, *626*, 1012–1025. [CrossRef] [PubMed]
70. Latora, V.; Marchiori, M. Efficient behavior of small-world networks. *Phys. Rev. Lett.* **2001**, *87*, 198701. [CrossRef] [PubMed]
71. Berche, B.; von Ferber, C.; Holovatch, T.; Holovatch, Y. Resilience of public transport networks against attacks. *Eur. Phys. J. B* **2009**, *71*, 125–137. [CrossRef]
72. Shanghai Municipal Bureau of Statistics; Survey Office of the National Burean of Statistics in Chongqing (Eds.) *2018 Shanghai Statistical Yearbook*; China Statistics Press: Beijing, China, 2018.
73. Shanghai Urban Master Planning (2017-2035). Available online: http://www.shanghai.gov.cn/newshanghai/xxgkfj/2035002.pdf (accessed on 15 December 2017).
74. Xing, Y.Y.; Lu, J.; Chen, S.D.; Dissanayake, S. Vulnerability analysis of urban rail transit based on complex network theory: A case study of Shanghai Metro. *Public Trans.* **2017**, *9*, 501–525. [CrossRef]
75. Yang, Y.; Liu, Y.; Zhou, M.; Li, F.; Sun, C. Robustness assessment of urban rail transit based on complex network theory: A case study of the Beijing Subway. *Saf. Sci.* **2015**, *79*, 149–162. [CrossRef]