Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 8711894, 12 pages
https://doi.org/10.1155/2022/8711894

Research Article

Transportation System Vulnerability Assessment considering Environmental Impact

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Received 23 February 2022; Revised 27 April 2022; Accepted 3 May 2022; Published 26 May 2022

Academic Editor: Alessandro Severino

Transportation system has a close bearing on the prosperity of society. However, transportation infrastructures are highly vulnerable to extreme events. Therefore, identifying the most critical component of the transportation system is among the first priorities of transportation network planners and managers. This paper proposes a novel framework to identify the most vulnerable component for a road transportation system. A key characteristic of vulnerability assessment is the travelers' response to the changes in the transportation network topology and capacity after an extreme event. Hence, the problem is formulated as a nonlinear programme with equilibrium constraints, considering travelers' route choice behavior. In the methodology, two types of vulnerability measures are developed to assess the vulnerability of road transportation system, namely, system travel time-based vulnerability (STTV) and system emissions-based vulnerability (SEV). The former is developed on the basis of short-term planning, while the latter is put forward on the basis of long-term planning. With these vulnerability measures, the proposed framework is then demonstrated using an extended Nguyen-Dupuis network under different demand levels and different capacity degradation levels, taking into account two modes: bus and car. The results indicate that different vulnerability measures can identify similar vulnerable components. Moreover, it is shown that the SEV can find more critical components than the STTV regardless of capacity degradation or demand growth. Our research helps to create a recovery plan by assigning priority to the critical transportation infrastructures.

1. Introduction

Transportation system plays a key role in social stability and economic development, being in addition an important factor in alleviating the saturation of a single mode [1]. A wide variety of transportation modes, including bus, car, subway, and railway constitute a transportation system, which provides alternative transport services. Transportation infrastructures, however, can be vulnerable to various kinds of extreme events, which cause travel delays and induce direct economic loss, as illustrated in Table 1. For example, the 1994 Northbridge earthquake caused about 140 road closures and a $40 billion monetary loss [2]. Hurricane Sandy that struck off the New York City, US, in October 2012 caused approximately $7.5 billion damage to the transportation system [3]. Also, we cannot forget the devastating losses due to the 8.0-magnitude earthquake in the Sichuan region, China, in 2008, resulting in 69,197 deaths, 374,176 injured, 18,222 missing, over $100 billion in economic loss, and significant damage to 21 highways [4, 5]. In particular, the heavy rainstorm that struck off Henan Province, China, in July 2021 caused 302 deaths, with 14.53 million sufferers, 50 missing, and a ¥114 billion monetary loss. Obviously, extreme events can severely degrade the performance of transportation network and increase the vulnerability of infrastructures. Thus, it is important to identify vulnerable infrastructures and prepare for unpredictable extreme events.

Table 1: Consequences associated with extreme events.

Extreme events	Year	Region	Direct economic loss
Earthquake	1994	Los Angeles City, the United States	\$40 billion
Hurricane	2005	State of Louisiana, the United States	\$125 billion
Earthquake	2008	Sichuan Province, China	\$100 billion
Tsunami	2011	Tohoku, Japan	\$170 billion
Hurricane	2012	New York City, the United States	\$7.5 billion
Heavy rainstorm	2021	Henan Province, China	¥114 billion

Many researchers have studied the vulnerability of a single transportation mode, but ignoring the relationship between different modes. Actually, different modes can provide multimodal transport services. In the event that some infrastructures on one mode of transportation are disrupted, travelers can choose another transportation mode nearby. As a result, this paper considers different modes of transportation system as a whole and focuses on the vulnerability assessment of a transportation system, so as to provide an effective assessment framework for improving the system service efficiency.

In proposing the assessment framework for effective system service efficiency, the first step is to determine the measures for vulnerability analysis. In this paper, both system travel time and system emissions are considered as vulnerability measures. It is important to note that an extreme event could cause damage to transportation infrastructures, reducing the capacity and the service level. This results in increased travel time for some travelers compared to normal days. Furthermore, due to the reduction of capacity and the increase of travel time, more emissions are generated by a disrupted transportation system, which has a critical impact on human health and social sustainable development.

This paper aims to narrow the research gap in the literature by proposing a vulnerability assessment framework for multimodal transportation system to identify the critical infrastructures that will bring the most serious impact under extreme events. In the case of an extreme event, travelers may reroute their travel when the transportation network topology and capacity change. Therefore, in this paper, user equilibrium (UE) traffic assignment is applied to capture the travelers' response.

The remainder of this paper is organized as follows: Section 2 includes a thorough literature review that focuses on various vulnerability measures and traffic assignment methods. Section 3 introduces two types of vulnerability measures and develops a user equilibrium model for transportation system. Section 4 presents numerical examples on an extended Nguyen-Dupuis network to show how the proposed framework is applied for system vulnerability analysis. Finally, Section 5 provides some concluding remarks and future extensions.

2. Literature Review

In real-life scenarios, the service efficiency as well as material infrastructures of transportation system is affected by extreme events. Infrastructure failures lead to network topology changes and capacity degradation, so travelers need to reroute their travel to minimize the travel time. Most obviously, travelers' travel time may become longer, which badly affects the service efficiency of the transportation system. In response to this, this paper mainly deals with the issue relating to the service efficiency. This section is divided into two subsections, which briefly discuss the literature related to vulnerability measurement and traffic assignment methods, respectively.

2.1. Vulnerability Measurement. A key issue in the vulnerability analysis of a transportation system is to identify the critical infrastructures [6], where the failures of the infrastructures would bring degradations to the system [7]. Once the critical infrastructures are identified, the robustness of the network can then be enhanced through reinforcing these components.

In recent years, a lot of attention has been focused on the vulnerability analysis of transportation system. Based on whether considering the congestion effect caused by traffic flows, vulnerability measures are classified into two types: topology-based measures and system-based measures [8]. In terms of topology, many researchers analyzed the vulnerability according to efficiency [9], degree [10, 11], betweenness [12, 13], average shortest path [14, 15], etc. In addition, some researchers use a multiple criteria assessment to deal with vulnerability analysis. For example, Furno et al. [16] proposed a novel framework to show the significant correlation between global efficiency and betweenness centrality. Yang et al. [17] defined vulnerability indices and identified the critical node due to the weighted degree and betweenness. Similarly, Lordan et al. [18] compared the reduction of the size of the giant component with the consideration of node degree and betweenness. Other than the prevailing topology-based measures, more measures have been introduced, such as accessibility index [13, 19] and capacity-based index [20, 21]. The topology-based measures are convenient in calculation; however they do not refer to the significant features of a system in the aftermath of an extreme event, such as the information of link types and the distribution of traffic demands.

On the other hand, system-based vulnerability measures include utility-based index [22], disruption index [23], network robustness index (NRI) [24–28], travel time [29–33], unified network performance measure (UNPM) [34–36], and network efficiency index [7, 37, 38]. As system travel time is considered to evaluate the vulnerability of transportation system in this paper, it falls into the system-based measures category.

Among these existing system-based vulnerability measures, the NRI and travel time-based measures are the most widely applied. Scott et al. [24] employed a NRI that describes the change in the total travel-time cost of removing a link to evaluate the network performance, instead of the traditional volume/capacity ratio. Likewise, both Rupi et al. [27] and Sullivan et al. [28] extended such an index for identifying and ranking the most critical components. It should be noted that the NRI is essentially based on the travel time. As a result, travel time-based measures are the most commonly used. For instance, Jenelius et al. [29] defined vulnerability indices and identified the critical link due to the weighted origin-destination travel time and unsatisfied demand. Since then, the travel time has been widely applied. Both Bagloee et al. [30] and Wang et al. [6] applied the total travel time to identify critical disruption scenarios. Meanwhile, Malandri et al. [33] and Hong et al. [32], in line with Voltes-Dorta et al. [31], analyzed the vulnerability of transportation networks on the basis of travel delay. However, only a single transportation mode was considered, which may not provide a useable strategy for evaluating the multimodal transportation.

Furthermore, a few studies have focused on topology feature simultaneously, as well as system performance feature. In order to better understand the impacts of extreme events, the system emissions-based measure is proposed. To our knowledge, a few studies recently have examined the relationship between transport network vulnerability and environmental impact. In order to mitigate network vulnerability and reduce traffic emissions, Nagurney et al. [36] developed environmental impact assessment indies to determine the impacts of capacity degradation. Zhao et al. [39] developed the land-use adaptation (LUA) model to analyze transportation network vulnerability. Compared with the NRI results, Reynaud et al. [40] developed a new emissions-based NRI (ENRI) to assess network link criticality. Shekar et al. [41] provided a dynamic traffic simulation approach to evaluate economic and environmental impacts of transportation network disruptions. Nevertheless, system emissions have not been included in the vulnerability analysis of multimodal transportation system in the literature above. Moreover, different levels of travel demand and capacity degradation levels have not been taken into account.

Compared with the single transportation mode above, network modeling and vulnerability assessment of multimodal transportation system have not been studied extensively. The highlights of the literature related to vulnerability analysis of transportation system are shown in Table 2. In the context of transportation system, Chen et al. [42] introduced a utility-based measure for assessing the disrupted transportation systems. Burgholzeret et al. [43] developed an event-driven and agent-based traffic micro simulation model that uses the network performance indicators to identify the critical links for the intermodal network and the criticality of the whole network. Dixit et al. [44] extended the reliability buffer time by considering multimodal transit journeys. Ouyang et al. [45] analyzed the vulnerability of complementary transportation systems consisting of railway and airline systems, where an accessibility index was developed from the vulnerability perspective. Likewise, Hong et al. [46] measured the vulnerability analysis of metro and high-speed rail systems based on accessibility and proposed three types of accessibility measures. Morellit and Cunha [47] proposed two indicators, network continuity and efficiency of alternative, to measure the impacts of extreme events on urban road traffic, in which the urban transportation networks including walking, cycling, and individual motoring were taken into account. Hong et al. [48] proposed a metric, passengers' intermodal transfer distance preference, to describe the complementary relationship in urban public transportation systems. Wang et al. [49] evaluated the vulnerability of a dynamic layered road-rail network by analyzing the node with largest degree. However, the topology-based measures for transportation system [45–49] paid no attention to the interdependent relationship between different modes. The system-based measures [42–44] studied the relationship of multimodal transport systems, but the equilibrated multimodal route choice behavior has not been taken into account.

2.2. Traffic Assignment Method. As previously mentioned, some travelers may reroute their travel to minimize the travel time after an extreme event.

Then, the combination of traffic assignment method and graph theory can be applied to travelers' route choice model [50, 51]. As to vulnerability analysis, the most common traffic assignment methods are system optimal (SO), UE, and shortest path. Among the family of SO, UE, and shortest path, SO and UE are equilibrium assignments, while the shortest path is disequilibrium assignment.

Some researchers have used the shortest path for the assignment of traffic flow on different modes, including rail network [10, 14], air traffic network [15, 31], and road network [25, 35, 37, 41]. Corresponding to topology-based measures, the shortest path method is applied in these literatures. In fact, the consideration of service features such as the changes in travel time caused by the increases of travel flow should be given more attention because they may increase the vulnerability of transportation system.

In terms of equilibrium assignments, researchers [30, 35, 36] embraced SO and UE assignment problems in their vulnerability analysis. Nevertheless, the discrepancy between the SO and the UE leads to traffic paradoxes. On the other hand, numerous studies have been conducted to investigate the UE problem on a single transportation mode [6, 29, 34, 38, 39], while few on multimodal transportation system. For example, in the case of a UE problem, Chen et al. [42] analyzed the vulnerability of transportation systems consisting of car network and transit network, without considering the relationship between different modes.

To the best of our knowledge, the UE method has not been widely used in multimodal transportation system, most of which do not take into account equilibrium. However, the framework introduced in this paper is applied to a transportation system, with the objective of evaluating the system vulnerability and improving the service efficiency.

Table 2: Studies of multimodal transportation system vulnerability.

References	Measures	Traffic assignment methods used	Relationship	Environmental impact
Chen et al. (2007)	System-based	UE	No	No
Burgholzeret al. (2013)	System-based	Simulation	No	No
Ouyang et al. (2015)	Topology-based	Not considered	Yes	No
Hong et al. (2017)	Topology-based	Not considered	Yes	No
Morelli and Cunha (2019)	Topology-based	Shortest path	No	No
Dixit et al. (2019)	System-based	Not considered	No	No
Hong et al. (2020)	Topology-based	Not considered	No	No
Wang et al. (2021)	Topology-based	Not considered	No	No
This paper	Combination-based	UE	Yes	Yes

To sum up, the main contributions of this paper are as follows:

(1) Introducing a new framework to assess the vulnerability of transportation system, in which travel time and environmental impact are considered simultaneously.

(2) Formulating a UE problem on multimodal transportation system based on the impacts of traffic flow and travelers' route choice behavior.

(3) Presenting numerical examples on an extended Nguyen-Dupuis network consisting of car and bus to illustrate how the proposed framework can be applied to obtain relevant information.

3. Methods

This paper presents the framework to evaluate transportation system vulnerability under extreme events. New measures of vulnerability assessment from the perspective of short-term planning (i.e., system-based) and from the perspective of long-term planning (i.e., combination of system-based and topology-based) are established. The UE model of transportation system is formulated to describe the travelers' route choice behavior.

3.1. Network Description of Transportation System. Transportation system consists of different transportation modes, such as car, bus, and truck. Obviously, different modes can provide alternative transportation services for travelers. Travelers can choose any mode of transport according to their route selection preference in general; however when some infrastructures on one mode are unavailable, they can transfer to other transportation modes. This relationship can reduce the vulnerability of transportation system and improve travel efficiency.

Specifically, a stochastic transportation system can be modeled by a network of multiple networks. Consider a general network modeled by $G = (S, C, V, A)$, where S is the set of single transportation modes, C is the set of combined transportation modes, V is the set of subgraph nodes, and A is the set of subgraph links. The nodes denote intersections and stations, which are connected by the links of various transportation modes. On the other hand, the links represent bus lines, road segments between stations, etc.

In a real network environment, both nodes and links can be degraded, but any node can be treated as a collection of nodes with connecting arcs [22]. Hence, node degradation can be treated as link degradation. Therefore, this paper interprets vulnerability associated with an extreme event, and the vulnerable infrastructure to the extreme event refers to the link of the network. Moreover, this paper makes the following assumptions:

(1) For a given extreme event, the travel demand between each origin and destination (OD) pair is constant.

(2) There are no additional connections between different modes sharing some nodes and links.

(3) The travel time associated with a link is monotonically increasing with respect to the flow on the link.

3.2. Notations. The notations in this paper and the respective units of measurement are listed in Table 3.

3.3. Two Vulnerability Measures. Vulnerability is a relatively important concept to study the performance of transportation networks during and after an extreme event. Therefore, transportation vulnerability can be defined as the extent to which the transportation network is susceptible to extreme perturbations [52]. In recent years, various vulnerability measures have been proposed to evaluate the consequence component of risk. However, among these vulnerability measures, the impact on both travel time and emissions was not taken into account. This paper introduces two types of vulnerability measures to analyze transportation system vulnerability: system travel time-based vulnerability (STTV) and system emissions-based vulnerability (SEV).

3.3.1. Quantification of STTV. From the viewpoint of short-term planning, total travel time is the focus of emergency managers' attention. As mentioned in Section 3.1, there is a relationship among the various transportation modes. Thus, it is necessary to discuss travel time from the perspective of system in order to appropriately evaluate the vulnerability of transportation system.

According to the description of total travel time on a single mode, the performance of transportation system before the extreme event can be expressed as

Table 3: Sets, parameters, and decision variables.

Notations		Units of measurement
Sets		
S	Set of single transportation modes	
C	Set of combination modes	
V	Set of subgraph nodes	
A	Set of subgraph links	
R_w^s	Set of routes connecting OD pair w in mode s, $w \in W$, $s \in S$	
R_w^c	Set of routes connecting OD pair w in mode c, $w \in W$, $c \in C$	
W	Set of OD pairs	
Parameters		
α	Constant parameter	
β	Constant parameter	
C_{a0}^m	Pre-disaster capacity of link a in mode m, $a \in A$, $m \in (S+C)$	veh/h
L_a^m	Length of link a in mode m, $a \in A$, $m \in (S+C)$	km
t_{a0}^m	Free-flow travel time of link a in mode m, $a \in A$, $m \in (S+C)$	min
q_w	Travel demand between OD pair w, $w \in W$	veh/h
Decision variables		
q_w^s	Travel demand between OD pair w in mode s, $w \in W$, $s \in S$	veh/h
q_w^c	Travel demand between OD pair w in mode c, $w \in W$, $c \in C$	veh/h
x_a^m	Post-disaster traffic flow of link a in mode m, $a \in A$, $m \in (S+C)$	veh/h
t_a^m	Post-disaster travel time of link a in mode m, $a \in A$, $m \in (S+C)$	min
f_w^{sr}	Traffic flow on path r between w in mode s, $w \in W$, $s \in S$	veh/h
f_w^{cr}	Traffic flow on path r between w in mode c, $w \in W$, $c \in C$	veh/h
C_a^m	Post-disaster capacity of link a in mode m, $a \in A$, $m \in (S+C)$	veh/h
T_G	Pre-disaster total travel time of transportation system	min
$T_{G'}$	Post-disaster total travel time of transportation system	min
E_G	Pre-disaster total CO emissions of transportation system	g/h
$E_{G\prime}$	Post-disaster total CO emissions of transportation system	g/h
γ_a^m	$\gamma_a^m = 1$, if link a is not completely damaged; otherwise $\gamma_a^m = 0$	
δ_a^{sr}	$\delta_a^{sr} = 1$, if link $a \in A$ belongs to path r in mode s; otherwise $\delta_a^{sr} = 0$	
δ_a^{cr}	$\delta_a^{mr} = 1$, if link $a \in A$ belongs to path r in mode c; otherwise $\delta_a^{cr} = 0$	

$$T_G = \sum_{m\in(S+C)} \sum_{a\in A} x_a^m t_a^m. \tag{1}$$

Similarly, the performance of transportation system after the extreme event can be written as

$$T_{G'} = \sum_{m\in(S+C)} \sum_{a\in A} x_a^m t_a^m \gamma_a^m. \tag{2}$$

The vulnerability measure STTV is interpreted as the ratio of the increment total travel time and the original travel time, which is

$$\text{STTV} = \frac{T_{G'} - T_G}{T_G}. \tag{3}$$

In this paper, the flow dependent travel time is determined by the Bureau of Public Roads (BPR) function:

$$t_a^m = t_{a0}^m \left(1 + \alpha \left(\frac{x_a^m}{C_a^m}\right)^\beta\right), \forall a \in A, m \in (S+C). \tag{4}$$

3.3.2. Quantification of SEV. It is well known that the damaged link may cause travel time delay, which leads to additional traffic emissions and negative environmental impacts. Nevertheless, a few studies have been conducted to investigate the relationship between transportation system vulnerability and environmental impact. In view of the above, it is of great significance to explore the relationship between vulnerability components and emissions. From the view of long-term planning, total emissions are the focus of emergency managers' attention.

Although there are various indicators for evaluating the degree of atmospheric pollution caused by vehicle traffic, carbon monoxide (CO) emission has been considered the most important one [39, 53–55]. Thus, without loss of generality, the indicators of atmosphere pollution in a transportation system refer to the CO emissions of the transportation system in this paper. Following Wallace et al. [56], we adopt the same emission estimation method as in transportation software, which is

$$E_G = \sum_{m\in(S+C)} \sum_{a\in A} x_a^m \cdot 0.2038 \cdot t_a^m \cdot \exp\left(0.7962 \cdot \frac{L_a^m}{t_a^m}\right). \tag{5}$$

The total CO emissions after the extreme event, $E_{G'}$, is defined by

$$E_{G'} = \sum_{m\in(S+C)} \sum_{a\in A} x_a^m \cdot \gamma_a^m \cdot 0.2038 \cdot t_a^m \cdot \exp\left(0.7962 \cdot \frac{L_a^m}{t_a^m}\right). \tag{6}$$

Similar to STTV, the SEV of transportation system is estimated as follows:

$$\mathrm{SEV} = \frac{E_{G'} - E_G}{E_G}. \tag{7}$$

Generally speaking, the larger the SEV, the more vulnerable the transportation system is. In line with SEV, the larger STTV implies a more vulnerable system.

3.4. Network Equilibrium. Most currently, existing methods of vulnerability analysis focus only on operating infrastructures while ignoring the travelers' choice behavior after the change of transportation infrastructures.

In this paper, Wardrop's first principle is adopted for modeling the travelers' route choice behavior in a transportation system. According to Wardrop's first principle, the UE traffic assignment problem can be mathematically formulated as follows:

$$\min \sum_{m\in(S+C)} \sum_{a\in A} \int_0^{x_a^m} t_a^m(x)\mathrm{d}x, \tag{8}$$

subject to

$$\sum_{r\in R_w^s} f_w^{sr} = q_w^s, \forall w \in W, s \in S, \tag{9}$$

$$\sum_{r\in R_w^c} f_w^{cr} = q_w^c, \forall w \in W, c \in C, \tag{10}$$

$$\sum_{s\in S} q_w^s + \sum_{c\in C} q_w^c = q_w, \forall w \in W, \tag{11}$$

$$f_w^{cr} \geq 0, \forall r \in R_w^c, w \in W, c \in C, \tag{12}$$

$$f_w^{sr} \geq 0, \forall r \in R_w^s, w \in W, s \in S, \tag{13}$$

$$x_a^m = \sum_{w\in W} \sum_{r\in R_w^s} \delta_a^{sr} f_w^{sr} + \sum_{w\in W} \sum_{r\in R_w^c} \delta_a^{cr} f_w^{cr}, \forall a \in A, s \in S, c \in C. \tag{14}$$

Equation (8) is the objective function to ensure that travelers choose a route from their origin to their destination with the lowest travel cost. Equations (9)–(11) are flow conservation constraints, and equation (12) and (13) are the non-negativity constraints. Finally, (14) specifies the relation between path flow and link flow.

4. Numerical Examples

Numerical examples are performed to demonstrate the effectiveness of the proposed framework for evaluating the transportation system vulnerability. The proposed method is applied to an extended Nguyen-Dupuis network consisting of bus network and car network. The network topology is given in Figure 1. Note that (4) applies primarily to road transportation system, but not to railway system. After all, compared with road transportation system, railway transportation system has higher punctuality. For the railway transportation system, its vulnerability grows faster than that of the road system because there are fewer nodes and edges.

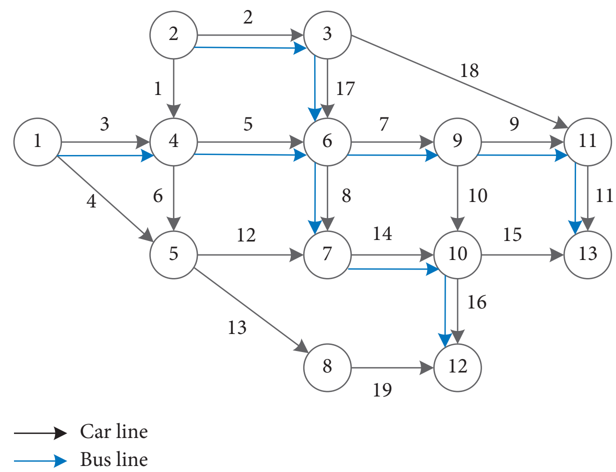


Figure 1: Extended Nguyen-Dupuis network topology.

4.1. Experimental Design and Parameter Setting. The extended Nguyen-Dupuis network comprises 13 nodes, 29 links, and 4 OD pairs. In order to facilitate the analysis, it is assumed that links-sharing data of different modes are the same. Then, the link length, link capacity, and free-flow travel time under normal condition are listed in Table 4, while in the BPR function, α and β are set to 0.15 and 4.0 for car network, and 0.5 and 2.0 for bus network, respectively. Without loss of generality, we analyzed the component vulnerability under different demand levels, i.e., normal level and high level. Table 5 shows the OD demands.

For a stochastic transportation system, links-sharing are usually the predominant focus of research. As a result, links with indexes 2, 3, 5, 7, 8, 9, 11, 14, 16, and 17 were chosen as the research objects of the transportation system vulnerability analysis. After an extreme event, links may be completely disrupted or partially closed, which forces travelers on those links to take other less advantageous routes.

4.2. Experiment Results. In this section, the capacity of all the links-sharing was assumed to be decreased to 0. We utilized Frank-Wolf algorithm to compute the equilibrium solutions and determine the vulnerability rankings of the links-sharing according to STTV and SEV.

4.2.1. Equilibrium Solutions. Each time, it is set that only one link can be removed. Accordingly, Figure 2 illustrates the equilibrium solutions by the Frank-Wolf algorithm. Figure 2(a) shows the equilibrium link flows when the damaged link is removed in turn under normal demand level, while Figure 2(b) for high demand level. It can be seen from Figure 2 that the equilibrium flows under the two demand levels are similar in terms of distribution. When the value of OD demand is large, the network does not become unreliable from the system point of view. Table 6 displays the results of the equilibrium flow for multimodal transport

Table 4: Characteristics of link.

Link no.	Car			Bus		
	L_a^m	t_{a0}^m	C_{a0}^m	L_a^m	t_{ao}^m	C_a^m
1	7	7	300			
2	9	9	200	9	9	200
3	9	9	200	9	9	200
4	12	12	200			
5	3	3	350	3	3	350
6	9	9	400			
7	5	5	500	5	5	500
8	13	13	250	13	13	250
9	5	5	250	5	5	250
10	9	9	300			
11	9	9	500	9	9	500
12	10	10	550			
13	9	9	200			
14	6	6	400	6	6	400
15	9	9	300			
16	8	8	300	8	8	300
17	7	7	200	7	7	200
18	14	14	300			
19	11	11	200			

Table 5: Travel demand of OD pairs.

OD pair	Demand	
	Normal level	High level
(1,12)	100	200
(1,13)	300	600
(2,12)	400	800
(2,13)	200	400

network, under normal condition. Comparing the equilibrium solutions under normal condition with that under damaged condition, it is observed that the network seems to be somewhat sensitive when link with indexes 3, 5, 7, 11, or 16 is removed. It may be because the failures of those links have significant impacts on the network performance. From Figure 2 and Table 6, it is also found that the traffic flows via the links near the disrupted link increase when an extreme event occurs. Taking the normal demand level as an example, the traffic flow of link 4 increases from 100 to 400 when link 3 is disrupted. In this case, traffic congestion appears on link 4; this is because the capacity of the link is 200. Unfortunately, at that time, the safety of the transportation system is decreasing while the vulnerability is increasing. It means that vulnerability is related to safety. After travelers reroute their travel, the travel demand is redistributed to go to a new equilibrium, which causes traffic congestion on some road segments.

4.2.2. Vulnerability Assessment. After obtaining the equilibrium link flows, we can analyze the vulnerability of the transportation system under different demand levels. As a means to this end, the STTV referring to (3) and the SEV referring to (7) were used to measure the system vulnerability. The values in vulnerability measures are listed in Tables 7 and 9. Table 7 also shows the total travel time and the system status type due to the removal of a link.

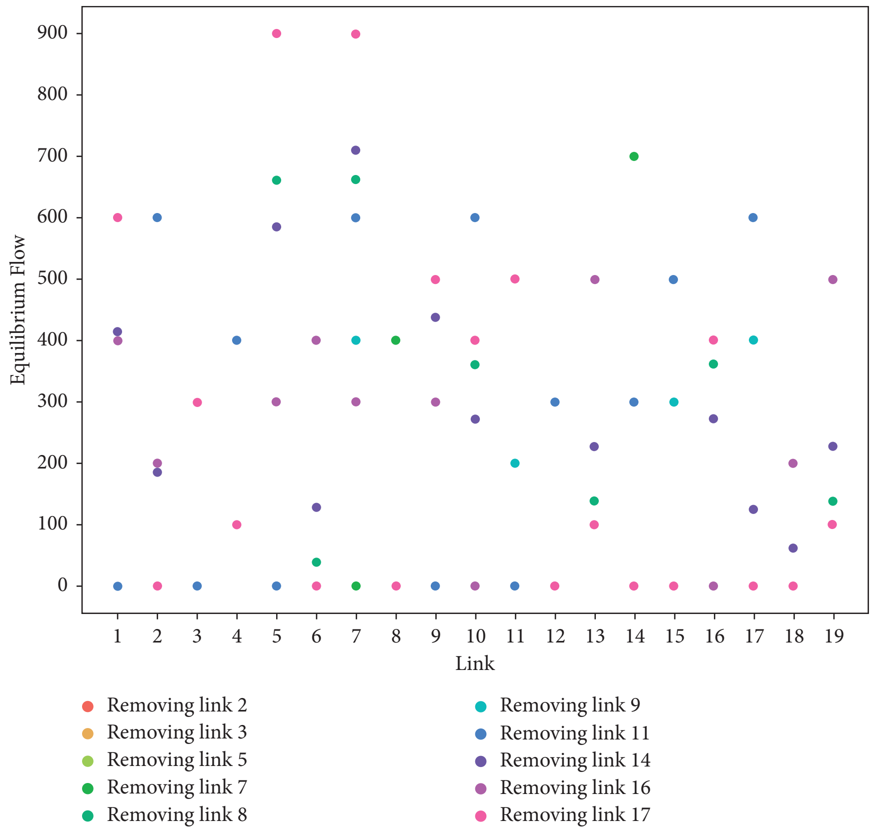
It can be seen from Table 7 that the system status shows two types. The negative type means that the damaged link is a vulnerable component, while the positive one means that the damaged link can be regard as a Braess Paradox link, as the total travel time without any disruption is 36,172.85 under normal demand level and 103,514.54 under high demand level. To facilitate comparison between data under different demand levels, the three most vulnerable components are listed in Table 8. Interestingly, it is found that the top three critical components and their rankings are exactly the same. This implies that similar vulnerable components may be identified under different demand levels.

Table 9 presents the total CO emissions and the system status type due to the removal of a link. It can be found that, with a higher demand, there are higher SEV values. Such observation means that the increment in travel demand improves the vulnerability of the transportation system. In addition, all the system status types are negative which differ from that in Table 7. It is likely because the environmental impact has been considered when planning the road, and the designed road without any disruption is optimal. Table 10 shows the top three vulnerable components under different demand levels. Here, we specifically compared the rankings of link 3, 5, 7, and 9 mentioned in Table 10. It is obvious that the vulnerability rankings of those links under different levels are the same, which is caused by the series connection of the four links. Moreover, the series connection impacts greatly with the growth of travel demand.

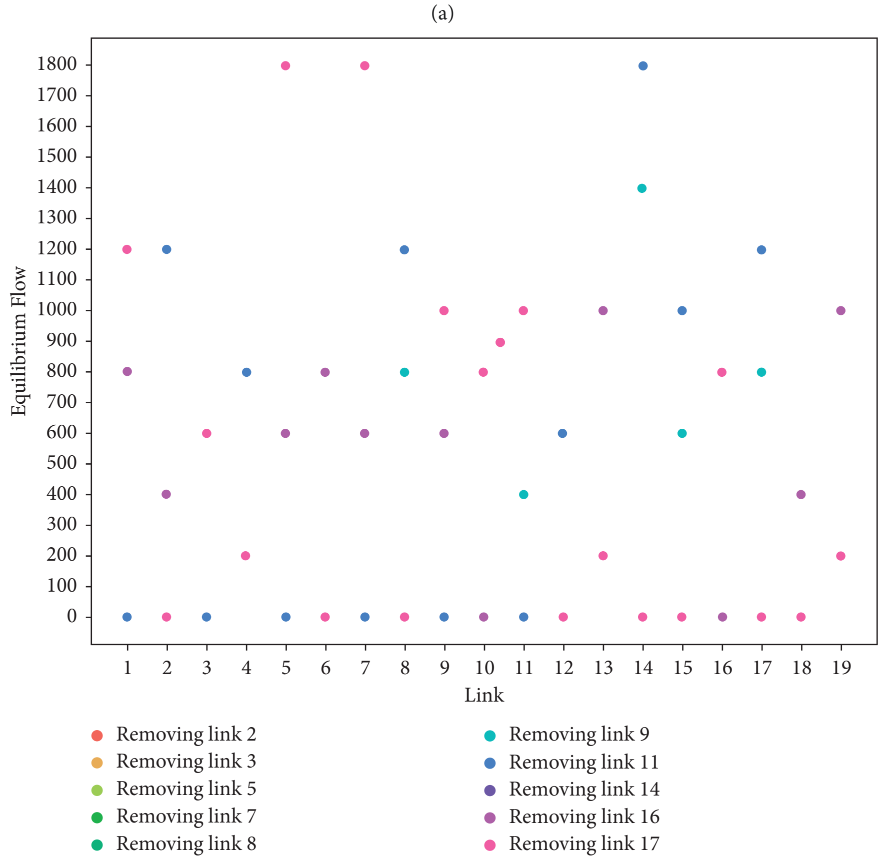
Comparing Table 8 with Table 10, it is found that using the SEV can discover more vulnerable components that are not found by using the STTV. After all, the SEV stresses sustainable development from a long-term planning perspective. Furthermore, high demand causes larger vulnerability than normal demand, while causing the same top three vulnerable components.

4.3. Effect of Capacity Degradation Level. As mentioned above, we investigated the system vulnerability when the capacity is decreased to 0. Nevertheless, after a given extreme event, the affected links may still be operational under capacity degradation. Therefore, it is necessary to consider the capacity degradation level for the vulnerability analysis in the transportation system. Assume that an extreme event occurs, and the links-sharing capacity decreases to 0.5 of the original capacity. To test the effect of capacity degradation level, we took the normal demand level as an example. The top three vulnerable components by the STTV and the SEV are shown in Table 11. The most vulnerable link under different measures is link 5. As expected, SEV can identify more vulnerable components, which can be explained as the synthetic effects of traffic flow and network topology.

In a real-life scenario, multiple links could fail simultaneously during an extreme event. As the number of alternative routes decreases, the service efficiency begins to decrease as well as the safety of the network. The problem is formulated as a combinatorial optimization problem, aiming to determine the most critical combination of vulnerable links. Additionally, factors such as the probability of



(a)



(b)

Figure 2: Equilibrium solutions: (a) under normal demand level; (b) under high demand level.

Table 6: Equilibrium solutions under normal condition.

Link no.	Equilibrium link flow	
	Normal demand level	High demand level
1	400.01	573.47
2	199.99	626.53
3	300.00	516.97
4	100.00	283.03
5	661.50	967.90
6	38.51	122.55
7	661.60	930.59
8	0.00	270.27
9	300.12	522.06
10	361.49	408.53
11	500.00	915.63
12	0.05	143.74
13	138.46	261.84
14	0.05	414.01
15	0.00	84.37
16	361.54	738.16
17	0.10	232.96
18	199.88	393.57
19	138.46	261.84

Table 7: STTV for the transportation system.

Link no.	Normal demand level			High demand level		
	Type	$T_{G'}$	STTV	Type	$T_{G'}$	STTV
2	Positive	35,836.67	−0.0093	Positive	73,160.00	−0.2932
3	Negative	46,558.54	0.2871	Negative	449,273.40	3.3402
5	Negative	38,121.55	0.0539	Positive	92,634.61	−0.1051
7	Negative	37,181.71	0.0279	Positive	89,814.76	−0.1323
8	Positive	36,172.85	0.0000	Positive	73,160.00	−0.2932
9	Negative	36,961.71	0.0218	Positive	81,814.76	−0.2096
11	Negative	43,102.06	0.1916	Negative	233,266.04	1.2535
14	Positive	34,929.02	−0.0344	Positive	73,160.00	−0.2932
16	Negative	93,835.91	1.5941	Negative	2,002,910.57	18.3491
17	Positive	35,836.67	−0.0093	Positive	73,160.00	−0.2932

Table 8: The three most vulnerable links considering STTV value.

Ranking	Normal demand level		High demand level	
	Link no.	STTV	Link no.	STTV
1	16	1.5941	16	18.3491
2	3	0.2871	3	3.3402
3	11	0.1916	11	1.2535

Table 9: SEV for the transportation system.

Link no.	Normal demand level			High demand level		
	Type	$E_{G'}$	SEV	Type	$E_{G'}$	SEV
2	Negative	21000.41	0.4084	Negative	148,729.47	3.1582
3	Negative	32944.09	1.2094	Negative	661,483.68	17.4938
5	Negative	32944.09	1.2094	Negative	661,483.68	17.4938
7	Negative	32944.09	1.2094	Negative	661,483.68	17.4938
8	Negative	15845.83	0.0627	Negative	148,729.47	3.1582
9	Negative	32944.09	1.2094	Negative	661,483.68	17.4938
11	Negative	45388.32	2.0440	Negative	1,298,908.48	35.3150
14	Negative	15431.80	0.0349	Negative	148,729.47	3.1582
16	Negative	45917.63	2.0795	Negative	443,773.62	11.4071
17	Negative	21000.41	0.4084	Negative	148,729.47	3.1582

Table 10: The three most vulnerable links considering SEV value.

Ranking	Normal demand level		High demand level	
	Link no.	SEV	Link no.	SEV
1	16	2.0795	11	35.3150
2	11	2.0440	3/5/7/9	17.4938
3	3/5/7/9	1.2094	16	11.4071

Table 11: The three most vulnerable links for partial closure.

Ranking	Link no.	STTV	Link no.	SEV
1	5	0.0388	5	0.0246
2	7	0.0353	3/7	0.0168
3	11	0.0332	11	0.0107

multiple simultaneous disruptions, number of disrupted links, and their corresponding damage levels should also be taken into account.

5. Conclusions

This paper focuses on the vulnerability analysis of transportation system, and the objective is to identify the most critical component under an extreme event. Particularly, the vulnerability analysis also considers the travelers' response to the changes in the transportation network topology and capacity after an extreme event. Two types of vulnerability measures from different perspectives are introduced, including system travel time-based vulnerability (STTV) and system emissions-based vulnerability (SEV). The former is a system-based measure from the perspective of short-term planning, while the latter also considers the topological properties from the perspective of long-term planning. Then, the vulnerability analysis problem is formulated as a user equilibrium model, which explicitly considers the effect of travelers' choice behavior. Finally, the proposed framework is illustrated on the extended Nguyen-Dupuis network consisting of bus and car to assess the vulnerability. The numerical results indicate the following: (1) the STTV can identify the same vulnerable components and their rankings under different demand levels; (2) the SEV can also be used to determine the rankings of vulnerable links and the impacts of their failures; (3) the SEV can find more critical components than the STTV regardless of capacity degradation or demand growth; (4) the rankings of vulnerable links are affected by the traffic flow and network topology, and it is better to restore the serial links to reduce the vulnerability of the transportation system. As demonstrated by the numerical examples, this paper contributes to practice by shedding light on how to identify the critical components in the transportation system. According to our findings, emergency managers can take more measures to reinforce the vulnerable links to decrease the vulnerability of the transportation system.

The proposed framework can be employed to a general transportation system, but there are still some deficiencies that need to be improved. A few directions are worthy of further investigations: (1) the proposed framework assumes that only one component is damaged, ignoring the probability of multiple components being damaged simultaneously. In future studies, these issues can be addressed by a combinatorial optimization framework; (2) in this paper, we only consider the road transportation system. However, there are other transportation systems. Therefore, a possible future research direction is the vulnerability analysis of the railway system. We will explore other applicable vulnerability measures, taking into account departure frequency, waiting time, and in-vehicle travel time. In addition, a better formula for the travel time which can be suitable for the railway system needs to be proposed to replace the BPR function; (3) the UE problem is formulated as a traffic assignment model with fixed travel demand. In fact, travelers may cancel their trips after extreme events. Therefore, one of the future research directions is to adopt a traffic assignment model with elastic demand to investigate how the vulnerability measure changes; (4) the two proposed vulnerability measures are considered separately, so it is necessary to pay attention to the trade-off between travel time and pollutant emissions.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

This research was supported by the Natural Science Foundation of the Jiangsu Higher Education Institutions of China (Grant no. 20KJB580006).

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