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Urban rail transit network vulnerability analysis considering land use characteristics

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Abstract
In terms of urban rail transit network vulnerability, most studies have focused on the network topology characteristics and travel cost changes after network incidents and analyzed rail transit network independently. The neglects of passenger flow distributions on the network and alternative public transport modes under rail network disruptions would either underestimate or overestimate the vulnerability of rail transit network, and thus lead to inaccurate results and decisions. This study presents an accessibility-based measure for urban rail transit network vulnerability analysis and explicitly accounts for rail passenger flow characteristics, travel cost changes, and alternative transit modes. The proposed method could be used for failures of station, link, or line as well as simultaneous disruptions of these network elements.

The accessibility measure is demonstrated with an example problem and compared with methods in the literature. It is shown that the proposed approach is capable of measuring the consequences on rail network, and the advantages of the accessibility method are demonstrated and compared. The methodology is applied to the urban rail transit network of Shenzhen, China in a multi-modal public transport networks. The results reveal that the consequences of disruptions on network accessibility are obviously different for stations with different passenger flow characteristics, and some undisrupted stations are found to be vulnerable under surrounding station failures. The proposed methodology offers reliable measurements on rail transit network vulnerability and decision implications for mitigation measures and investment priorities under rail network disruptions.

Keywords: Network vulnerability analysis; Urban rail transit; Accessibility; Multi-modal transit network; Disruption

1. Introduction

Urban rail transit consisting of rail and light rail is playing an essential role in people's daily intra-city travels. The importance of urban rail transit could be observed from the large passenger flows it carries especially in cities, such as Shanghai and Beijing, China, where urban rail transit is undergoing rapid development. It is announced by Shanghai Rail and Beijing Municipal Commission of Transport in March, 2016 that the daily rail transit passenger flows exceed 10 million in the two cities. This number is expected to increase with the continuous rail transit network construction and ever-growing travel demand. Urban rail transit network has to be resilient and robust to provide reliable services for such large amount of population every day. Any type of incident on rail transit network will pose great threats on people's daily travel making the rail network vulnerable (Rodríuez-Núñez and García-Palomares, 2014). The impacts on commuters' travel decisions could even go beyond the direct travel time losses (Cox et al., 2011; Van Oort, 2014).

Consequently, there is growing research interest in transportation network vulnerability analysis in recent decades. Attention has been attracted in the vulnerability analysis of highway and urban road network under natural or man-made disruptions (Jenelius et al., 2006; Taylor et al., 2006; Chen et al., 2007; Lu and Peng, 2011; Taylor, 2012; Mattsson and Jenelius, 2015), and public transport network vulnerability hasn't been of much concern until recent years (Mishra et al., 2012; Rodríguez-Núñez and García-Palomares, 2014; Cats and Jenelius, 2015; Cats et al., 2016). In case of failures especially emergent disruptions, public transport network could be more vulnerable than road network due to its low network redundancy and large number of people affected. This vulnerability is particularly highlighted for urban rail transit network.

Although no agreement has been reached on the exact definition of transportation network vulnerability, the methodology addressing vulnerability is now well established by addressing the probability of incidents (or exposure of transportation network to disruptions) and consequence measures under disruptions. During the past decade, literature on transportation network vulnerability mainly contributes to the development of methodologies measuring consequences on network performance after disruption events. These methodologies could be categorized into exposure-importance approach (Jenelius et al., 2006), accessibility measure (Sohn, 2006; Taylor and Susilawati, 2012; Chen et al., 2015), game theory method (Bell, 2008), and so on (Chen et al., 2007). The above methods are mainly applied to road network based on a full network scan approach in the beginning (Sohn, 2006; Taylor et al., 2006; Lu et al., 2015). Later researches try to overcome the disadvantage in computation time of the full scan method by either identifying links for further analysis based on certain criteria (Knoop et al., 2012; Cats et al., 2016) or calculating "impact area" of the affected link to downscale the network for analysis (Chen et al., 2012).

Different from the above vulnerability analysis of road network, urban rail transit network vulnerability is usually studied based on complex network theory exploring the network topology characteristics under incidents. Degree, betweeness, centrality measures, and connectivity methods are employed for the measurement of rail transit network vulnerability, robustness, and resilience (Derrible and Kennedy, 2010; Zhang et al., 2015; Dimitrov and Ceder, 2016). A detailed presentation of measures in the literature is summarized by Mishra et al. (2012). This tradition of vulnerability analysis would be important for the planning and designing of urban rail transit network. However, under disruptions the vulnerability of urban rail transit network might go beyond the issue of pure network topology but a problem of combination of network topology and passenger supply and demand, especially considering the huge amount of passengers served. As a result, another approach direction in urban transit network vulnerability analysis sharing similar concept to the above road network vulnerability method has been shaped recently. Based on total travel time and passenger flow on each link, De-Los-Santos et al. (2012) measure passengers' robustness under link and station failure by introducing with-bus-bridging and without-bus-bridging cases for the Madrid rail transit network. Rodríguez-Núñez and García-Palomares (2014) developed a public transport network vulnerability approach based on travel time and changes in trip distribution. The methodology is applied to the Madrid Rail system, and critical links and the importance of circular line are identified. Cats and Jenelius (2014) integrate betweenness centrality and dynamic costs of operators and passengers together to measure the public transport network vulnerability of Stockholm, Sweden revealing that betweenness centrality itself may not be a good indicator of link importance. To evaluate the effectiveness of strategies reducing impacts of disruptions on public transport network, Cats and Jenelius (2015) propose passenger utility measures quantifying network-wide consequences on rapid public transport networks of Stockholm, Sweden while integrating stochastic passenger supply and demand, dynamic route choice, and operation capacity limitation. Recently, the probability or exposure side of public transport network vulnerability has been addressed by Cats et al. (2016) accounting for passengers' exposure to link failures by elaborating the frequency and time duration of possible disruption events in the Netherlands.

It could be learnt from the above review that the majority of existing urban rail transit network vulnerability analysis methodologies is however rooted in network and graph theory neglecting the large population it carries (Mishra et al., 2012; Mattsson and Jenelius, 2015). Recent contributions have been made to include travel time, passenger flow, and link-based passenger exposure in transit network analysis. However, the importance of a link or station in terms of passenger volumes is seldom considered in the vulnerability methodologies such as Rodríguez-Núñez and García-Palomares (2014). As concluded by Knoop et al. (2012), different links are found to be the most important based on the criteria used. The exclusive of this importance would underestimate the vulnerability of links or stations which have small average travel time changes but a huge number of affected people under disruptions. The inclusion of passenger importance is particularly essential for the vulnerability analysis of rail transit in developing countries with developing rail network and changing trip distributions. As it could be found that most of the vulnerability literature focuses on the urban rail transit network in developed countries which would have small passenger demand variation, and this may not be applicable to developing countries with growing and changing rail ridership demand. In case of disruptions, people may not only want to know the vulnerability of the network but also interested in working stations or links mostly affected, but such information is rarely provided in the literature. Methodologies of vulnerability analysis usually treat rail transit network independently without considering the interdependency nature between multi-modal urban transit networks in reality, which would overestimate the vulnerability of urban rail transit network under disruptions. People would transfer to other public transport modes nearby if a rail transit station is failed or closed, and exclusive of this alternative in urban rail transit network vulnerability analysis may reach inaccurate results and conclusions.

In order to address the above research gaps, this study presents and applies a unique location-based accessibility approach for the vulnerability analysis of urban rail transit network. Unlike most studies on the vulnerability of public transport networks as well as the accessibility method for road network vulnerability, this study explicitly accounts for the importance of stations and transfers to other public transport modes under rail network disruptions. The proposed rail transit network vulnerability could not only be measured for station disruptions but also for link and line failures based on a combination of the accessibility method and graph theory approach. The proposed methodology is described in a step by step process in Section 2. To evaluate the accessibility-based methodology, an example problem is then presented demonstrating results of various vulnerability measures in Section 3. Section 4 shows a case study on Shenzhen urban rail transit network (SURTN), and a method of identifying candidate stations for a full scan analysis is used. Finally, Section 6 summarizes the findings of this research and concludes the paper.

2. Methodology

A significant body of literature has contributed to the development and improvement of accessibility for different purposes (Hansen, 1959; Bhat et al., 2002; Litman, 2016). Accessibility is also proved to be an important measure in transportation network vulnerability analysis (Sohn, 2006; Taylor et al., 2006; Lu and Peng, 2011) and mostly developed for applications on road network. The accessibility of public transport network has recently attracted a lot of attention and become an important direction of research (Nassir et al., 2016). We propose a transit accessibility method for measuring the vulnerability of rail transit network under disruptions. The method is developed for failures of station, link, and line. Normally, stations are more exposed and vulnerable to disruptions as stations have more complex passenger activities and infrastructure compositions and more probability of becoming terrorists' targets than links. The mathematical construct of the proposed methodology starts with a station-based accessibility measure as follows.

This study proposes an accessibility index for metro station vulnerability analysis.

Based on the classic Hansen integral accessibility index, the importance of each metro station and the dependency of land use on metro network are both accounted for the improvement of the accessibility index. Therefore, the improved accessibility index is defined as

$$RA_i = C_i A_i \tag{1}$$

Equation 1 shows the calculation of the proposed accessibility index, where RA_i represents the accessibility of metro station i including land use dependency; C_i denotes the dependency of land use on metro within walkable distance of station i; A_i is a location-based accessibility of metro station i.

The dependency of land use C_i is then be formulated as:

$$C_i = L_i(\frac{w_i^c + w_i^s}{2}) \tag{2}$$

Where, L_i describes the mixed degree of land use within walkable distance of station i; w_i^c is the car alternative availability of the land use around station i; w_i^s represents the ground bus alternative availability within walkable distance of station i.

The degree of mixed land use index L_i is introduced by Bhat et al. (2007) and calculated as

$$L_i = 1 - \left\{ \frac{\left|\frac{r_i}{L} - \frac{1}{4}\right| + \left|\frac{m_i}{L} - \frac{1}{4}\right| + \left|\frac{o_i}{L} - \frac{1}{4}\right| + \left|\frac{s_i}{L} - \frac{1}{4}\right|}{3/2} \right\} \tag{3}$$

Where, r_i shows the residential land area around station i; m_i denotes the manufacturing land are; o_i is the commercial and office land area around station i; s_i is the other land area around station i.

In this work, the land area within walkable distance of a metro station is interpreted as all the floor area of certain land use and equal to the area of land on the ground multiplied by the plot ratio of a building.

w_i^c is measured as the car ownership ratio of the people living or working within walkable distance of station i. In specific, a car alternative availability ratio is calculated for each station as the car alternative availability of a station divided by the maximum value of this availability of station in a study area. In this way, the car alternative availability is standardized to [0,1].

w_i^s shows the availability of the alternative ground buses. It could be measured with the number of bus stops within walkable distance of a metro station i. Similarly, the bus alternative for station i could also be normalized.

As for the degree of mixed land use index, when different land use types are optimally mixed, that is, $r/L=m/L=o/L=s/L=1/4$, and the mixed degree of land use L_i equals to

1. This means that when the four land use types reach equilibrium ($r/L=m/L=o/L=s/L$), land use has the least dependency on the metro. In reality, the equilibrium land use condition demonstrates diverse travel behavior around a metro station, and this could balance travel demands to an optimal extent while improving transport accessibility of the area. Therefore, the closer of land use match to the equilibrium, the larger the value of L_i and thus the less dependent the land use on the metro. When there is only one type of land use around a station, and L_i is calculated as 0, however, it almost impossible to happen since there may always exist some other land use types likes roads. Hence, the calculated value of the mixed degree of land use will be within (0,1].

For the alternative availability indices of two modes, the larger the values denote the higher possibility of using these alternatives, which will decrease the dependency on metro travel and increase the accessibility of an area. Based on the normalized calculation, the values of both alternative availability indices are scaled to 0 and 1. Besides, these two alternative modes have few chance to be equal to 0 simultaneously, thus the calculated value of C_i will always be larger than 0, it ensures the avoidance of the unreasonable case under which the result of accessibility equals to zero.

Therefore, mixed land use index and two alternative availability indices are all positively correlated with the dependency degree index C_i. If the land use types are more balanced, and more other travel alternatives around a metro station area available, the dependency of people's travel on metro would be lower, all of which will result in increasing accessibility of the land. In another word, the higher the value of C_i is, the greater the accessibility will be, and the maximum value of this dependency is 1.

For A_i in Equation 1, it can be defined similarly to the improved accessibility index for transportation network vulnerability analysis introduced by Lu and Peng (2011) as

$$A_i = w_i^p \sum_{j=1}^{n-1} w_j^p \left(\frac{f(t_{ij})}{f^0(t_{ij})}\right)^{-\alpha} \qquad (4)$$

Where, w_i^p is the weight of total number of people departing and arriving metro station i, denoted by N_i^{da}, and it is calculated by making a ratio to the total number of people departing and arriving from the whole metro network at the same time, denoted by N^{da}; w_j^p is the weight of number of travelers from station j ($j \neq i$) to station i, denoted by N_{ji}, and it is calculated by making a ratio to the total number of people whose destination is station j, denoted by N_i; $f^0(t_{ij})$ is the travel cost between stations

i and j without network degradation; $f(t_{ij})$ is the travel cost between stations i and j after network degradation; α stands for travel cost decay parameter(>0); and n represents the number of metro stations in the study area.

$$w_i^p = \frac{N_i^{da}}{N^{da}} \quad (5)$$

$$w_j^p = \frac{N_{ji}}{N_i} \quad (6)$$

The main advantage of the above proposed accessibility index in this paper could be concluded that it considers the relationship between surrounding land use and metro network, and quantifies the dependency of land use on metro network while including alternatives of other travel modes. Another advantage is that the components of this index are normalized making the values of the final improved accessibility index ranges from 0 to 1, thus comparable among all stations, therefore, it will be helpful for the rapid identification of the most important stations.

The degree of metro network degradation is measured based on the accessibility reduction before and after network degradation.

$$DD^l = \sum_{i=1}^{n} RA_i^0 - \sum_{i=1}^{n} RA_i^l \quad (7)$$

where

DD^l: degree of metro network degradation if station(s) or link(s) l fails;

RA_i^0: accessibility of metro station i without metro network degradation;

RA_i^l: accessibility of metro station i if station(s) or link(s) l fails.

Specifically, the accessibility change for individual station under network degradation could also be calculated to identify stations mostly affected. The accessibility change rate for each station under station(s) or link(s) l fails is calculated as

$$RAR_i^l = \frac{RA_i^0 - RA_i^l}{RA_i^0} \quad (8)$$

where

RAR_i^l: the accessibility reduction ratio of metro station i under the failure of station(s) or link(s) l.

As mentioned before, vulnerability is the susceptibility of metro network to incidents which may result in serious consequences, where the susceptibility is the combined result of the probability of the events and the consequences. The consequences can be measured by the proposed reduction in the network accessibility. As a result, the metro network vulnerability could be measured as

$$V_d = prob_d \times DD^l \quad (9)$$

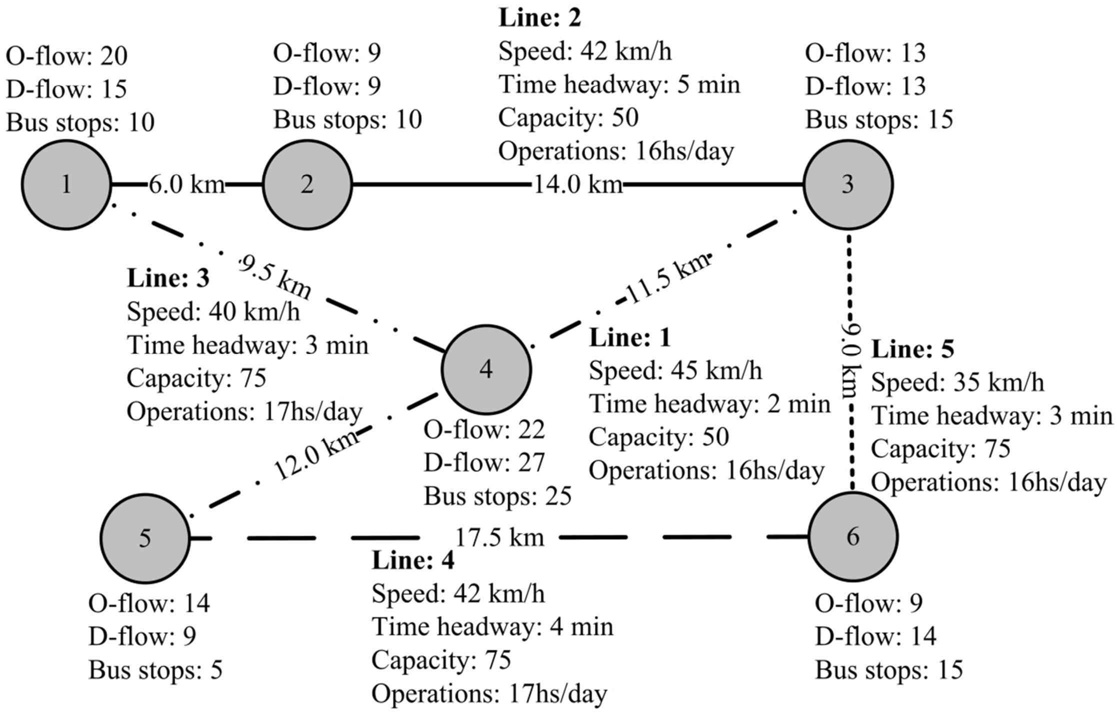
where
V_d: the vulnerability of metro network degradation under disruption(s) d;
$prob_d$: the probability of metro network degradation under disruption(s) d.

Based on Eqs. (7), (8), and (9), rail transit network accessibility changes could be measured with scenarios of single or multiple network elements disruptions. Criticality of disrupted station(s), link(s), and lines(s) could also be calculated and compared regarding the changes of network accessibility, and thus critical rail transit infrastructures would be identified and prioritized.

3. Example problem

The above methodology is described with an example problem as follows. The example network is shown in Fig. 1(a), consisting of five bidirectional rail transit lines and six stops. The characteristics of each line (speed, time headway, capacity, and operation frequency) and station (departure and arrival passengers and number of bus stops around the station) are shown in the Figure. The OD passenger flows between stations are also given in Fig. 1(b). Ground buses running parallel to each rail line are available. It is assumed that disruptions occur in an emergency, passengers in the transit network could not change origins and destinations but routes and modes, and thus there is no change in the departure and arrival passengers for each station before and after disruptions. The travel costs are defined as the total travel time of rail transit and bus transit consisting of in-vehicle travel time, transfer time, and time headway.

(a)



(b)

Station ID	1	2	3	4	5	6
1	0	2	3	9	2	3
2	2	0	1	4	1	1
3	3	1	0	5	1	2
4	6	3	5	0	3	5
5	3	1	2	5	0	2
6	2	1	1	4	1	0

Fig. 1. (a) Example of the urban rail transit system. (b) OD flows between transit stations.

The above data were input into the proposed methodology, and calculation was conducted in Matlab (R2008a). Methodologies that are widely used in previous studies such as degree centrality (Zhang et al., 2015), connectivity index (Mishra et al., 2016), and Hansen integral accessibility (Taylor et al., 2006) were also calculated for the example network. The six stations are assumed to be failed one by one, and then each methodology is calculated for the six stations. A summary of the results is shown in Table 1.

The widely adopted degree centrality method only considers the network topology characteristics, and thus needs less data and computation time. As a result, stations 3 and 4 with the same topology have the same values and are both identified as the most important stations. Other stations are calculated with values of 0.4. This method fails to include passengers and transit vehicle characteristics of a rail transit system, and would reach inaccurate results. The connectivity method goes one step further by addressing the transit vehicle characteristics such as capacity, frequency, and speed. As shown in Table 1, station 3 is calculated as the most important station followed by stations 5, 6, 4, and so on. However, station 4 has much more OD flows than station 3, and thus more people would be affected when station 4 is failed. The connectivity index still ignores passenger distribution on the network since the consequences of a disruption event are normally evaluated by the number of people affected. What's more, the above two methods provide no information about the impacts on other working stations if a station is disrupted. The Hansen integral accessibility method considering the importance of passenger generation stations and the impedance between generation and attraction stations could measure the impacts on other working stations and identify the most affected working stations. But this accessibility index does not include the importance of attraction stations and the availability of other transit services. Under this method, the individual value of each station could provide rare information until compared with values of other stations. The above disadvantages are addressed and improved with the proposed station-based accessibility approach. For example, the Hansen integral accessibility concludes that station 1 is more important than station 5 under disruptions, but station 1 has more bus stops and its vulnerability would decrease with the availability of more bus alternatives than station 5. This reaches the same conclusion as the proposed method that station 5 is more important and vulnerable as shown in Table 1.

Table 1

Comparison of rail station failure measures for vulnerability analysis.

Measure	Station values						Most affected working stations
	1	2	3	4	5	6	
Degree centrality	0.4	0.4	0.6	0.6	0.4	0.4	N/A
Connectivity index	1.33	0.30	3.06	1.37	2.95	1.62	N/A
Hansen integral accessibility	75.58	53.52	86.01	134.55	70.45	59.02	Available
Proposed accessibility approach	0.343	0.376	0.419	0.485	0.400	0.399	Available

4. Case study

The proposed methodology is applied to the urban rail transit network of Shenzhen, China. The accessibility-based network vulnerability approach is detailed based on station failures on SURTN since link and line failures are calculated based on station failure in the methodology.

4.1. Case study description

With the third public transport network in China, Shenzhen has a transit ridership of over 10.5 million per day. Shenzhen bus transit operates 919 bus routes with a daily ridership of 5.9 million. Consisting of 5 lines and 118 stations including 13 transfer stations, SURTN has a length of 178.0 km and ranks the sixth in the country. However, it has the fourth rail transit ridership in China with nearly 3.0 million passengers per day after Beijing, Shanghai, and Guangzhou. The peak day rail ridership in Shenzhen would reach 3.5 million. With another 6 lines under construction, SURTN will be extended to 11 lines with a total length of 434.9 km in 2020. As a job-immigrant city in China, Shenzhen's rail transit is expected to play a more and more important role in people's daily travel. As shown in Figure 2, passenger flow on SURTN is mainly distributed on the southeastern part of the network, and the network would become vulnerable with such large passenger volume under disruptions.

4.2. Data

In order to analyze the vulnerability of SURTN under station failures, the following network and passenger flow data are used. The urban rail transit network of Shenzhen with stations and links is shown in Figure 2 for the year of 2013. The network for analysis also contains Shenzhen bus transit network in the year. The station data include average daily OD trip matrix between rail stations in 2013 and the number of bus stops within 600 m of rail stations (Jun et al., 2015). The candidate rail stations for analysis are selected based on the station OD passengers and the station location on the network, that is, stations with large passenger volume, transfer stations, and stations far away from city center but having a relative high ridership are chosen as candidate stations for analysis. The travel time of rail transit includes in-vehicle travel time, transfer time, and vehicle time headway. This study attempts to calculate network performance under emergent incidences such as vehicle breakdown, signal failure, terrorist attacks, and so on, and thus OD trips are assumed to be unchanged before and after disruptions.

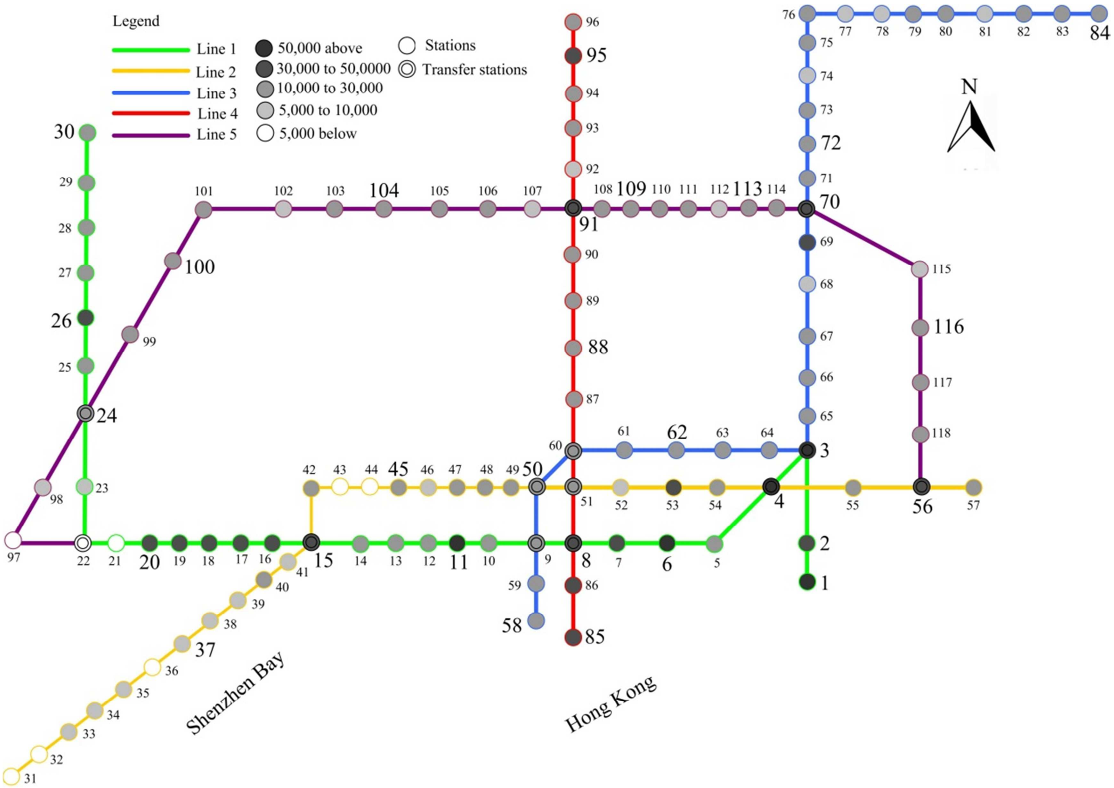


Fig. 2. Shenzhen urban rail transit network and passenger volume distribution.

5. Results and discussion

As shown by the IDs with a larger font size in Figure 2, 30 stations were chosen for analysis. The stations were assumed to be disrupted individually, and station-based network accessibility was calculated under each disruption. The consequence of a station failure is measured with the network-wide accessibility reduction comparing with its original value of 1. Multiple failures of station were then analyzed for the network. The calculation of each disruption scenario consumes 30 seconds including 4 seconds of the network accessibility calculation in Matlab. The calculation results are shown as follows.

5.1. Measuring network accessibility under individual station failures

Network accessibility of SURTN was calculated for each of the 30 station failure scenarios, and results are shown in Fig. 3. Among all the candidate stations, the failure of station 4 would result in the most network accessibility reduction. Located in the central business district, station 4 has the most passenger volume among all the rail stations in Shenzhen, but does not have the highest bus availability, that is, bus stop and passenger volume ratio. When station 4 is disrupted, a large volume of affected passengers could not find enough bus alternatives to evacuate, and thus poses the most risk on the rail transit network. Following station 4, stations 3, 11, 26, 6, and 1 also cause high accessibility reduction if disrupted. All of these stations are on Line 1 which was built the earliest and goes through the most developed area of Shenzhen City. Station 62 is proved to be the least important station whose failure causes the least network accessibility reduction. Situated in a less populated area of the city, station 62 has only 30% of rail ridership but 5 times of bus availability of station 4, which would account for the least importance of station 62. The failure of station 37 causes a small network accessibility reduction may be due to its low ridership which is only 10% of the ridership of station 4. Substantial accessibility reductions could be observed for most of the transfer stations, since most of them have relative high ridership. However, failures of transfer stations 50 and 24 generate low network accessibility reductions which are even lower than non-transfer stations. Station 24 has a relative low ridership, and as a suburban station its importance would be low under disruptions. Serving in the central area of the city, station 50 has higher ridership and bus availability than station 24. Particularly, the OD trips of station 50 are mainly distributed among the surrounding stations, and the short distance trips would be less affected once station 50 is closed. Station 30 has the most importance increase under failure comparing with the rank based on passenger volume. One reason would be the pretty low bus availability around the station, and the other could be explained by its widely distributed OD flows which could be seriously affected for long-distance bus alternative travels if station 30 is disrupted. These passenger flow and bus alternative characteristics could be captured with the proposed methodology. It’s worth note that all the disrupted stations are still accessible but have substantial reductions (more than 80%) in their accessibility.

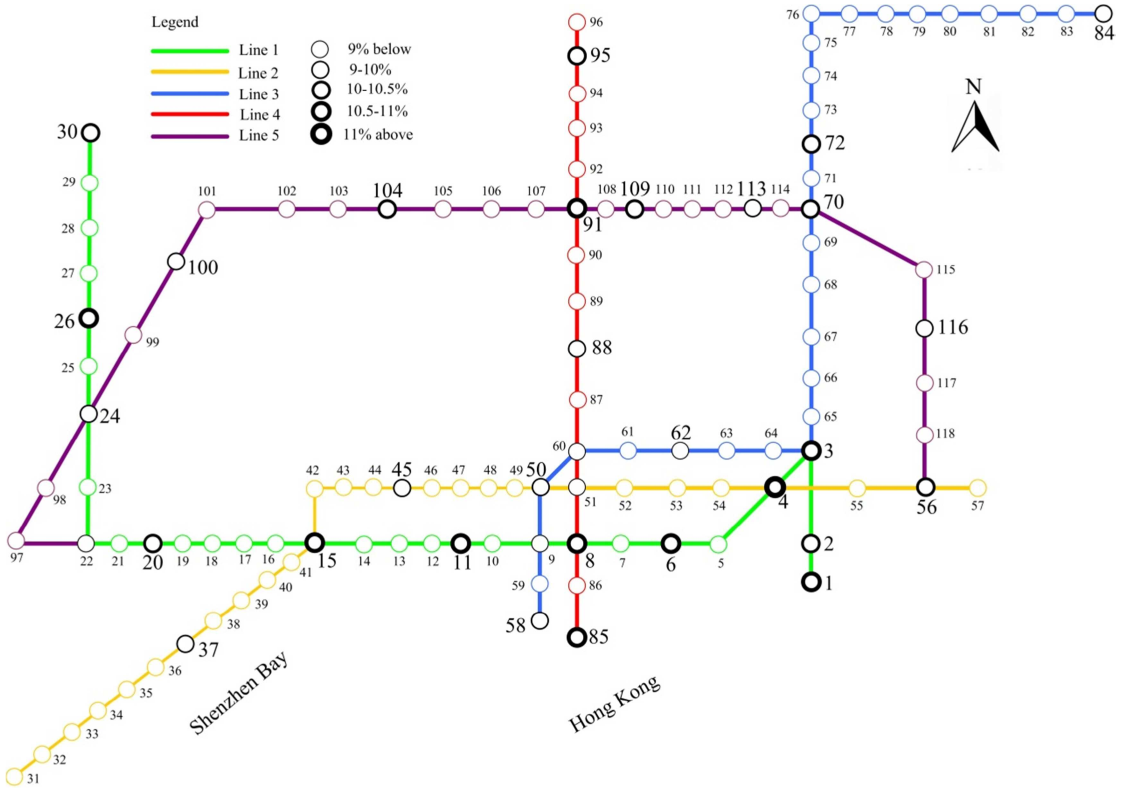


Fig. 3. Network-wide accessibility reduction under failures of 30 stations.

The top-15 stations whose failures result in the most accessibility reductions are shown in Table 2. Passenger volume of each station is ranked for the top-15 stations out of the 30 stations. The network accessibility values do not vary too much under these station failures, however, the station importance rank is different from the rank of original passenger volume. Stations 4 and 3 are shown to be the most important stations, and no differences are reported under both ranks. As discussed above, the most difference between the two ranks is observed under station 30 followed by stations 70 and 26. Such stations should be paid particular attentions as they do not seem to be very important under normal situation but turn out to be seriously affecting network accessibility if failed, or show high importance levels normally but are not that critical once disrupted. Once a station is failed, some working stations could be affected to different extents because of network topology and passenger flow interrelationships between them. The top-5 most affected working stations under each station failure are also identified in Table 2. The five most affected working stations mainly belong to the same rail line as the disrupted stations, which demonstrates that most indirect impacts of a station failure are imposed on stations sharing the same line. Moreover, the most affected working stations include not only surrounding stations of the disrupted station but also far away stations with large passenger flow. Station 86 is shown to be the most affected station under failures of stations 8 and 15, as the OD trips of station 86 to and from stations 8 and 15 are the most among other stations. Station 18 turns out to be the most affected station if station 3, 11, 20, or 26 is disrupted. This is because that OD trips of station 18 between stations 20 and 26 are high which are almost ten times of other stations, and the bus passenger volume ratios are low for stations 3 and 11 and once disrupted travel costs from stations 3 and 11 to station 18 would be high. Besides, stations 28 and 91 are also shown to be the top-5 most affected stations under many station failures, and these stations should be paid more attention under disruptions.

Table 2

Top-15 stations with most impacts on network accessibility.

Station ID	Passenger volume rank	Network accessibility after station disruption (%)	Accessibility reduction rank	Most affected working stations
4	1	88.623	1	5, 18, 28, 94, 116
3	2	89.058	2	18, 71, 94, 90, 28
6	3	89.204	5	8, 91, 7, 30, 18
1	4	89.337	6	28, 18, 94, 5, 3
11	5	89.297	3	18, 91, 12, 116, 28
8	6	89.381	7	86, 6, 18, 90, 91
15	7	89.789	10	86, 30, 18, 90, 5
26	8	89.307	4	18, 28, 91, 30, 116
85	9	89.285	8	91, 18, 90, 86, 94
70	11	89.681	15	91, 118, 116, 117, 3
91	12	89.348	9	116, 86, 90, 94, 71
109	13	89.664	12	91, 118, 117, 18, 28
20	14	89.380	11	18, 28, 30, 17, 3
72	17	89.726	14	91, 18, 66, 117, 28
30	18	89.633	13	28, 18, 116, 91, 24

5.2. Network accessibility under multiple station failures

The proposed methodology is applied to simultaneous multiple station failures on SURTN. Six scenarios are proposed, and the network accessibility is calculated for each scenario in Table 3. As shown in the Table, scenarios with large passenger volume do not necessarily cause high network accessibility reduction, and scenarios with three stations normally have more impacts on network accessibility than those of two stations. The top-5 most affected working stations under each scenario are also included in the results. Similar to individual station failures, the most affected working stations are mainly those on the same line with disrupted stations. Stations 18 and 19 are shown to be the mostly affected under four multiple station failure scenarios, and station 18 appears in three of the six scenarios. This could be explained by the high OD trip distributions of station 18 on stations of Line 1 and those in the southeast of the network, and when stations in these areas are failed the accessibility of station 18 would be importantly affected. Together with results in Table 2, it could be reached that stations 116, 117, and 118 are vulnerable to station failures on the same line especially to disruptions of transfer station, since they show high accessibility reductions under these failures.

Table 3
Network accessibility under multiple station failures.

Station IDs	Passenger volume rank	Network accessibility after disruptions (%)	Accessibility reduction rank	Most affected working stations
3, 4	1	71.766	3	18, 94, 5, 24, 90
11, 45, 70	2	64.802	1	19, 40, 91, 116, 118
8, 30, 50	3	64.822	2	19, 86, 91, 90, 92
1, 20	4	72.626	4	18, 28, 25, 24, 3
56, 91	5	72.880	5	116, 117, 118, 54, 114
24, 26	6	73.043	6	91, 30, 28, 18, 113

Urban rail network accessibility under link and line failures could be measured based on station failures, that is, individual or multiple stations disruptions. The vulnerability of rail transit network should also include the probability of station, link, or line failure. The network vulnerability is the product of failure probability and network accessibility reduction. Besides, types of disruption and its time duration should also be included in the vulnerability analysis.

6. Conclusions

Urban rail transit network vulnerability is largely researched on network topology issues in previous studies, and passenger flow characteristics should be included in vulnerability approaches considering its influence on network performance.

This study presents and applies an accessibility-based vulnerability method to explicitly account for the passenger flow characteristics under conditions of station(s), link(s), and line(s) disruptions. The vulnerability approach is presented with the help of an example network. Distinct results are shown between the proposed method and existing indices in the literature. The proposed approach makes better sense by capturing the passenger flow distribution and ground bus alternative. Most topology-based methods could not provide further information except for the evaluated station, while the proposed approach could assess impacts not only on the network but also on other stations. The case study on the rail transit network of Shenzhen, China further demonstrate that the consequences of station disruptions on network performance differ obviously with different passenger flow distributions and bus alternative availability.

Results of the proposed measure could be learnt by public transport planners and operators to design and manage a resilient urban rail transit network. The vulnerability of network could be reduced with network plan and design measures during the rail transit network expansion especially for the most important stations. Bus and other transit network should be planned in coordination with the urban rail transit network to enhance the robustness of the transit network as a whole. Under emergencies of rail transit, bridging bus design and operation decisions could be made based on the identified impacts of disrupted stations on the network. Besides measures taken for the disrupted rail stations, ground bus bridging and passenger evacuation plans could also be adopted for the most affected working stations.

The main limitation of the presented approach is the more data needed than previous methods. Fortunately, these passenger flow data are widely available from multiple sources in public transport. The process of these data and calculation would consume a little more time than the network topology methods, but the total time for each scenario is only half minute which would be acceptable with more in-depth results learnt. An additional limitation relates to the behavioral assumption that all the affected passengers would take bus as alternative, but in reality some may take other transit modes such as taxi and others may wait until disruptions are fixed. Detailed passenger behavioral analyses at different travel stages with revealed preference and stated preference data under different rail disruptions would benefit the analysis of rail transit network vulnerability within multi-modal public transport networks.

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References

Bhat, C., Guo, J.Y., 2007. A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. Transportation Research Part B: Methodological 41(5), 506-526.

Bhat, C., Handy, S., Kockelman, K., Mahmassani, H., Gopal, A., Srour, I., Weston, L., 2002. Development of an urban accessibility index: Formulations, aggregation, and application. Center for Transportation Research, The University of Texas at Austin.

Bell, M.G.H., Kanturska, U., Schmöcker, J.D., Fonzone, A., 2008. Attacker-defender models and road network vulnerability. Philosophical Transactions of the Royal Society A 366, 1893-1906.

Cats, O., Jenelius, E., 2015. Planning for the unexpected: The value of reserve capacity for public transport network robustness. Transportation Research Part A 81(11), 47-61.

Cats, O., Yap, M., Van Oort, N., 2016. Exposing the role of exposure: Public transport network risk analysis. Transportation Research Part A 88(6), 1-14.

Cats, O., Jenelius, E., 2014. Dynamic vulnerability analysis of public transport networks: Mitigation effects of real-time information. Network Spatial Economy 14(3), 435-463.

Cervero, R., Rood, T., Appleyard, B., 1995. Job accessibility as a performance

indicator: An analysis of trends and their social policy implications in the San Francisco Bay Area. University of California Transportation Center.
Chen, A., Yang, C., Kongsomsaksakul, S., Lee, M., 2007. Network-based accessibility measures for vulnerability analysis of degradable transportation networks. Networks and Spatial Economics 7(3), 241-256.
Chen, B.Y., Lam, W.H.K., Sumalee, A., Li, Q., Li, Z.C., 2012. Vulnerability analysis for large-scale and congested road networks with demand uncertainty. Transportation Research Part A 46(3), 501-516.
Chen, X.Z., Lu, Q.C., Peng, Z.R., Ash, J.E., 2015. Analysis of transportation network vulnerability under flooding disasters. Transportation Research Record 2532, 37-44.
Cox, A., Prager, F., Rose, A., 2011. Transportation security and the role of resilience: A foundation for operational metrics. Transport Policy 18(2), 307-317.
De-Los-Santos, A., Laporte, G., Mesa, J.A., Perea, F., 2012. Evaluating passenger robustness in a rail transit network. Transportation Research Part C 20(1), 34-46.
Derrible, S., Kennedy, C., 2010. The complexity and robustness of rail networks. Physica A 389(17), 3678-3691.
Dimitrov, S.D., Ceder, A., 2016. A method of examining the structure and topological properties of public-transport networks. Physica A 451(6), 373-387.
Jenelius, E., Petersen, T., Mattsson, L.-G., 2006. Importance and exposure in road network vulnerability analysis. Transportation Research Part A 40(7), 537-560.
Jun, M.J., Choi, K., Jeong, J.E., Kwon, K.H., Kim, H.J., 2015. Land use characteristics of subway catchment areas and their influence on subway ridership in Seoul. Journal of Transport Geography 48(10), 30-40.
Knoop, V.L., Snelder, M., Van Zuylen, H.J., Hoogendoorn, S.P., 2012. Link-level vulnerability indicators for real-world networks. Transportation Research Part A 46(5), 843-854.
Litman, T., 2016. Evaluating accessibility for transportation planning: Measuring people's ability to reach desired goods and activities. Available at: http://www.vtpi.org/access.pdf, accessed May 3rd, 2016.
Lu, Q.C., Peng, Z.R., 2011. Vulnerability analysis of transportation network under the scenarios of sea level rise. Transportation Research Record: Journal of Transportation Research Board 2263, 174-181.
Lu, Q.C., Peng, Z.R., Zhang, J., 2015. Identification and prioritization of critical transportation infrastructure: A case study of coastal flooding. Journal of Transportation Engineering-ASCE 141(3), 04014082.
Mishra, S., Welch, T.F., Jha, M.K., 2012. Performance indicators for public transit connectivity in multi-modal transportation networks. Transportation Research Part A 46(7), 1066-1085.
Mattsson, L.-G., Jenelius, E., 2015. Vulnerability and resilience of transport systems-A discussion of recent research. Transportation Research Part A 81(11), 16-34.
Nassir, N., Hickman, M., Malekzadeh, A., Irannezhad, E., 2016. A utility-based travel impedance measure for public transit network accessibility. Transportation Research Part A 88, 26-39.

Rodríguez-Núñez, E., García-Palomares, J.C., 2014. Measuring the vulnerability of public transport networks. Journal of Transport Geography 35(2), 50-63.

Sohn, J., 2006. Evaluating the significance of highway network links under the flood damage: An accessibility approach. Transportation Research Part A 40(6), 491-506.

Taylor, M.A.P., 2012. Network vulnerability in large-scale transport networks. Transportation Research Part A 46(5), 743-745.

Taylor, M.A.P., D'Este, G.M., Sekhar, S.V.C, 2006. Application of accessibility based methods for vulnerability analysis of strategic road networks. Networks and Spatial Economics 3(6), 267-291.

Taylor, M.A.P., Susilawati, S., 2012. Remoteness and accessibility in the vulnerability analysis of regional road networks. Transportation Research Part A 46(5), 761-771.

Van Oort, N., 2014. Incorporating service reliability in public transport design and performance requirements: International survey results and recommendations. Research in Transportation Economics 48(12), 92-100.

Zhang, X., Miller-Hooks, E., Denny, K., 2015. Assessing the role of network topology in transportation network resilience. Journal of Transport Geography 46, 35-45.