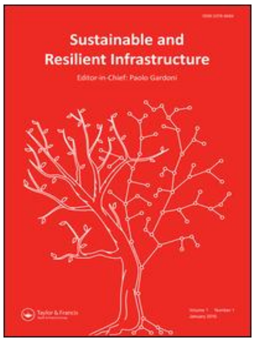


Sustainable and Resilient Infrastructure

ISSN: 2378-9689 (Print) 2378-9697 (Online) Journal homepage: http://www.tandfonline.com/loi/tsri20

Resilience metrics and measurement methods for transportation infrastructure: the state of the art

Wenjuan Sun, Paolo Bocchini & Brian D. Davison

SUSTAINABLE AND RESILIENT INFRASTRUCTURE, 2018
https://doi.org/10.1080/23789689.2018.1448663

REVIEW ARTICLE

Resilience metrics and measurement methods for transportation infrastructure: the state of the art

Wenjuan Sun[a], Paolo Bocchini[a] and Brian D. Davison[b]

[a]Department of Civil and Environmental Engineering, ATLSS Engineering Research Center, Lehigh University, Bethlehem, PA, USA; [b]Department of Computer Science and Engineering, Lehigh University, Bethlehem, PA, USA

ABSTRACT
Transportation infrastructure plays an important role in supporting the national economy and social well-being. Extreme events have caused terrible physical damages to the transportation infrastructure, with long-term socioeconomic impacts. An increasing number of studies focus on the resilience analysis of transportation infrastructure to support planning and design, as well as efficient management. As a comprehensive review, this paper covers different metrics for resilience assessments, with discussions of fundamental challenges due to uncertainties and interdependencies. It points out that validations of resilience assessments are limited due to the general scarcity of data, which may hinder practical applications. Finally, directions for future research are suggested. This paper provides an organized overview of the many lines of research in the field, accomplishments, and open gaps. It indicates useful starting points for researchers new to this field, and serves as a reference for teams already active on this topic.

ARTICLE HISTORY
Received 16 May 2017
Accepted 29 January 2018

KEYWORDS
Transportation infrastructure; resilience metrics; resilience analysis methods; uncertainty; infrastructure interdependencies

1. Introduction

The national economy and well-being depend on reliable and resilient infrastructures, with the transportation infrastructure playing one of the key roles. In the United States, there are over 4 million miles of roads, 600,000 bridges, 19,000 airports, and 3000 transit providers, forming complex networks of transportation infrastructure (United States Department of Transportation [USDOT], 2016). Transportation networks support the mobility of goods and people and provide the accessibility to important resources (such as shelters and emergency vehicles) and vital services (such as wheelchair lifts and accessible buses) in emergency circumstances. Among transportation networks in the U.S., 65% of major roads are rated below good condition and 25% of bridges cannot handle the current traffic (The White House, 2014). Transportation infrastructure with deteriorated and vulnerable components may not withstand extreme events, such as natural hazards and man-made disasters. Extreme events would cause significant physical damages to the transportation infrastructure, leading to negative social impacts and large economic losses. For instance, Hurricane Sandy caused about $7.5 billion of damage to the transportation system in New York City and over $70 billion of economic loss to both New Jersey and New York (United States Department of Commerce [USDOC], 2013). Recently, Hurricane Harvey brought 27 trillion gallons of rainwater on Texas and Louisiana, flooded many roadways and destroyed millions of cars, forcing tens of thousands to evacuate from their homes, with estimated economic loss over $190 billion (Dottle et al., 2017). Hurricane Irma caused power outages for over 4 million customers and significantly damaged highways, railways, and airports in Florida, Georgia, and the Carolinas. (Chappell, 2017; Department of Homeland Security [DHS], 2017; Office of Cyber & Infrastructure Analysis [OCIA], 2017).

Such catastrophic impacts attract increasing attention on enhancing the performance of the transportation infrastructure during such extreme events. A variety of performance analyses have been conducted for the transportation infrastructure with regard to both vulnerability and resilience. These last two terms have been used in various ways, sometimes leading to confusion. Resilience and vulnerability are interrelated concepts. Both vulnerability and resilience are specific to the perturbation, meaning that a system may be more vulnerable or resilient to some disturbances rather than to others (Gallopín, 2006). However, resilience and vulnerability

CONTACT Paolo Bocchini paolo.bocchini@lehigh.edu

have a distinct meaning. Vulnerability is the susceptibility of a system to a given hazard (Berdica, 2002; Jenelius et al., 2006). It is usually applied to evaluate the system susceptibility pre-event, which does not account for the recovery process. There are diverse views on how to quantify vulnerability because of different understandings of the precise meaning of the term (Faturechi & Miller-Hooks, 2015; Zhou et al., 2010a). Conversely, resilience is the ability of a system to respond to, absorb, adapt to, and recover from a disaster (DHS, 2008). It is related to the dynamics (i.e., absorptivity, adaptability, and transformability) of transportation infrastructure, covering the damage, but focusing mostly on both the response and recovery phases. Resilience can represent both vulnerability and consequence estimations when measuring risk (DHS, 2008).

The concept of resilience originated in ecology (Holling, 1973, 1986), and then it has been widely applied to multiple engineering fields (Bruneau et al., 2003; Bruneau & Reinhorn, 2007; National Research Council [NRC], 2011; PPD-21, 2013). In a comprehensive definition of resilience, there are 11 aspects that need to be considered (Figure 1), including 4 dimensions (i.e., technical, organizational, social, and economic), 4 basic properties (i.e., robustness, rapidity, redundancy, and resourcefulness), and 3 outcomes (i.e., more reliable, faster recovery, and lower consequences) (Bruneau et al., 2003). Over time, the definition of resilience has gradually incorporated additional aspects. For instance, recent trends push the learning process in restoration to be taken into the consideration in resilience analyses, where learning refers to users' changing expectations on infrastructure performances and infrastructure's adaptations to new non-stationary circumstances (Intergovernmental Panel on Climate Change [IPCC], 2014).

Resilience analyses of the transportation infrastructure have the benefit of improving physical operability, system safety, optimizing management and investment, with positive socioeconomic impacts. In resilience analyses, resilience metrics allow decision-makers to quantitatively assess potential impacts of investment and policies for the transportation infrastructure (Zhang et al., 2015). In early research work, resilience analyses incorporated qualitative descriptions for communities (Kendra & Wachtendorf, 2003; National Institute of Standard & Technology [NIST], 2016a, 2016b; Federal Emergency Management Agency [FEMA], 2016a). These descriptive metrics provide ways to evaluate the preparedness for various disasters (Johansen et al., 2016), but they are not adequate to objectively compare the resilience of different communities/systems. To address this aspect, quantitative resilience measurements have been introduced in analytical and numerical approaches to support better decision-making for transportation infrastructure (Adjetey-Bahun et al., 2016; Ip & Wang, 2011; Miller-Hooks et al., 2012) and lifelines (Çağnan et al., 2006; Chang & Shinozuka, 2004; Rose & Liao, 2005). For instance, Bocchini, Frangopol, Ummenhofer, and Zinke (2014) used the resilience index (Reed et al., 2009) on the basis of the functionality recovery curve of bridges after a seismic event. Miller-Hooks et al. (2012) and Zhang and Miller-Hooks (2015) considered the resilience of a transportation system as the capability to resist and absorb disaster impacts and rapidly adapt through redundancies and excess capacities, and they measured the system resilience using throughput and capacity.

In these resilience analyses, numerous metrics are used with different application areas. There have been multiple studies critically reviewing resilience metrics and research issues. Johansen et al. (2016) summarized resilience metrics for communities, which may not be directly applicable to transportation infrastructure. Hosseini, Barker, and Ramirez-Marquez (2016) presented the state-of-the-art of resilience definitions and assessment approaches for systems in general, not tailored to the transportation infrastructure. Faturechi and Miller-Hooks (2015) focused on performance metrics and assessment methods for the transportation infrastructure in resilience analyses, but no practical tools were discussed for regional resilience assessments.

Figure 1. Eleven aspects of resilience (Bruneau et al., 2003).

This study complements that work with a critical review of available metrics and methods in resilience analyses of the transportation infrastructure and points out challenging issues (such as uncertainties, interdependencies, and validations), with discussions on available guidelines and tools for practical applications. The major contributions of this study are the following. (1) The metrics and analysis methods of the resilience of the transportation infrastructure have been comprehensively synthesized, based on over 200 recent articles and reports on this topic. (2) Key principles of resilience research are reviewed, such as research focus and methods, challenges, and research gaps are discussed. This study is intended to benefit scholars in this field and practitioners who are interested in the resilience analysis of the transportation infrastructure. The specific objectives are the following: (1) to promote a mindset based on the resilience concept for applications to transportation infrastructure, and (2) to facilitate the choice of the appropriate metric(s), analysis methods, and practical tools for regional resilience assessments.

The rest of this paper presents metrics and methods for resilience analyses, with the structure shown in Figure 2. Resilience metrics should capture the impact of an event on functional and socioeconomic aspects. In order to clarify how to measure the functionality for transportation infrastructure, functionality metrics are presented first, and then functionality-related resilience metrics are summarized, followed by socioeconomic resilience metrics. After that, methods for applying these metrics for regional resilience assessments are presented, along with discussions of challenges with respect to uncertainties, interdependencies, validations, and practical applications. The article ends with major findings and future research recommendations.

2. Functionality metrics for transportation infrastructure

How to quantify resilience is a challenging question (Carpenter et al., 2001; Schoon, 2005). A resilient transportation infrastructure system should have a small probability of failure, redundant connectivity, minimal time to full recovery, and limited propagations of the effects. Since the resilience of transportation infrastructure is tightly related to its functionality, we collect metrics that are frequently used for measuring functionality and then discuss how to define resilience metrics on the basis of functionality recovery curves and evaluate socioeconomic impacts.

The following sections classify functionality metrics into two categories: topological and traffic-related. Topological functionality metrics represent topological features of a transportation network. Some topological metrics capture the redundancy of the transportation network, and the redundancy affects the post-event functionality and recovery. In fact, transportation networks with redundancy are more likely to effectively recover to an acceptable functionality level, because there are potentially multiple recovery strategies. This is certainly an important feature, which is likely to improve the outcome of a constrained optimization problem such as recovery planning. Conversely, traffic-related functionality metrics measure both topological features of the network and properties related to traffic flow and system capacity. The definition of every functionality metric is presented, followed by a discussion of the application of these functionality metrics to the resilience assessment of transportation infrastructure.

2.1. Topological functionality metrics

Transportation infrastructure consists of many networks (e.g., roads and railroads); therefore, graph theory is often used to measure topological characteristics, especially focusing on connectivity and centrality.

2.1.1. Connectivity

In graph theory, connectivity is the minimum number of nodes or edges that need to be removed to disconnect the remaining nodes from each other (Diestel, 2016). In general, a greater number of interconnection paths between two nodes means lower isolation and higher accessibility of transportation system, corresponding to a greater redundancy of the transportation network. The functionality of a transportation network can be improved with an increase in the network connectivity, such as adding

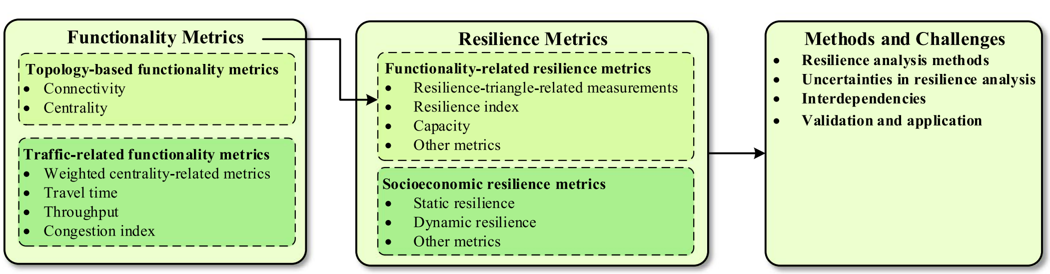


Figure 2. Metrics and methods for resilience analyses.

redundancy and improving the capacity of important links and interconnected nodes.

Table 1 presents some parameters to measure connectivity, including cyclomatic number, alpha index, beta index, gamma index, average degree, and cyclicity. Cyclomatic number is the number of fundamental circuits in the network, and a larger cyclomatic number represents more interconnected nodes within the network. Alpha index, beta index, and gamma index represent the ratio of cycle numbers to possible cycle numbers, the ratio of number of links to number of nodes, and the ratio of link numbers to maximum possible link numbers, respectively. Average degree is the average number of arcs incident on the nodes. Larger values of alpha index, beta index, gamma index, and average degree indicate the greater interconnectedness of the network. Cyclicity is the largest number of nodes in a cycle, where a node is reachable from itself. Alpha, beta, and gamma indices were widely used to measure network connectivity in the 1960s (Haggett & Chorley, 1969; Kansyky, 1963). Later, average degree and cyclicity have become more commonly used to measure topological characteristics of transportation networks. For instance, Derrible and Kennedy (2010) used cyclicity for the robustness analysis of 33 metro systems worldwide. Zhang et al. (2015) applied the six connectivity-based parameters in the resilience analysis of transportation networks. In their analysis, cyclicity is defined in a different way as the ratio between the number of times a random walk led to cycle back to a previously visited node and the number of random walk, with the value ranging between 0 and 1. All these metrics of connectivity can be readily used in the vulnerability and resilience assessment context. For instance, Sudakov and Vu (2008) measured local vulnerability with respect to connectivity in a network as the number of edges that need to be removed to locally lose connectivity.

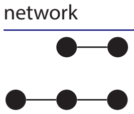
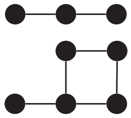
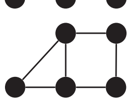
2.1.2. Centrality

The concept of network centrality was originally used in social networks to identify the most important node (Bonacich, 1972) and then gradually applied to other network systems. Centrality allows one to identify the critical nodes, whose reliability has a great influence on network efficiency. Table 2 gives a summary of centrality measures. Generally speaking, centrality measures can be organized into three categories: connectivity-based, distance-based, and time-based centralities.

Connectivity-based centrality measures include degree centrality (Cheng et al., 2015; Pinnaka et al., 2015; Wang et al., 2011; Zhang et al., 2013), eigenvector centrality (Kim & Anderson, 2013), and commuter flow centrality (Cheng et al., 2015). Degree centrality is a first centrality measure, defined as the number of links incident upon a node. Eigenvector centrality is also called Gould's index, widely used for air traffic network analysis (Cook et al., 2015; Spizziri, 2011). The eigenvector centrality of a node is proportional to the sum of the centralities of the nodes that it connects to (Bonacich, 2007). Commuter flow centrality is the total number of commuters through the node per hour (Cheng et al., 2015). These three measures allow one to quantify the functionality related to connectivity and to identify important nodes in disaster resilience analyses.

Distance-based centrality measures include closeness centrality (Cheng et al., 2015; Julliard et al., 2015) and betweenness centrality (Cheng et al., 2015; Jordan, 2008; Julliard et al., 2015; Leu et al., 2010; Rokneddin et al., 2013; Wang et al,, 2015; Wang et al., 2008). The closeness centrality of a node is the inverse of the average shortest

Table 1. Connectivity-related measures in graph theory.

Illustration network	Measure: Cyclomatic number	Alpha index	Beta index	Gamma index	Average degree	Cyclicity index
	$\mu = e - v + p,\ \mu \geq 0$ (1)	$\alpha = \frac{e-v+p}{2v-5},\ 0 \leq \alpha \leq 1$ (2)	$\beta = \frac{e}{v},\ \beta \geqslant 0$ (3)	$\gamma = \frac{e}{3(v-2)},\ 0 \leqslant \gamma \leqslant 1$ (4)	$AD = \frac{\sum_i n_i}{v},\ AD \geqslant 0$ (5)	Cyclicity ≥ 0
	0	0.00	0.60	0.33	1.20	0
	1	0.20	1.00	0.56	2.00	4
	2	0.40	1.20	0.67	2.40	3

Note: *e* is the number of edges; *v* is the number of nodes; *p* is the number of non-connected subplot; μ is the cyclomatic number; α is calculated by dividing the number of cycles by the possible number of cycles; β is the ratio between the number of edges and the number of nodes; γ is the ratio of number of edges to the maximum possible number of edges; average degree is the average number of edges per node.

Table 2. Centrality measurements for transportation network.

Category	Metric	Definition	Advantages	Disadvantages
Connectivity-based centrality	Degree centrality (Pinnaka et al., 2015; Wang et al., 2011; Zhang et al., 2013)	$C_{deg}(i) = \sum_{j=1}^{n} a_{ij}$ (6)	• Reflecting network connectivity • Useful for disconnected networks	• Coarse measure of connectivity • Not representative of full network
	Eigenvector centrality (Kim & Anderson, 2013)	C_{eig} the largest eigenvalue of $\mathbf{B} = [b_{ij}]$, $\mathbf{Bx} = \boldsymbol{\alpha}\mathbf{x}, \alpha x_i = \sum_{j=1}^{n} b_{ij} x_j$ (7)	• Measuring popularity and risk	• Linear superposition of topological features
	Commuter flow centrality (Cheng et al., 2015)	$C_f(i) = \sum_{j \in V} h_{ij} + \sum_{j \in V} h_{ji} + \sum_{j \in V, k \neq i, j \neq k} h_{jk}(i)$ (8)	• Dynamically depending on traffic flow	• Computationally expensive
Distance-based centrality	Closeness centrality (Cheng et al., 2015; Julliard et al., 2015)	$C_{cls}(i) = \frac{1}{d(i)}$ (9)	• Reflects accessibility of the node	• Not suitable for stochastic networks or large networks
	Betweenness centrality (Cheng et al., 2015; Julliard et al., 2015; Leu et al., 2010; Wang et al., 2008)	$C_{btw}(i) = \sum_{j \in V} \sum_{k \in V, k > j} \frac{g_{jk}(i)}{g_{jk}}$ (10)	• Direct expression of connectivity of the node to other nodes in the shortest path	• Not suitable for large networks
Time-based centrality	Time delay centrality (Cheng et al., 2015)	$C_{del}(i) = \frac{\sum_{j \in V, j \neq i} \frac{t_{alt}(i,j)}{t_{exp}(i,j)} + \sum_{j \in V, j \neq i} \frac{t_{alt}(j,i)}{t_{exp}(j,i)}}{2(n-1)}$ (11)	• Dynamically depending on traffic flow	• No contribution of commuter flow to time delay
	DelayFlow centrality (Cheng et al., 2015)	$C_{dfow}(i) = \frac{\sum_{j \in V, j \neq i} h_{ij} \frac{t_{alt}(i,j)}{t_{exp}(i,j)} + h_{ji} \frac{t_{alt}(j,i)}{t_{exp}(j,i)} + \sum_{j \in V, j \neq i} h_{jk}(i) \frac{t_{alt}(j,k)}{t_{exp}(j,i) + t_{exp}(i,k)}}{\sum_{j \in V} in(j)}$ (12)	• Considering the contribution of commuter flow to time delay	• Computationally expensive • Not suitable for large networks

Note: Given unidirectional graph V, E as a representation of the transportation network, V is the set of nodes, and E is the set of links between nodes. n is the number of nodes in the network. Assuming the total number of commuters entering and exiting the transportation network are the same.

1. Element $a_{ij} = \begin{cases} 1, & \text{if there is a direct link between nodes } i \text{ and } j. \\ 0, & \text{eitherwise.} \end{cases}$
2. The i^{th} input in the eigenvector describes the accessibility of node i to the surrounding links in the network.
3. $d(i) = \sum_{j \in V} d(i,j)$, where $d(i,j)$ is the shortest path in terms of distance between nodes i and j.
4. g_{jk} is the number of shortest paths between nodes j and k; $g_{jk}(i)$ is the number of shortest paths between nodes j and k through node i.
5. h_{ij} is the number of commuters from node i to node j per hour; h_{ji} is the number of commuters from node j to node i per hour; $h_{jk}(i)$ is the number of commuters from node j to node k through node i per hour.
6. $t_{exp}(i,j)$ is the expected time taken to travel from node i to node j; $t_{alt}(i,j)$ is the time taken to travel from node i to node j using an alternative means of transportation.
7. $\sum_{j \in V} in(j)$ is the total number of commuters flowing into the transportation network, $in(j)$ is the number of commuters entering into node j.

path distance from the node to any other node in the network. Betweenness centrality was originally proposed by Anthonisse (1971) and Freeman (1977), to describe to what extent a particular node lies between other nodes in the network. A node with a great betweenness centrality is on the shortest paths connecting many nodes. Therefore, it would be a critical node in the network that should be considered for pre-event strengthening interventions and given the top priority in post-event restoration to increase the resilience of the transportation network.

Time-based centrality measures include time delay centrality and DelayFlow centrality. Time delay centrality describes the extent of delay to the people affected through a linear combination of the additional time required by every trip. Time delay centrality does not consider how the commuter flow contributes to time delay, whereas DelayFlow centrality addresses this problem (Cheng et al., 2015). These metrics are useful for resilience analyses to make time-sensitive decisions in the emergency response phase (0–3 days) and short-term restoration phase (3–60 days).

2.2. Traffic-related functionality metrics

Besides the topological aspects, information about the traffic flow features and system capacity is another important aspect to evaluate the functionality of the transportation infrastructure. In this respect, the following section presents the definitions of traffic-related metrics and briefly introduces their applications in resilience analyses of the transportation infrastructure.

2.2.1. Weighted centrality-related metrics

To capture traffic-related characteristics, such as travel distance and travel time, networks can have weighted nodes or links (Dall'Asta et al., 2006). The weights in the transportation networks typically are the length of the road segment, the traffic capacity of the link, or the traffic flow on the link. When length is used as weight, the resulting metric is still topological, when flow is used, the metric is traffic-related, when capacity is used, the metric can be assigned to either category. For simplicity, we address all weighted network metrics in this section. Here are some examples of centrality-related measures for weighted network: network efficiency, weighted betweennness centrality, and weighted degree centrality.

Network efficiency is a parameter originally defined by Latora and Marchiori (2001), with the weight as the distance of each link in the network. It is a global measure of the efficiency of the network. Network efficiency has been applied to computer networks (Latora & Marchiori, 2001, 2004), mass transit networks (Latora & Marchiori, 2002), bridge networks (Guidotti et al., 2017), road networks (Dehghani et al., 2014), and other transportation networks (Nagurney & Qaing, 2007).

Weighted betweenness centrality is used for various weighted complex networks (Zhang et al., 2014), such as highways (Mohmand & Wang, 2013), bridge networks (Rokneddin et al., 2013), and subway systems (Sun & Guan, 2016). It can identify crucial nodes within a large infrastructure network in order to enhance them prior to an event.

Weighted degree centrality can be determined from the distribution of degree centrality for a weighted network. Based on the concept of weighted degree centrality, Ip and Wang (2011) used the weighted average number of reliable independent paths from one node to another within the network to investigate node resilience, and the weighted sum of resilience of all nodes to assess the overall resilience of the Chinese national railway network. It is useful for evaluating the status of interdependent paths within the transportation network.

2.2.2. Travel time

The damage caused by extreme events may lead to travel delay; therefore, travel time can indicate the impact of disruptive events. In network traffic analyses, travel time may refer to link travel time of the critical link and total travel time of the entire network (Omer et al., 2011). The link travel time can be estimated in several ways, such as the BPR curve (Horowitz, 1991), equilibrium-based traffic analysis (Shimizu et al., 2010), and surveys through GPS (Macababbad & Regidor, 2011; Parthasarathi et al., 2013). Total travel time is the weighted mean of link travel time for all disrupted links, with the demand assigned as the link weight (Fotouhi et al., 2017; Omer et al., 2011). Other authors defined the total travel time as the sum of the time required by all trips departing in one day or in one peak hour (Shinozuka et al., 2003).

2.2.3. Throughput

Throughput in the transportation network is the total sum of flows of shipment/passengers between origination and destination pairs divided by their respective distance, under a specific scenario. Throughput was chosen as one of two variables used to analyze the functionality and vulnerability of transportation systems in Yamagata, Japan after the 2011 tsunami using simulation methods (Trucco et al., 2013). In the context of disaster management, Zhang and Miller-Hooks (2015) chose to maximize throughput as the functionality objective to schedule short-term recovery activities of the transportation network. Similarly, Adjetey-Bahun et al. (2014) used the number of passengers that reach their destinations as one of their

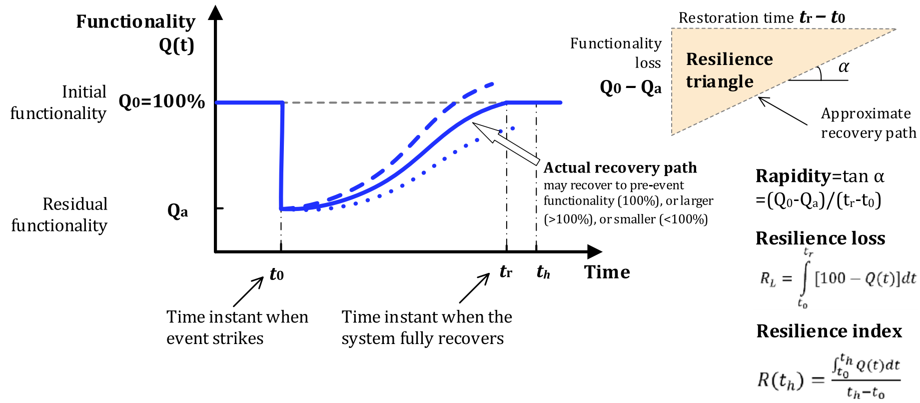


Figure 3. Resilience triangle and resilience index $R(t_h)$.

functionality metrics for a railway transportation system for the crisis management plan. Throughput is also useful for evaluating the evacuation capability of transportation systems in emergency circumstances.

2.2.4. Congestion index

The congestion index measures the travel delay in a transportation infrastructure network due to the disruption of extreme events. Different ways to measure the congestion index have been developed. The congestion index was originally proposed by Taylor (1992) and D'Este, Zito, and Taylor (1999) for measuring the congestion in terms of the ratio of link delay (i.e., difference between actual and acceptable travel time) to the acceptable travel time. This congestion time is limited in application to a roadway segment or a particular route (Aftabuzzaman, 2007). Lindley (1987) then used the congestion severity index to measure the freeway congestion using the total vehicle-hour delay per million vehicle miles of travel. In the 1990s, roadway congestion index (RCI) was developed as a weighted average of vehicle miles traveled and lane miles of freeways and principal arterial roads (Schrank & Lomax, 1997; Schrank et al., 1990). There are some arguments that RCI can represent traffic density rather than actual congestion (Gordon et al., 1997). Hamad and Kikuchi (2002) calculated congestion index using a fuzzy inference approach to combine two conventional transportation metrics, travel speed and delay. Their congestion index is a value between 0 and 1, where 0 indicates the best travel condition and 1 corresponds to the worst travel condition.

3. Resilience metrics for transportation infrastructure

Resilience of transportation infrastructure should be assessed in both functional and socioeconomic aspects. On the basis of functionality metrics, resilience analyses of the transportation infrastructure are conducted either by directly comparing the functionality measures before and after the event or using functionality-based resilience metrics that cover the functionality recovery process. Other analyses use resilience metrics that are able to quantify the impact of an event on the society and the economy. The following sections present how to quantify the resilience in both functional and socioeconomic aspects. Even though the focus of this paper is on transportation systems, most of these metrics are also applicable to other infrastructures.

3.1 Functionality-based resilience metrics

3.1.1. Resilience triangle-related measurements

Bruneau et al. (2003) defined the first influential and quantitative resilience metric based on the functionality recovery curve and introduced the concept of resilience triangle. The basic idea of the resilience triangle is that there is a significant and sudden decrease of functionality due to an extreme event at time instant t_0, followed by a gradual recovery of functionality, until the system is fully functional at time instant t_r.

The resilience triangle shown in Figure 3 consists of three edges: one edge showing the decrease of functionality at t_0, the second edge showing the recovery time ($t_r - t_0$), and the slope of the third edge showing recovery speed. Recovery time ($t_r - t_0$) is the amount of time taken to fully recover to the final performance that satisfies the overall demand (Bruneau et al., 2003; Chang et al., 2013; Pimm, 1991). Rapidity shows the recovery speed of system functionality, which is the outcome of robustness, redundancy, and resourcefulness (Tierney & Bruneau, 2007). Rapidity is an important property of resilience in the recovery process. The three edges of the resilience triangle capture some features of resilience. However, no single edge or feature is sufficient to fully describe such a multifaceted property as resilience.

In this regard, defining a metric via the resilience triangle may comprehensively represent the functionality loss, and the speed and duration for functionality recovery. For instance, the area of the resilience triangle can estimate the resilience loss R_L due to an event (Bruneau & Reinhorn, 2007; Bruneau et al., 2003). Larger values of resilience loss indicate less resilient systems. This metric was originally developed for quantitative resilience analyses of communities under earthquakes, and it has the advantage of being easily generalized for other types of systems and disturbances (Biringer et al., 2013). In the original definition (Bruneau et al., 2003), it is assumed that the initial system functionality is 100% before the event and the final system functionality will eventually recover to 100%. In reality, this is not always the case. The infrastructure system may not be fully functional before the event and can recover to less than full functionality after the event due to other disruptions afterward (Ayyub, 2014; Biringer et al., 2013), or not being able to afford the expenses for full recovery. In other cases, the recovery can instead enhance the functionality and bring it to a level better than the pre-event condition, i.e., larger than 100% (Ayyub, 2014, 2015). The original definition of resilience loss may not be able to capture such effects very well.

There have been some other resilience metrics that are defined based on the resilience triangle. Vugrin, Warren, Ehlen, and Camphouse (2010) proposed optimal resilience (OR) cost and recovery-dependent resilience (RDR) cost to evaluate impacts of different recovery schemes. These two metrics are calculated from system impact (i.e., resilience loss R_L) and recovery cost, with OR presenting the resilience cost of an optimal recovery scheme and RDR representing resilience cost under a particular recovery scheme. OR and RDR are suitable for comparative resilience studies to identify the best recovery scheme.

3.1.2. Resilience index

Resilience index is defined in the following equation (Reed et al., 2009):

$$R(t_h) = \frac{\int_{t_0}^{t_h} Q(t)dt}{t_h - t_0} \tag{13}$$

where $R(t_h)$ is the resilience index at time t_h; $Q(t)$ is the system functionality at time t, which is typically called the restoration function of a system; t_0 is the time when the event strikes, and t_h is the time horizon of the analysis.

Resilience index attempts to comprehensively represent resilience with one parameter, with the value varying between 0 and 1 (Reed et al., 2009). It has been widely used for resilience analyses of various infrastructure systems,

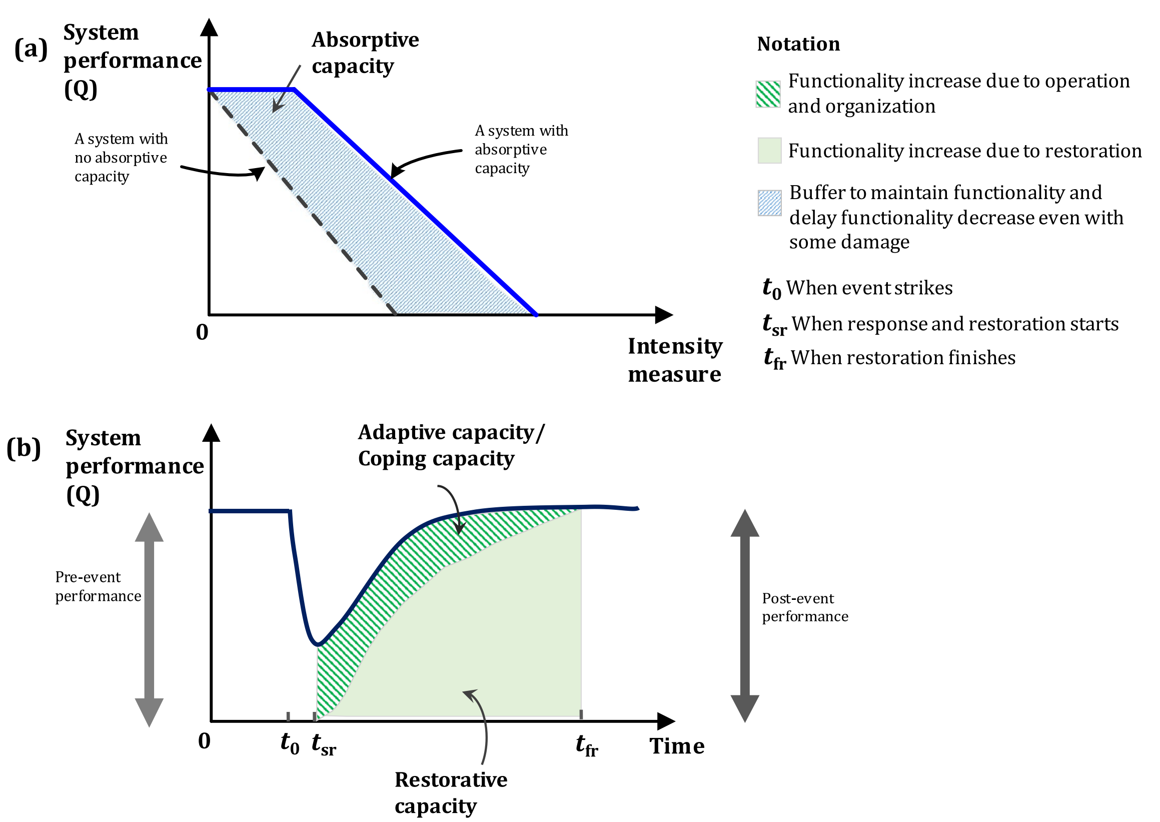


Figure 4. Illustration of absorptive capacity, adaptive capacity, coping capacity, and restorative capacity.

such as power and communication systems (Reed et al., 2009), hospitals (Cimellaro et al., 2009; Cimellaro et al., 2010), bridges (Frangopol & Bocchini, 2011; Karamlou & Bocchini, 2015, 2016a), buildings (Dong & Frangopol, 2015a, 2016), transportation network (Karamlou et al., 2016), and tunnels (Huang & Zhang, 2016).

3.1.3. Capacity

Capacity is a widely used parameter to quantify network resilience, usually in the form of absorptive capacity, adaptive capacity, restorative capacity, and coping capacity. Absorptive capacity describes the ability to absorb perturbations due to an event. Coping capacity is the ability to respond to and recover from the event perturbations (Burkett, 2013; Miller-Hooks et al., 2012). Transportation networks with a higher coping capacity have a greater resilience (Zhang et al., 2015). Some studies even combine the two capacities as absorptive coping capacity in resilience assessments (de Weijer & MaCandless, 2015). Adaptive capacity is the system's ability to gradually adapt itself, in terms of organization structure and operational function, from the disruption using alternative resources and processes (Brooks & Adger, 2005). Restorative capacity is the ability of the system to restore itself within a reasonable budget in a relatively short time (Hosseini et al., 2016; Vugrin et al., 2011; Vugrin et al., 2015). Both adaptive capacity and restoration capacity are related to the recovery phase. After the event, adaptive capacity is the increased efforts to maintain overall performance by reorganizing, substituting, and rerouting processes in a temporary duration, whereas restorative capacity corresponds to restorative efforts to bounce back the original performance or even better. Similarities with the concepts presented by the resilience triangle are clear, but Figure 4 shows that these metrics are different. For example, a transportation network with redundant roadways may be able to provide full functionality despite some damages from seismic activities, demonstrating the absorptive capacity. If severe seismic damages lead to a functionality loss, the transportation infrastructure may still recover the functionality by reorganizing two undamaged lanes that were originally for one-way traffic to two temporary lanes for two-way traffic, when the nearby lanes for the traffic in the opposite direction are damaged. The functionality recovery through temporary reorganizations rather than restoration activities demonstrates the adaptive/coping capacity. After a seismic event, repair crews restore damaged bridges and pavement with equipment and resources; the functionality recovery through restoration activities corresponds to the restorative capacity.

To elucidate the concepts of the four capacities, we propose the graphic illustration in Figure 3. Absorptive capacity is represented by the shaded area in Figure 4(a), which demonstrates the system's capability to absorb some damage while remaining at a certain level of performance. Restorative capacity is the shaded area under the functionality recovery curve that is purely due to restoration activities. Conversely, adaptive capacity and coping capacity are considered to be similar (Burkett, 2013), defined as the area corresponding to the functionality increase due to the operational adjustments and reorganizations. It is worth noting that the four capacities are features of the transportation infrastructure in response to a specific event, and the same transportation infrastructure may result in different functionality loss and recovery under a different event scenario.

The aforementioned four capacities have been widely used for resilience assessments. According to Gunderson and Pritchard (2002), the resilience of a large-scale system is related to vulnerability and adaptive capacity. They defined adaptive capacity as the ability of the system to devote resources to respond to a disturbance. In traffic analyses, the adaptive capacity is the ability of adjacent highways and nearby roadways to accommodate the additional traffic after extreme events. Vugrin and his co-workers comprehensively analyzed the disaster resilience of supply chains (Vugrin et al., 2011) and hospitals (Vugrin et al., 2015) using absorptive capacity, adaptive capacity, and restorative capacity. The vulnerability of transportation systems under extreme weather in Northwestern European countries is measured by the extreme weather risk indicator as a ratio of the product of exposure and susceptibility, divided by coping capacity (Leviäkangas & Aapaoja, 2015; Leviäkangas et al., 2013; Molarius et al., 2014).

In addition, there are some other capacity measures available. For instance, Morlok and Chang (2004) quantified the unused capacity of a network as the resilience metric in the analysis of freight transportation on railway networks, and capacity flexibility is achieved by varying traffic quantities, commodity mixes, and flow patterns. Based on the user equilibrium concept, network reserve capacity is used to take into account both the route choice behavior of travelers and the congestion effect on networks, with the assumption that users will minimize their travel time by choosing the shortest travel path (Pant, 2012; Xu et al., 2012).

3.1.4. Other functionality-based resilience metrics

There have been a number of resilience metrics related to the loss of functionality and restoration time in different forms. These resilience metrics may be related to either one functional measure or a set of functional measures. Compared with resilience metrics related to a single functionality metric, resilience metrics related to multiple functionality metrics have the advantage of representing the system performance of transportation infrastructure more comprehensively.

The following examples use one functional resilience measure for resilience assessments. Murray-Tuite and Mahmassani (2004) proposed a disruption index for quantifying the resilience of transportation networks with redundancy, diversity, and mobility. Garbin and Shortle (2007) proposed to measure the resilience of network systems using the percentage of links damaged versus the network performance and the percentage of nodes damaged versus the network performance, representing the redundancy of the network, which in turn is part of the resilience and similar to the absorptive capacity. To evaluate the demand in a freight network, Miller-Hooks and her co-workers used network resilience as the expected value of the post-event demand divided by the pre-event demand for the network (Chen & Miller-Hooks, 2012a; Miller-Hooks et al., 2012). Francis and Bekera (2014) used functionality degradation that depends on the probability of an event and the probability density function of system failure under the event, and the resilience factor that depends on the restoration time, the functionality immediately after the event, and the new functionality after restoration. In the disaster resilience analysis of roadway networks in China under two historical events, Hu, Yeung, Yang, Wang, and Zeng (2016) used recovery efficiency as the recovery percentage of the network functionality compared to its original functionality, with the network functionality defined as the weighted inverse distance in the network. Chan and Schofer (2016) measured the resilience of the mass transit system, using the aggregate measure of lost service days (LSD) to compare planned revenue vehicle miles (RVM) and delivered RVM. There are two advantages using LSD to measure resilience: (1) it is a general representation based on the operating conditions of the transportation system and (2) it is of easy application to systems and components at other scales, such as ferry, bus, and airlines.

There have been many studies deriving resilience parameters from travel time for the transportation infrastructure. Some studies used the additional travel time of an original route or the travel time of an alternative route to represent the impact of an event. Werner et al. (2005) measured the resilience in terms of the increase in travel time after an earthquake event. Adams, Bekkem, and Bier (2010) evaluated the resilience of road corridors using a set of metrics, one of which is travel time for alternative routes identified from ArcGIS. Some other studies used the normalized travel time as one of the metrics, which is the ratio of the normal travel time to the disrupted travel time. By tracking the normalized travel time over time, the resilience assessment of the transportation network can well reflect the functionality disruption due to an event and the following functionality recovery at different times. To measure the resilience of regional road networks, Omer et al. (2011); Omer, Mostashari, and Nilchiani (2013) used multiple resilience metrics to capture the disaster impacts on traffic, environment, and economy; one of the metrics is travel time resilience that is defined as the ratio of the travel time under normal circumstances and the disrupted scenario. Some studies directly used the normalized travel time as the only resilience metric, by defining resilience as a ratio of the pre-event total travel time to the post-event total travel time, where the total travel time is calculated according to traffic flow and travel time of all links in the transportation network (Faturechi, 2013; Fotouhi et al., 2017). All of these metrics are closely related to how fast passengers can travel after the event, which influences the effectiveness of humanitarian help and restoration in the emergency response phase after an extreme event. A transportation network with a short travel time after the disruptive event is more likely to transport people in a timely manner for evacuations and deliver resources for restorations, which is desirable for resilient mass transportation systems.

During the restoration process, functionality varies with time. The aforementioned resilience metrics treat resilience as a fixed scalar value, not as a function of time. One exception could be if the time horizon t_h in the resilience index $R(t_h)$ is made to vary in order to consider the resilience evolution over time. Some other resilience metrics can also address the resilience evolution (Ayyub, 2014; Ouyang et al., 2012; Ouyang & Wang, 2015). For instance, by comparing the actual functionality with a target functionality over time, Ouyang and Wang (2015) defined resilience $\hat{R}(t_h)$ as follows, assuming the event strikes at $t = 0$.

$$\hat{R}(t_h) = \frac{\int_0^{t_h} Q_A(t)dt}{\int_0^{t_h} Q_T(t)dt} \tag{14}$$

where $\hat{R}(t_h)$ is the resilience at time t_h related to the target functionality; $Q_A(t)$ is the actual functionality at time t; $Q_T(t)$ is the target functionality at time t (typically $Q_T(t) \leq 100\%$ in the restoration process because of the lower expectation immediately after the disruption); t_h is a period of interest. In addition, Ouyang et al. (2012) also proposed annual resilience (AR) to assess resilience of infrastructure under multiple inter-related hazards, which is the expected value of $\hat{R}(t_h)$ over a year. Both $R(t_h)$ and $\hat{R}(t_h)$ have the value ranging between 0 and 1, representing the functionality recovery over time, with a greater value indicating a more resilient system.

On the other hand, the following studies use a set of metrics to measure the system resilience from multiple aspects related to functionality. Mileti (1999) measured the resilience in terms of four metrics: extraordinary damage, productivity losses, life quality, and quantities of assistance required from outside. Murray-Tuite (2006) measured transportation resilience using multiple metrics from four aspects: adaptability, safety, mobility, and recovery. In addition to the four aspects, a resilient transportation system requires six other aspects: redundancy, diversity, efficiency, autonomous components, strength, and collaboration (Godschalk, 2003). Therefore, she suggested to use multiple resilience metrics of the 10 aspects to comprehensively measure the resilience of transportation infrastructures in future studies. Chang and Nojima (2001) proposed their own set of resilience metrics to evaluate the performances of road networks after the Kobe earthquake: length of available roads, minimum travel distance between the nodes, and weighted minimum travel distance of different subareas. These three metrics are easy to measure and facilitate the implementation process, but these metrics cannot consider accessibility, potential moving, and recovery, or network rearrangements (Arcidiacono et al., 2012). To analyze the pre-event resilience of transportation network for preparedness, Serulle, Heaslip, Brady, Louisell, and Collura (2011) used a fuzzy inference approach and proposed a new transportation network resiliency index. This index is comprehensive and covers nine aspects in the transportation infrastructure network, including road availability capacity, road density, alternate infrastructure proximity, intermodality level, average delay, average speed reduction, personal transportation cost, commercial–industrial transport cost, and network management. Sensitivity analyses show that the resilience of transportation networks can be greatly enhanced by improving the following three aspects: road available capacity, alternate infrastructure proximity, and network management.

3.2. Socioeconomic resilience metrics

There are various socioeconomic benefits of a resilient transportation infrastructure, such as lower gas consumption due to less traffic congestions and shorter waiting times after the event, and positive impacts on the environment due to less pollution. Due to extreme events, physical impacts of the transportation infrastructure can be easily measured, but socioeconomic impacts such as psychological, political, and economic impacts may gradually develop over a long time, and they are difficult to quantify. In this study, available metrics are summarized to represent socioeconomic impacts of disrupted transportation infrastructure due to extreme events in two categories: system-based and capital-based.

Traditionally, system-based economic resilience research was mainly focused on the business continuity and operability after extreme events (Briguglio et al., 2006; Cox et al., 2009; Rose, 2004a,b, 2007); later an economic resilience index for the transportation infrastructure was introduced (Cox et al., 2011). Rose (2007, 2009) defined economic resilience as the ability of a system to maintain function under an event, with two economic resilience indices related to the economic output for a given time: static resilience and dynamic resilience. Static resilience focuses on the short term, immediately after the disaster, with the value ranging from 0 to 1. Compared to static resilience, dynamic resilience takes repair and reconstruction into consideration, requiring longer time durations.

$$\text{Static Resilience} = \frac{\Delta WC - \Delta EP}{\Delta WC} \tag{15}$$

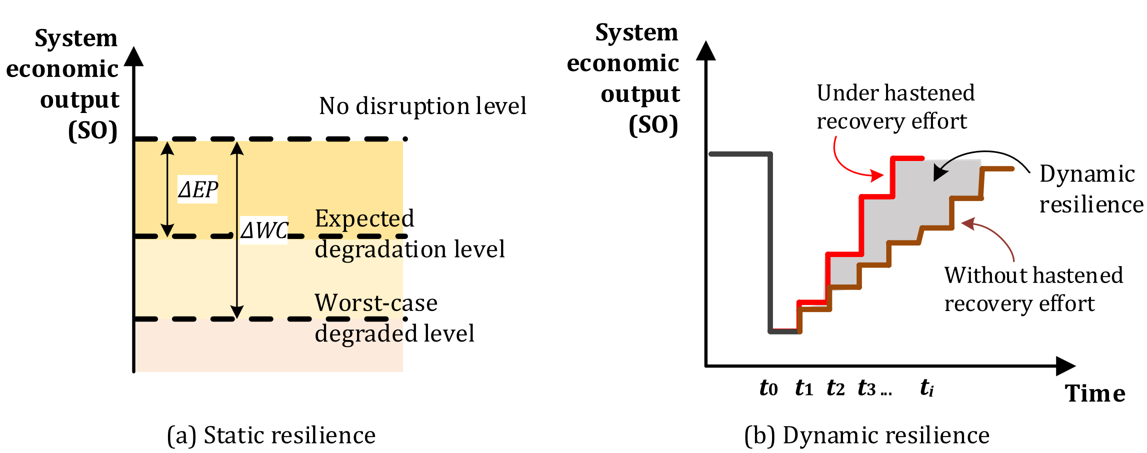


Figure 5. Illustration of static resilience and dynamic resilience (Rose, 2007).

Table 3. Resilience measurement methods.

Classification of Measurement Methods		References	Resilience Metrics	Further Descriptions
Qualitative		Bruneau et al. (2003), Brabhaharan et al. (2006), Wang and Elhag (2007), Freckleton et al. (2012), Lee et al. (2013)	• Most studies use a set of resilience metrics, such as vulnerability, stability, capacity, congestion index, etc. • Network resilience index is a frequently used metric by fuzzy inference approach.	• Assess system using qualitative terms (such as high, medium, and low) as outputs of resilience, accessibility, and availability
Quantitative	Component-based analysis	Nair et al. (2010)	• Average ratio of throughput achieved and total demand	• Assume 5 scenarios, including terrorisms, arson, earthquake, and flooding • Quantify vulnerability as results of inherent reliability and short-term recovery activities for ports and other intermodal components in freight systems
		Enjalbert et al. (2011)	• Global resilience • Local resilience	• Study human behaviors during train driving activities and assess instantaneous resilience of human machine system in trains/tramways
		Karamlou and Bocchini (2015)	• Resilience index • Expected direct loss	• Conduct probabilistic resilience analysis for components and the bridge using simulations
		Oswald et al. (2013), Oswald and Treat (2013)	• Vulnerability • Corridor resilience • Travel time redundancy	• Calculate vulnerability in GIS • Determine corridor resilience based on travel time index in GIS
		Bocchini et al. (2014)	• Direct impact ($) • Indirect impact ($) • Total impact ($)	• Apply the resilience concept to perform the analysis of damaged bridges under earthquake scenarios and then calculate the expected economic costs
		Voltes-Dorta et al. (2017)	• Aggregate delay • Relocation rate	• Case study of Palma de Mallorca airport under several scenarios of unexpected closure by analyzing aggregate delay and relocate rate of passengers
	Network (/System)-based analysis	Basoz and Kiremidjian (1996)	• Connectivity • Serviceability	• Implement risk assessment method in GIS and land use transportation system for emergency response planning and management
		Hamad and Kikuchi (2002)	• Congestion index	• Use fuzzy inference approach to analyze congestion over roadway segments
		Murray-Tuite (2006)	• A set of metrics for four dimensions: adaptability, safety, mobility, and recovery	• Determine transportation resilience for two cases: system optimum and user equilibrium traffic assignments
		Tampère et al. (2007)	• Incident impact factor	• Identify vulnerable links in road network due to incidents
		Tatano and Tsuchiya (2008)	• Indirect cost	• Use a spatial computable general equilibrium (SCGE) model to assess economic impacts on transportation network under an earthquake
		Omer et al. (2013)	• Travel time resilience • Environmental resilience • Cost resilience.	• Proposed Networked Infrastructure Resilience Assessment (NIRA) framework to facilitate decision-making process using multiple resilience metrics
		Goodchild et al. (2009)	• Truck trip per day Economic impacts	• Use a GIS-based statewide freight transportation network model to assess the resilience of distribution network in WS state
		Heaslip et al. (2010)	• Time-dependent resilience index	• Propose a framework to quantify transportation resilience combining network availability, network accessibility, traveler perception, and transportation cost
		Tu et al. (2012)	• Network's topology vulnerability index • Link's vulnerability-based criticality index	• Identify vulnerable link in simplified road network
		Vugrin et al. (2010)	• Systemic impact, total recovery effort	• Determine resilience cost in critical infrastructure assessment
		Serulle (2010), Serulle et al. (2011)	• Transportation network resiliency index	• Use fuzzy inference system to assess transportation resilience with a time-dependent resilience index at system level • Model interdependent problem variables and use some intuitive values for input variables in the resilience quantification

Ip and Wang (2011)	• Network resilience • Node resilience • Friability	• Use an undirected graph to represent roadway networks to calculate node resilience and then network resilience, and friability
Omer et al. (2011)	• Network travel time resilience • Net present value	• Propose the Networked Infrastructure Resilience Assessment (NIRA) framework to assess network resilience after impacts and use decision tree analysis to select the best resiliency strategies for the local road network
Pant (2012)	• Network resilience	• Measure the network resilience for disaster scenarios
Miller-Hooks et al. (2012)	• Network resilience	• Assess the post-event resilience of freight transportation network under multiple potential damage scenarios
Taylor et al. (2006), Taylor and Susilawati (2012)	• Accessibility • Remoteness index	• Identify vulnerable portions of the regional road network using network vulnerability analysis considering economic impacts
Bocchini and Frangopol (2012a,b)	• Resilience • Total present cost	• Optimize restoration activities and schedules for bridges in a transportation network after a severe earthquake
Chen and Miller-Hooks (2012a)	• Resilience level	• Use stochastic mixed-integer program to quantify network resilience and identify an optimized set of post-event activities
Ouyang et al. (2012)	• Annual resilience (time-dependent metric)	• Develop a multi-stage framework to analyze infrastructure resilience in term of preparedness and capacity to resist and recover from hazards of different types • Focused only on technical aspect • Multiple hazards are not correlated in this study
Omer et al. (2013)	• Travel time resilience Environmental resilience Cost resilience	• Use the Networked Infrastructure Resilience Assessment (NIRA) framework to assess the resilience for a regional transportation network
Croope (2013)	• Number of lanes • Pavement condition index • Capacity • Service level	• Build initial vulnerability assessment with contingency plans in GIS • Analyze resilience of transportation network
Lhomme et al. (2013)	• Resistance capacity • Absorption capacity • Recovery capacity	• Analyze road network resilience at the risk of flood in Web-GIS to calculate absorption capacity
Faturechi and Miller-Hooks (2014)	• Travel time resilience	• Develop a two-level three-stage stochastic program with equilibrium constraints to measure and maximize travel time resilience
Jin et al. (2014)	• Intrinsic metro network resilience	• Develop a two-stage stochastic model to assess intrinsic metro network resilience with bus services as optimization techniques for localized integration
Lee et al. (2014)	• Resilience cost	• Evaluate resilience of transportation infrastructure in terms of economic investment needed to restore full services
Osei-Asamoah and Lownes (2014)	• Global efficiency • Relative size of giant component	• Apply link-based disruption approach to two real surface transportation networks under two disruption strategies
Franchin and Cavalieri (2015)	• Resilience metric	• Propose a resilience metric considering the characteristics of network efficiency and displaced population due to the earthquake • Develop a simulation framework to evaluate resilience of a community
Xu et al. (2015)	• Travel alternative diversity • Network space capacity	• Optimize network models to evaluate network redundancy
Karamlou and Bocchini (2016a)	• Resilience index	• Optimize restoration sequences of bridges for a transportation network using genetic operators to maximize resilience
Ramachandran et al. (2016)	• Resilience time	• Uses an interdependent model to simulate resilience time for effective reconstruction of supply-chain strategic infrastructure elements after tornado in GIS
Chen et al. (2017)	• Network resilience level	• Build a model to measure resilience level of a given port-hinterland container transportation network (PHCTN) under emergency events from the shipper perspective by considering connectivity, travel time, and capacity
Zhang et al. (2017)	• Total recovery time • Skew of the recovery trajectory	• Perform post-event scheduling optimization for bridge network

Table 4. Uncertainties in the resilience analysis of transportation infrastructure.

Method	Reference	Sources of uncertainties considered	Description
Scenario analysis	Nair et al. (2010)	• Capacity	Generate five scenarios to analyze resilience of ports and other intermodal components
	Frangopol and Bocchini (2011)	• Recovery	Generate an earthquake scenario to optimize resilience for rehabilitation of bridges in transportation network by assuming recovery rate as linear
	Bocchini and Frangopol (2012a)	• Capacity • Demand	Determine the expected damage of bridges from fragility analysis in HAZUS under a given seismic scenario
	Karamlou and Bocchini (2016a)	• Damage	Generate an earthquake scenario to analyze the restoration schedule for damaged bridges in a large transportation network
Fuzzy approach	Cho et al. (2002)	• Capacity • Decision	Incorporating uncertainties through fuzzy approach for risk assessment
	Hamad and Kikuchi (2002)	• Performance	Use fuzzy inference method to account uncertainty
	Wang and Elhag (2007)	• Damage • Functionality	Use fuzzy approach and output linguistic terms to assess bridge risk
	Gürcanli and Müngen (2009)	• Event • Decision	Use fuzzy set method
	Serulle (2010)	• Capacity • Decision	Use fuzzy approach to assess resilience of transportation infrastructure
	Pinto et al. (2012)	• Damage	Assess sensitivity and accident severity using fuzzy approach
	Dojutrek et al. (2015)	• Event • Capacity • Damage	Use a fuzzy method to access security of transportation infrastructure
Probabilistic model	Chang et al. (2000)	• Event • Damage	Assign likelihood to exceeding various levels to the hazard scenarios and determine the system performance degradation
	Nielson and DesRoches (2007)	• Capacity • Demand	Conduct fragility analysis for highway bridges considering the contribution of components
	Padgett and DesRoches (2007)	• Capacity • Demand	Conduct fragility analysis and sensitivity analysis
	Jeong and Elnashai (2007), Mackie and Stojadinovic (2004), Mackie et al. (2008), Kwon and Elnashai (2009)	• Capacity • Demand	Conduct fragility analysis of bridge structures
	Banerjee and Shinozuka (2008)	• Capacity • Demand	Consider uncertainties in seismic risk assessment of highway transportation system
	Gehl et al. (2009)	• Capacity • Demand	Establish fragility surface for reinforced concrete structures
	Ghosh and Padgett (2010)	• Capacity • Demand • Aging	Considering aging effect on the fragility analysis of bridges with corrosion-induced deterioration
	de Felice and Giannini (2010)	• Capacity	Conduct fragility analysis of old bridges
	Selva and Argyroudis (2013)	• Event	Develop a formal Bayesian inference scheme for probabilistic seismic hazard assessment
	Decò et al. (2013)	• Capacity • Recovery	Conduct resilience of bridges with fragility analysis of bridges with possible restoration functions
	Wang et al. (2014)	• Capacity	Conduct probabilistic risk assessment of tunnel
	Karamlou and Bocchini (2016b)	• Restoration	Consider probabilistic distribution of duration of restoration tasks of each damaged component in a bridge to determine the probabilistic restoration function
	Karamlou and Bocchini (2017)	• Capacity • Demand • Restoration	Propose functionality fragility surface to integrate fragility curve and restoration function

Table 5. Models for infrastructure interdependencies.

Interdependency model	Maturity	Reference	Interdependency relationship	Interdependency type	Trans.	Power	Commu.	Water	Emergency service	Other infrastructure systems
Empirical/ Analytical models	Medium	Rinaldi et al. (2001)	NE	P, C, G, L	✓	✓	✓	✓	✓	
		Dudenhoeffer et al. (2006)	NE	P, C, G, L	✓	✓	✓	✓	✓	
		Cimellaro et al. (2016)	Interdependency table	P, C, G, L	✓	✓		✓	✓	
		Zimmerman (2004)	Database, and effect ratio	P, G	✓	✓	✓	✓		
		Mendonça and Wallace (2006)	Interdependency table	P, C, G, L	✓	✓	✓	✓	✓	Finance, government services, oil and gas
		Sharkey et al. (2015)	Interdependency table	P, C, G, L	✓	✓	✓	✓	✓	Public service, energy, commercial supply chain
		González et al. (2016)	Interdependency cost matrix	P, G, L		✓		✓		Gas
		Dunn and Wigert (2004)	Interdependency chart	P, C, G, L	✓	✓	✓		✓	Fuel
		Bigger et al. (2009)	Interdependency flowchart	P, C, G, L	✓	✓	✓	✓		Agriculture
		Dueñas-Osorio and Kwasinski (2012)	Cross-correlation function (CCF) based parameters	P, C, G		✓	✓	✓		
		Cimellaro et al. (2014)	CCF-based parameters	P, C, G, L		✓		✓		Gas
		Krishnamurthy et al. (2016)	CCF based parameters	P, C, G, L		✓	✓			
		Kotzanikolaou et al. (2013)	Dependency table	P, C, G, L	✓	✓		✓		Agriculture
		Ezell et al. (2000)	Event tree analysis	P, C, G, L						Not specifying any sector
		Volkanovski et al. (2009)	Fault tree analysis	P, C, G, L		✓				
Input-output model	Medium to high	Haimes et al. (2005a, 2005b)	Interdependency matrix	P, C, G, L	✓	✓	✓		✓	Industrial machinery, construction, retail trade, etc.
		Aung and Watanabe (2009, Chapter 17)	Interdependency matrix	P, C, G, L	✓	✓	✓	✓	✓	Finance, etc.
		Santos (2006)	Leontief technical coefficient matrix	P, C, G, L	✓	✓			✓	Fishery, agriculture
		Lian and Haimes (2006)	Interdependency matrix, and capital coefficient matrix	P, C, G, L	✓	✓	✓		✓	Machinery manufacturing, insurance carriers
		Reed et al. (2009)	Interdependency matrix, and dynamic coefficient matrix	P, C, G, L		✓	✓			
		Setola et al. (2009)	Interdependency coefficient matrix, and capital coeffi-cient matrix	P, C, G, L	✓	✓	✓	✓		Finance
		Pant et al. (2014)	Normalized interdependen-cy matrix, resilience matrix	P, C, G, L	✓	✓	✓	✓		Agriculture, mining, manufacturing, wholesale trade, finance, entertainment, government
		MacKenzie and Barker (2013)	Interdependency matrix, and diagonal matrix of resilience coefficients	P, C, G, L	✓	✓	✓		✓	Agriculture, government, finance, real state, education, arts, etc.
Agent-based model	Medium	TRANSIMS (2016)	NE	P, G	✓					Human
		Ehlen and Scholand (2005)	NE	P, C, G, L		✓				Human
		Zhang, Peeta, and Friesz (2005)	NE	P, C, G, L	✓					Human
		Outkin, Flaim, Seirp, and Gavrilov (2008, Chapter 10)	NE	P, G, L		✓	✓			Financial
		Bouarfa (2015)	NE	P, G, L	✓		✓			Human
		Nan and Sansavini (2017)	NE	P, C, G, L		✓				Human
Network model	High	Johansson and Hassel (2010)	Dependency edges	P, C, G, L	✓	✓	✓			
		Ouyang and Dueñas-Osorio (2011)	Flow of resources	P		✓				Gas
		Johansson and Hassel (2012)	Dependency edges	P, G	✓	✓	✓	✓		
		Holden et al. (2013)	Internetwork flow	P		✓		✓		
		Ouyang and Wang (2015)	Interdependent restoration schedules	P		✓				Gas

Note: ✓ means that the corresponding sector is considered in the interdependence analysis; NE means no explicit parameters; in the column of 'Interdependency type', P, C, G, L represent physical, cyber, geospatial, and logic interdependencies, respectively.

Table 6. Examples of resilience tools and planning guidelines related to transportation infrastructure.

Tools	Resilience Metric	Analysis method / model	Description	Source
HAZUS (FEMA, 2010)	Physical damage, economic loss, social impact	Scenario analysis	It is a tool to use Geographic Information Systems (GIS) for assessing physical, economic, and social impacts on structure and infrastructure due to multiple hazards: earthquake, flood, and hurricane.	https://www.fema.gov/hazus-software
MAEViz (MAECENTER, 2016)	Seismic impacts and socioeconomic losses	Scenario analysis	This open source tool is a seismic risk assessment software. It follows the consequence-based risk management methodology to generate damage estimates and test multiple mitigation strategies.	http://mae.cee.illinois.edu/software/software_maeviz.html
Achieving Hazard-Resilient Coastal and Waterfront Smart Growth (NOAA, 2015)	No specific metric is explicitly suggested.	No specific method/ model is explicitly suggested, and best practice examples use HAZUS and other tools for risk analysis.	This material describes planning and assessment methods for communities to meet goals against coastal hazards in life, safety, economic, environmental, and transportation aspects.	https://www.epa.gov/sites/production/files/documents/epa-noaa_hazard_resilience.pdf
BIPS 02: Integrated Rapid Visual Screening Series (IRVS) for Mass Transit Stations BIPS 03: Integrated Rapid Visual Screening Series (IRVS) for Tunnels (DHS, 2011a, 2011b)	Resilience score (0~100%)	Resilience score is determined according to performance and risk. Based on resilience score, the transit station/tunnel is categorized into high, medium, or low resilience level.	These tools require inputs by filling a data collection form, and the resilience rating is assessed. It aims to quantify, qualify, and mitigate the risks to mass transit systems and tunnels.	https://www.wbdg.org/FFC/DHS/bips_02.pdf https://www.wbdg.org/FFC/DHS/bips_03.pdf
Coastal Resilience Index (Sempier et al., 2010)	Coastal resilience index	Use 'yes' and 'no' questions and other list to collect information for resilience assessment	This self-assessment tool is used by community leaders to identify weakness in the community. It can identify weakness in the community.	https://toolkit.climate.gov/tool/coastal-resilience-index
Infrastructure Survey Tool (IST) (DHS)	Overall protective measures index	The survey data is composed of weighted score of various factors for a facility to calculate the overall protective measures index.	This security survey tool is web-based. The survey is conducted with facility owners and operators to identify and document the facility resilience. This tool is for steady-state analysis, special event planning, and incident management.	https://www.dhs.gov/infrastructure-survey-tool
NIST Technical Note 1795 (NIST, 2013)	Not available	Not available	This note helps to develop guidelines and standards for disaster resilient building environment. It gives examples of standards and regulations to evaluate and rehabilitate existing buildings and infrastructure system.	http://nvlpubs.nist.gov/nistpubs/TechnicalNotes/NIST.TN.1795.pdf
OnTheMap for Emergency Management (USCB)	Various parameters to describe socioeconomic impacts	Collect historic data to perform scenario-based analysis	This tool shows historical hazards in the United States and associated socioeconomic impacts on the map.	http://onthemap.ces.census.gov/em/
Science Application for Risk Reduction (SAFRR) scenarios (USGS)	Various parameters to describe socioeconomic impacts	Hypothetical scenario analysis through simulations	This agency develops multiple hazard models to evaluate impacts in a regional map.	http://www.usgs.gov/natural_hazards/safrr/projects/
Shake Maps and Prompt Assessment of Global Earthquakes for Response (PAGER) Alerts (USGS)	Fatality and economic loss	Collect data for historical earthquake events	The PAGER system is a database that provides fatality and economic loss impact estimates due to earthquake worldwide.	http://earthquake.usgs.gov/earthquakes/pager/
Integrating Extreme Weather Risk into Transportation Asset Management (AASHTO)	Various performance metrics	Set goals and objectives first, develop metric(s), and monitor performance data.	This white paper aims to provide guidance and suggestions for transportation asset management against extreme weather.	http://climatechange.transportation.org/pdf/extrweathertamwhitepaper_final.pdf
Climate Change & Extreme Weather Vulnerability Assessment Framework (FHWA)	Vulnerability rating, and adaptive capacity	Integrate vulnerability rating by collect pictures and data of historical events	This federal framework assesses the vulnerability of asset in transportation infrastructure to extreme weather.	http://www.fhwa.dot.gov/environment/climate_change/adaptation/publications/vulnerability_assessment_framework/fhwahep13005.pdf

$$\text{Dynamic Resilience} = \sum_{i=1}^{N} SO_{HR}\left(t_i\right) - SO_{WR}\left(t_i\right) \quad (16)$$

where ΔWC is the economic output difference of a system in the undisrupted case and the worst case; ΔEP is the economic output difference between the undisrupted case and the expected case, shown in Figure 5; N is the number of time steps considered; t_i is the ith time step; $SO_{HR}\left(t_i\right)$ is the system economic output under hastened recovery efforts at t_i; $SO_{WR}\left(t_i\right)$ is the system economic output without hastened recovery efforts at t_i. System economic output in the two equations is the service output provided by a system, such as daily traffic for a transportation system, water output for a water distribution system, and electricity output for an electric power system. The worst case represents the greatest disruption that is caused by a disaster, and the expected case represents the expected performance of system output (Figure 5(a)).

Static resilience and dynamic resilience can be applied to different systems at both macro- (entire economy) and micro- (household, component) levels, but the limitation is that the worst case must be known for the scenario in the analysis (Biringer et al., 2013). The concept of evaluating system resilience in terms of socioeconomic impact in short term (static resilience) and long term (dynamic resilience) has been adopted in different formats. It has been applied to the London transportation system following the bombings in July 2005 (Cox et al., 2009; D'Lima & Medda, 2015) and the business continuity afterward considering infrastructure interdependencies (Rose & Krausmann, 2013). It is found that resilience is greatly influenced by interdependencies between sectors, which will be further discussed in a later section.

In the mitigation after a disaster, the displaced population can represent social impacts. Franchin and Cavalieri (2015) developed a resilience metric considering both network efficiency of critical infrastructure systems and displaced population after an earthquake. By measuring the displaced population at different times, the time-dependent resilience analysis of critical infrastructures can quantify the progress of the recovery process.

Resilience is a feature meaningful at the system level, but it is related to individuals as well. There have been studies that try to quantify the resilience looking at the capital of individuals and communities. Freckleton, Heaslip, Louisell, and Collura (2012) proposed a framework to calculate total network resiliency that is determined from multiple input attributes falling into four aspects: individual, community, economy, and recovery, in order to comprehensively represent how transportation service meet the needs of individual users and community, under scarce resource constraints, and the ability to anneal and recover. This framework has been applied to analyze the resilience of transportation network in Salt Lake City, Utah, in order to provide the means for prioritizing improvement projects for transportation infrastructures. Gardoni and Murphy (2008, 2010) proposed disaster recovery index ($RDI(t)$) to represent the well-being of society at time t and evaluated the societal impact of a disaster as disaster impact index ($DDI(t)$), which is ΔRDI from the original $RDI(0)$ to $RDI(t)$. Both $RDI(t)$ and $DDI(t)$ are quantified by capabilities of individual well-being, such as longevity, health, affiliation, and mobility. Both $RDI(t)$ and $DDI(t)$ vary with time t, capturing the resilience in the recovery phase using social capital parameters.

4. Methods and challenges

4.1. Resilience analysis methods

Methods for performing resilience analysis can be categorized as qualitative and quantitative, shown in Table 3. Qualitative methods have been used to evaluate the resilience of the transportation infrastructure using one metric or a set of metrics only in a descriptive way, such as high, medium, and low, for resilience, accessibility, and availability. These methods can provide a preliminary understanding of the resilience of transportation infrastructure, which is useful for enhancing public preparedness and supporting decision-making. They cannot efficiently compute resilience for large, complex, and interdependent infrastructure networks, or quantitatively compare retrofit plans and restoration plans.

Conversely, quantitative methods can quantify system resilience at both component level and network level. Component-based analyses can assess critical components in the transportation infrastructure, such as bridges (Karamlou & Bocchini, 2015), intermodal components (Nair et al., 2010), and human–machine systems (Enjalbert et al., 2011). This type of analysis can assess the resilience of critical components and identify the most vulnerable ones in a transportation infrastructure. On the other hand, network-based analyses can quantify the system resilience in terms of travel time, functionality, and economic impacts at system level (Karamlou & Bocchini, 2016a).

There are two categories of methods to perform quantitative resilience analyses: analytical methods and simulation methods. Analytical methods use different logical models to analyze possible responses and failure states. The logical models include event tree analysis (Santos et al., 2014), fault tress analysis (Akgün et al., 2015; Gheorghe et al., 2005; Jacques et al., 2014), damage scenario tree (Tahmasebi, 2016), failure mode and effect analysis (Lhomme et al., 2011), Bayesian analysis (Murray-Tuite, 2010), analytical hierarchy process (Mabrouki et al., 2014), among others. These models are complicated for large networks with a great variety of possible scenarios and decision options, preventing their applications in many practical cases (Faturechi & Miller-Hooks, 2014).

With advancements in computational hardware and cost-effective algorithms, various simulation models are used to conduct resilience analyses for large network systems, such as the graph-theoretical approach (Mishra et al., 2012; Schintler et al., 2007; Svendsen & Wolthusen, 2005), game-theoretic model (Bhavathrathan & Patil, 2015; Gomez et al., 2015), Markov chain model (Ferreira, de Picado-Santos et al., 2011; Goh et al., 2012), utility-theoretic model (Chan, 2015; Zhang et al., 2015), and human reliability analysis (Kirwan et al., 2008; Nan & Sansavini, 2017; Stanton et al., 2006). These simulation models are capable of quantifying the network resilience and identifying vulnerable components within the network under various scenarios in a cost-effective way, by investigating a large number of randomly selected cases. Based on the comparison of simulation results, better investment decisions on retrofits and maintenance activities can be made for more resilient transportation infrastructure to withstand and rapidly recover from future events.

Quantitative resilience analyses are able to calculate possible failures and recovery schemes and determine associated probabilities to represent uncertain factors embedded in the analyses. Such uncertainties may lie in the event model, material properties, functionality, damage state, recovery activities, and human behaviors. Resilience analyses should use appropriate methods to address uncertainties and their propagations to represent how the transportation infrastructure withstands the possible disturbances and recover afterward. The following section will discuss challenges to properly address uncertainties.

4.2. Uncertainties in resilience analysis

In resilience analyses, representing the actual performance is challenging due to many uncertain factors, such as inherent randomness of material properties (Padgett & DesRoches, 2007), structural capacity and demand (Jia et al., 2017), unpredictable potential failures of infrastructure systems (Woods & Wreathall, 2003), dynamic characteristics of the surrounding environment (Archibald, 2013), and unforeseen human-related factors (Sheridan, 2008; Werner et al., 2005). Table 4 summarizes available techniques to address the uncertainties in resilience analyses. Presently, simulation is the most widely used approach to address uncertainties in different fields. In particular, stochastic simulation methods have been increasingly adopted for the resilience assessment of the transportation infrastructure (Chang et al., 2010) and other interdependent infrastructures (Di Muro et al., 2016). The simulation methods to address uncertainties can be classified into scenario analyses (Nair et al., 2010), fuzzy approaches (Cho et al., 2002; Gürcanli & Müngen, 2009; Pinto et al., 2012; Wang & Elhag, 2007), and probabilistic models (Chang et al., 2000; Decò et al., 2013; Ghosh & Padgett, 2011; Jeong & Elnashai, 2007; Karamlou & Bocchini, 2016b, 2017; Mackie et al., 2008; Wang et al., 2014).

In scenario analyses, one or more disaster scenarios are studied, sometimes considering the occurrence probability of the scenario (Christou et al., 2018; Han & Davidson, 2012; Jayaram & Baker, 2010). Historical scenarios and the worst case scenarios are commonly used to evaluate the resilience of transportation infrastructure by comparing the system functionality before and after an extreme event.

Fuzzy approaches use fuzzy logic and fuzzy numbers to quantitatively assess risk, security, mobility, and resilience of transportation infrastructure (Dojutrek et al., 2015; Pant, 2012; Serulle, 2010). Fuzzy-based approaches use simple models to simulate the experience and knowledge of human operators to determine a course of action, even though the surrounding environment conditions are not completely clear. However, it is limited to simple networks due to difficulties in describing large-scale simulations using quantitative input (El Rashidy, 2014).

Probabilistic methods use probabilistic distributions to describe uncertainties in different aspects, such as event, demand, damage state, recovery, and decision-making. Event uncertainties lie in occurrence frequency, location, and intensity (Bocchini et al., 2016, Chapter 2; Pitilakis et al., 2013a; Selva & Sandir, 2013). Event uncertainties can be incorporated in resilience analyses through probabilistic models (Duan et al., 2016). The variability of geometric, material, structural properties, and demand can be addressed by fragility analyses (Banerjee & Shinozuka, 2009; de Felice & Giannini, 2010; Gehl et al., 2009; Jeong & Elnashai, 2007; Jia et al., 2017; Karamlou & Bocchini, 2016b; Banerjee & Shinozuka, 2009; Kwon & Elnashai, 2009; Nielson & DesRoches, 2007; Padgett & DesRoches, 2007; Tsionis & Fardis, 2013). Based on the concept of fragility analyses, functionality–fragility surfaces, adding time-related information, can predict functionality recovery over time at different intensity levels in a probabilistic manner (Karamlou & Bocchini, 2017). Uncertainties in thresholds of damage states on capacity curves are usually handled through design codes (FEMA, 2010), expert judgments (Ghosh & Padgett, 2010), experimental data (Mackie & Stojadinovic, 2004; Perrault et al., 2013), analytical approaches and simulations (Azevedo et al., 2010; Banerjee & Shinozuka, 2008; Cho et al., 2002; Choi et al., 2004; Choi & Mahadevan, 2008; Nielson & DesRoches, 2007; Pinto et al., 2012; Wang et al., 2014). However, there are still debates on thresholds of damage states and parameters of fragility curves for structures of the same types (Trucco et al., 2013, Chapter 9).

Uncertainties related to recovery come from resource availability, duration and mode of tasks, and information flow, among others. Because of these uncertainties, developing an accurate model for the restoration function $Q(t)$ is extremely difficult. Restoration functions have been developed from surveys, mathematical derivations, and simulations, resulting in different formats. For the case of bridges, restoration functions have been developed in lognormal (Shinozuka et al., 2003), stepwise (Karamlou & Bocchini, 2016b; Padgett, 2007), linear (Bruneau & Reinhorn, 2007), normal cumulative distribution function (Zhou et al., 2010b), sinusoidal (Decò et al., 2013), and exponential (Biondini, Camnasio, & Titi, 2015; Dong & Frangopol, 2015b; Titi & Biondini, 2013) formats. Lognormal restoration functions are typically used to capture long-term restorations over large regions. Stepwise restoration functions are suitable for individual bridges with discrete functionality states during restoration. Linear ones assume that the recovery of functionality progresses at a constant rate. This is the most reasonable assumption when no additional information is available. Sinusoidal and exponential restoration functions can consider idle time, restoration duration, residual functionality and targeted functionality as parameters. More sophisticated recovery models have also been developed, for instance based on resource constrained project scheduling for the repair tasks (Karamlou & Bocchini, 2016b; Karamlou et al., 2017). In all these models, the mentioned uncertainties can be accounted for by considering the parameters as random variables (e.g., the recovery slope in the linear model, or the task durations in the scheduling-based model). In this way, each set of random input parameters fed to the model will generate a sample of the restoration function. This has been done in several of the cited papers. The effect of these uncertainties on the restoration function can also be visualized by means of probabilistic restoration curves, which present the probability of recovering to a certain functionality level over time (Karamlou & Bocchini, 2017). These general concepts can be applied to structures of different types and systems spreading over a large region.

Another set of uncertainties is associated with the decision-making process and reflects the fact that humans might make different decisions under the same scenario. The outcome of the uncertain decision-making process has a combination of influencing factor: average income, economic growth, awareness level, personality, emotions, preparedness, local politics, lack of data, and biased survey results (O'Rourke, 2007; Sheridan, 2008; Zoumpoulaki et al., 2010). Decision-making uncertainties may be evaluated by human reliability analysis (Boring, 2010) and agent-based models (Bouarfa et al., 2013; Lemoine et al., 2016), stochastic optimization (Chen & Miller-Hooks 2012b), or by investigating extreme cases (e.g., for the case of flow of information, see Karamlou & Bocchini, 2016b).

4.3. Interdependencies

Transportation infrastructure depends on and supports the other infrastructure systems in different ways, so that a small failure in one system may propagate to the others and lead to catastrophic damages in a large geographic region (Comes & Van de Walle, 2014; Ouyang, 2014; Rinaldi et al., 2001). Resilience analyses of transportation infrastructure without considering interdependencies may yield inaccurate results, especially for the cases of transportation infrastructure with sophisticated interactions with other systems. For instance, underground transportation infrastructure requires complicated interactions between subway trains, the electric power system, and the telecommunication system to support full functionality; modeling interdependencies is necessary for accurate resilience assessments of underground transportation infrastructure.

Based on the nature of interactions between the transportation infrastructure and other infrastructures, interdependencies are classified into four categories: physical, cyber, geographic, and logical (Rinaldi et al., 2001). Physical interdependencies denote the reliance on the flow of resources between infrastructures (e.g., traffic lights rely on the power distribution system). Cyber interdependencies represent the reliance of information transfer between components and/or networks (e.g., SCADA systems that control electrical power systems to manage subway trains). Geospatial interdependencies indicate that components across multiple infrastructures are influenced by the same event due to physical proximity (e.g., a pipeline carried by a road viaduct). All the other interdependencies are classified as logical (e.g., traffic congestions on highways as people choose driving over flying due to low gas prices in holidays). In order to perform resilience analyses of transportation infrastructure with consideration of interdependencies, a dedicated model should be chosen. The available options (see Table 5) are classified into empirical and analytical models, input–output models, agent-based models, and network models.

Empirical and analytical models evaluate interdependencies based on survey data, historical data, fault tree and event tree analyses, and time-series analysis. Using expert survey data to develop an interdependency table (The Lifeline Council [TLC], 2014) or adjacency matrix (Guidotti et al., 2016) it is possible to identify the type and strength of interdependency relationships. Because of the simplicity, the interdependency table and adjacency matrix have been widely used for regional resilience assessments of various infrastructure systems (including transportation infrastructure), despite a potential drawback of being subjective. Discrete event simulations, such as fault tree analysis, event tree analysis, Petri net, and Muir Web have been used to study failure outcomes under a scenario and the associated probability of failure, with applications to disaster risk analyses of tunnels (Hyun et al., 2015), bridges (Davis-McDaniel et al., 2013; LeBeau & Wadia-Fascetti, 2007), and critical infrastructure systems (Guikema, 2009; O'Reilly et al., 2007; Sultana & Chen, 2009; Utne et al., 2011; Zio & Ferrario, 2013). Time series analysis derives cross-correlation function (CCF)-related parameters based on the functionality recovery curves of interdependent infrastructures (Cimellaro et al., 2014; Dueñas-Osorio & Kwasinski, 2012; Krishnamurthy et al., 2016). This method has been applied to regional resilience assessments in Japan (Cimellaro et al., 2014) and in Chile (Dueñas-Osorio & Kwasinski, 2012; Krishnamurthy et al., 2016). All the aforementioned models require either sufficient experience or field measurements to capture interdependency relationships at the system level.

Input–output models are suitable to evaluate the economic aspect of transportation infrastructure considering interdependencies with other systems under a disaster scenario in a large spatial domain, statewide or nationwide. The economic interactions between any two systems within a period are quantified via coefficients in an interdependency matrix (González et al., 2016; Gordon et al., 2007; Haimes et al., 2005a,b; Leontief, 1951). The interdependency matrix consists of constant scalar terms, if the system does not change through time. Actual interdependencies are likely to change with time; therefore, some studies use an interdependency matrix that includes time-dependent variables (Cimellaro et al., 2016; Fantini et al., 2014). A challenging issue is that it is difficult to either calibrate the interdependency coefficients or evaluate interdependencies at the component level.

In agent-based models, critical components in infrastructure systems can be viewed as agents, and agents interact with each other and the surrounding environment based on certain rules (Ehlen & Scholand, 2005; Huynh et al., 2014). Physical, cyber, and geographic interdependencies are usually considered in agent-based models. This approach models human behaviors and major components; therefore, it is suitable for resilience analyses of transportation systems considering traveler's behaviors under a given hazard scenario. Its disadvantages are the great influence of assumptions on agent behaviors on simulated interdependencies and the difficulty of validating simulation results (Ouyang, 2014).

Network models simulate every infrastructure as a network that consists of nodes and links. A multi-layered infrastructure network framework can be used for resilience analyses of multiple interdependent infrastructures (Zhang & Peeta, 2011). Functional and geospatial interdependencies are commonly investigated among infrastructure networks, and the network functionality is evaluated using the connectivity analysis and the flow analysis. For this purpose, knowledge of the system structure and the connectivity among components is necessary (Pitilakis, 2011). Network models have been applied to perform resilience modeling considering the interdependencies between transportation and other infrastructure systems, such as railway system and the associated power and telecommunication systems (Johansson & Hassel, 2010), power and communication systems (Cimellaro et al., 2014; Dueñas-Osorio & Kwasinski, 2012; Krishnamurthy et al., 2016), hospital and transportation networks (Dong & Frangopol, 2017; Shah & Babiceanu, 2015).

The concept of infrastructure interdependencies is intuitive, but the complexity of these models increases sharply as too many interactions are considered among transportation infrastructure and the other infrastructures. The aforementioned studies generally evaluate interdependencies between transportation and other infrastructures; however, very few of them can well represent interactions in a rigorous way due to the complex nature of the interdependencies in both spatial and temporal domains. For instance, appropriately addressing the discrepancy in terms of temporal scales of the restoration processes for different infrastructures is a challenging problem. Restoring a bridge or a tunnel takes months, sometime years, but power lines are usually restored in hours or days (and switches that can protect such lines operate in milliseconds). Therefore, the same interdependency model sometimes has to span multiple orders of magnitude in terms of time scales. Despite these challenges, it is essential to evaluate resilience of transportation systems with the consideration of interdependencies. There have been some improvements in this aspect, but more accurate interdependency models are still in need. An accurate interdependency model should be capable to comprehensively address dynamic interactions among components and infrastructure systems and the associated uncertainties. Moreover, it should be general enough to be applicable to interdependent relationships of different types.

4.4. Validation and application

Effective resilience analyses for the transportation infrastructure require appropriate input data and would also benefit from validation with appropriate data. Input data represent information about inventory and interactions, such as location and structural type of individual components, in order to establish a rigorous model of the transportation infrastructure and to represent the associated interdependencies. Validation data refer to information useful for evaluating the accuracy and effectiveness of the resilience analysis, such as survey data. Data may be collected from the field, experiments, and expert surveys, or generated from simulations. There have been some databases established and freely open to the public, such as fragility functions for buildings (FEMA, 2012), bridges (Pitilakis et al., 2013a; Pitilakis et al., 2013b, Chapter 1), tunnels (American Lifelines Alliance [ALA], 2001), embankments (ATC-13, 1985), and roads (National Institute of Building Sciences [NIBS], 2004); highways and local roadways nationwide (Data.Gov, 2016; FHWA, 2016; USDOT, 2016). These data can be used as input in resilience analyses of the transportation infrastructure. In some cases, agencies and companies may not be willing to share their inventory data for reasons of national security and competitive advantage, but the situation is improving.

It is challenging to perform the proper validation of the available techniques for resilience assessments. For specific scenarios, historical data, data collected from planned restorations, or data generated from first-principle models can be used for the validation of resilience analyses. Survey data can be used to validate general qualitative relations. All these validations are limited due to the general scarcity of data; thus, it may not be possible to ensure the accuracy of resilience assessments in future scenarios. This makes the complete validation extremely difficult, which in turn hinders the practical applications. However, there have been efforts supported by multiple federal agencies, encouraging data collection at both network and component levels. Such efforts are expected to make the comprehensive validation of resilience analyses possible in the future. Future research on validations should focus on the following areas: (1) suggesting standardized methods for data collection and building database platforms for sharing data, (2) establishing a common set of metrics so that resilience analyses from different methods are comparable, and (3) most importantly collecting essential data at both the network and component levels.

Despite the fact that current resilience analyses may lack validations, there are many tools and guidelines for practical resilience assessments, shown in Table 6. For instance, Hazus-MH can perform the regional risk evaluation and loss estimation, by considering resilience factors such as inventories, excess capacity, and ability of increasing imports and exports for the indirect loss module (Rose & Krausmann, 2013; FEMA, 2016b). These tools and guidelines provide regional assessment methods for the transportation infrastructure (Croope & McNeil, 2011) and other critical sectors (FEMA, 2010; MAECENTER, 2016; DHS, 2014a; 2014b; 2016). They are useful for timely identifying vulnerable components and effective plans for preparation, mitigation, and restoration.

However, some tools may be limited to specific geographic locations, hazard types, and infrastructure sectors. For instance, the coastal resilience index (Sempier et al., 2010) is only used for coastal regions, BIPS02 is only applicable to the risk assessment of mass transit stations and BIPS03 is only for tunnels (DHS, 2011a, 2011b), and MAEViz is for risk assessment due to only seismic events (MAECENTER, 2016). Moreover, some guidelines may provide general descriptions instead of explicit technical suggestions to improve resilience. Therefore, enhanced versions of these guidelines and tools with detailed technical suggestions tailored to local transportation infrastructures are still needed in practice. Researchers may overcome these drawbacks by: (1) providing user-friendly manuals for tools, as well as technical explanations for experts who want to extend/tailor the tools for their own transportation infrastructure, (2) enhancing current tools or developing new ones to comprehensively evaluate different aspects of the transportation infrastructure, and (3) encouraging stakeholders and engineers to apply these tools and guidelines by offering training.

5. Concluding remarks

Resilience analyses can identify key influencing parameters and vulnerable components in the transportation infrastructure. It helps decision-makers develop informed and effective management plans for transportation infrastructures subjected to extreme events. There has been a large amount of research on resilience assessments of the transportation infrastructure using various metrics and methods. This study reviewed the most important ones. It identified gaps and challenges in current research and suggested future research directions for the validation and implementation.

Resilience of transportation infrastructure is tightly related to its functionality. Therefore, prevalent metrics for determining the functionality of the transportation infrastructure are summarized at the beginning of this study. Based on these functionality metrics, functionality-based resilience metrics are defined to comprehensively represent different aspects of resilience. In addition, the impacts of the event can also be quantified by socioeconomic resilience metrics. To perform a thorough resilience analysis for the transportation infrastructure, we can integrate strengths of different metrics into a comprehensive metric from technical, organization, and socioeconomic aspects, or use a set of metrics from different aspects. By comparing the selected metric(s) before and after an event or tracking the metric(s) throughout the recover process, we can evaluate how resilient the transportation infrastructure is.

Resilience analyses make use of resilience metrics in qualitative and quantitative methods. Qualitative resilience analyses use conceptual and empirical frameworks to provide a descriptive assessment of resilience. It can provide limited insights about the resilience performance of the transportation infrastructure. Quantitative resilience analyses use analytical methods and simulations to provide more detailed information about vulnerable components and to compare retrofit plans and restoration schedules. Consequently, qualitative resilience assessments would be beneficial for decision-making to get a general idea of the resilience of a large transportation network, and quantitative resilience assessments can be useful to provide more detailed technical information.

There are many challenges in performing resilience analyses, especially in addressing uncertainties and interdependencies and in conducting validations and applications. An increasing number of resilience studies of the transportation infrastructure utilize simulation models to consider uncertainties and interdependencies. Establishing databases at both the component and network levels would be helpful for conducting validations and developing efficient plans for retrofit and restoration. With rapid advancements in this area, we can expect enhanced guidelines and more user-friendly tools to be developed for practical applications in the near future.

Acknowledgments

The authors would like to thank the anonymous reviewers for their extremely valuable comments and helpful suggestions to improve this manuscript.

Disclosure statement

No potential conflict of interest.

Funding

The support provided by the National Science Foundation [grant number CMMI – 1541177] and Pennsylvania Department of Community & Economic Development [PIT-16-12] is gratefully acknowledged. The opinions and conclusions presented in this paper are those of the authors and do not necessarily reflect the views of the sponsoring organization.

Notes on contributors

Wenjuan Sun is a research associate in the Department of Civil and Environmental Engineering at Lehigh University. Her research focuses on developing computational models in solving various engineering problems to support sustainable and resilient infrastructures. At the system level, she develops simulation models to evaluate system resilience and infrastructure interdependencies in a probabilistic manner. At a finer level, she develops models to characterize and simulate mechanical properties of infrastructure materials.

Paolo Bocchini is the Frank Hook assistant professor of Civil Engineering in the Department of Civil and Environmental Engineering at Lehigh University. He is a faculty member of the Advanced Technology for Large Structural Systems (ATLSS) Engineering Research Center. Bocchini's research team focuses on the application of probabilistic and computational modeling to problems in structural engineering and civil engineering. In particular, the most recent areas of activity are infrastructure and community resilience, regional hazard modeling, and durability of infrastructure systems. Bocchini is also the vice-chair of the Data, Metrics and Tools Standing Committee within the Community Resilience Panel, and he also serves in various roles in several other national committees.

Brian D. Davison is an associate professor of Computer Science in the Department of Computer Science and Engineering and the director of the Undergraduate Minor in Data Science at Lehigh University. His research mainly focuses on web search and mining, focusing on the integration of text and link analysis applied to search, recommendation and classification problems on the Web and social networks. Davison serves as the joint editor-in-chief of the ACM journal – Transactions on the Web. He has also served as an organizer, the committee chair or co-chair for over a dozen international conferences and workshops.

ORCID

Wenjuan Sun http://orcid.org/0000-0003-0546-2389
Paolo Bocchini http://orcid.org/0000-0002-5685-2283
Brian D. Davison http://orcid.org/0000-0002-9326-3648

References

Adams, T. M., Bekkem, K., & Bier, V. M. (2010). *Operational resiliency of the BeloitHudson interstate highway corridor*. National Center for Freight & Infrastructure Research & Education (CFIRE), University of Wisconsin-Madison.

Adjetey-Bahun, K., Birregah, B., Chatelet, E., & Planchet, J.-L. (2014, May). *A simulation-based approach to quantifying resilience indicators in a mass transportation system*. Proceedings of the 11th International ISCRAM Conference, University Park, PA, USA, pp. 75–79.

Adjetey-Bahun, K., Châtelet, E., & Planchet, J.-L. (2016). A model to quantify the resilience of mass railway transportation systems. *Reliability Engineering & System Safety, 153*, 1–14.

Aftabuzzaman, M. (2007). *Measuring traffic congestion – A critical review*. The 30th Australasian Transport Research Forum, Melbourne, Victoria, Australia, Vol. 30, 01095066.

Akgün, İ., Gümüşbuğa, F., & Tansel, B. (2015). Risk based facility location by using fault tree analysis in disaster management. *Omega, 52*, 168–179.

American Lifelines Alliance (ALA). (2001). *Seismic fragility formulations for water systems, Part 1– Guideline* (p. 104). Reston, VA: ASCE-FEMA.

Anthonisse, J. M. (1971). *The rush in a directed graph* (Technical Report BN9/71). Amsterdam: Stichting Mathematisch Centrum.

Archibald, E. (2013). *Infrastructure resilience at the project level: Considering hazard risk and uncertainty for infrastructure decisions*. MSc Thesis, University of Delaware.

Arcidiacono, V., Cimellaro, G. P., Infuso, A., & Reinhorn, A. M. (2012, July 8–12). *Road network's disaster resilience assessment methodology*. In Bridge maintenance, safety. Management, resilience and sustainability. Proceedings of the Sixth international IABMAS Conference, Stresa, Lake Maggiore, Italy. London: Taylor & Francis Group.

ATC-13. (1985). *Earthquake damage evaluation data for California*. Redwood City: Applied Technology Council.

Aung, Z., & Watanabe, K. (2009). A framework for modeling interdependencies in Japan's critical infrastructures. In C. Palmer & S. Shenoi (Eds.), *Critical infrastructure protection III* (pp. 243–257). Hanover, NH, USA: Springer.

Ayyub, B. M. (2014). Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk Analysis, 34*(2), 340–355.

Ayyub, B. M. (2015). Practical resilience metrics for planning, design, and decision making. *Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 1*(3), 04015008.

Azevedo, J., Guerreiro, L., Bento, R., Lopes, M., & Proença, J. (2010). Seismic vulnerability of lifelines in the greater Lisbon area. *Bulletin of Earthquake Engineering, 8*(1), 157–180.

Banerjee, S., & Shinozuka, M. (2008). Mechanistic quantification of RC bridge damage states under earthquake through fragility analysis. *Probabilistic Engineering Mechanics, 23*(1), 12–22.

Banerjee, S., & Shinozuka, M. (2009). *Uncertainties in seismic risk assessment of highway transportation systems*. In A. K. K. Tang, & S. Werner (Eds.), *Proc., TCLEE 2009 Conf. on Lifeline Earthquake Engineering in a Multihazard Environment*. Reston, VA: ASCE.

Basoz, N., & Kiremidjian, A. (1996). *Risk assessment for highway transportation systems* (Rep. No. 118). Stanford, CA: J. A. Blume Earthquake Engineering Center, Stanford University.

Berdica, K. (2002). An introduction to road vulnerability: What has been done, is done and should be done. *Transport Policy, 9*(2), 117–127.

Bhavathrathan, B. K., & Patil, G. R. (2015). Capacity uncertainty on urban road networks: A critical state and its applicability in resilience quantification. *Computers, Environment and Urban Systems, 54*, 108–118.

Bigger, J. E., Willingham, M. G., Krimgold, F., & Mili, L. (2009). Consequences of critical infrastructure interdependencies: Lessons from the 2004 hurricane season in Florida. *International Journal of Critical Infrastructures, 5*(3), 199–219.

Biondini, F., Camnasio, E., & Titi, A. (2015). Seismic resilience of concrete structures under corrosion. *Earthquake Engineering Structural Dynamics, 44*(14), 2445–2466.

Biringer, B. E., Vugrin, E. D., & Warren, D. E. (2013). *Critical infrastructure system security and resiliency*. Boca Raton, FL: CRC Press, Taylor & Francis Group.

Bocchini, P. & Frangopol, D. M. (2012a). Restoration of bridge networks after an earthquake: Multicriteria intervention optimization. *Earthquake Spectra, 28*(2), 427–455.

Bocchini, P., & Frangopol, D. M. (2012b). Optimal resilience- and cost-based postdisaster intervention prioritization for bridges along a highway segment. *Journal of Bridge Engineering, 17*(1), 117–129.

Bocchini, P., Frangopol, D. M., Ummenhofer, T., & Zinke, T. (2014). Resilience and sustainability of civil infrastructure: Toward a unified approach. *Journal of Infrastructure Systems, 20*(2), 04014004.

Bocchini, P., Christou, V., & Miranda, M. J. (2016). Correlated maps for regional multi-hazard analysis: Ideas for a novel approach. In P. Gardoni & J. M. LaFave (Eds.), *Multi-hazard approaches to civil infrastructure engineering* (pp. 15–39). Chicago, IL: Springer.

Bonacich, P. (1972). Technique for analyzing overlapping memberships. *Sociological Methodology, 4*, 176–185.

Bonacich, P. (2007). Some unique properties of eigenvector centrality. *Social Networks, 29*(4), 555–564.

Boring, R. L. (2010). *Bridging resilience engineering and human reliability analysis* (PSAM 10). Idaho Falls, ID: Idaho National Laboratory.

Bouarfa, S., Blom, H. A. P., Curran, R., & Mariken, H. C. (2013). Agent-based modeling and simulation of emergent behavior in air transportation. *Complex Adaptive Systems Modeling, 1*, 1–15. doi:10.1186/2194-3206-1-15

Bouarfa, S. (2015). *Agent-based modelling and simulation of safety and resilience in air transportation* (Ph.D. dissertation). Delft University of Technology.

Brabhaharan, P., Wiles, L. M. M., & Frietag, S. (2006). *Natural hazard road risk management. Part III: Performance criteria* (Land Transport New Zealand research report 296, pp. 126).

Briguglio, L., Cordina, G., Farrugia, N., & Vella, S. (2006). Conceptualizing and measuring economic resilience. In L. Briguglio, C. Cordina, & E. J. Kisanga (Eds.), *Building the economic resilience of small states* (265–287). Malta: Islands and Small States Institute; London: Commonwealth Secretariat.

Brooks, N., & Adger, W. N. (2005). Assessing and enhancing adaptive capacity. *Adaptation policy frameworks for climate change: Developing strategies* (pp. 165–181). Cambridge: Policies and Measures. Cambridge University Press.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra, 19*(4), 733–752.

Bruneau, M., & Reinhorn, A. M. (2007). Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra, 23*(1), 41–62.

Burkett, V. R. (2013). Coping capacity. In P. T. Bobrowsky (Ed.), *Encyclopedia of Natural Hazards* (pp. 119–121). Dordrecht, NL: Springer.

Çağnan, Z., Davidson, R. A., & Guikema, S. D. (2006). Post-earthquake restoration planning for Los Angeles electric power. *Earthquake Spectra, 22*(3), 589–608.

Carpenter, S., Walker, B., Anderies, J. M., & Abel, N. (2001). From metaphor to measurement: Resilience of what to what? *Ecosystems, 4*(8), 765–781.

Chan, R., & Schofer, J. L. (2016). Measuring transportation system resilience: Response of rail transit to weather disruptions. *Natural Hazards Review, 17*(1), 05015004.

Chan, Y. (2015). Network throughput and reliability: Preventing hazards and attacks through gaming—Part 2: A research agenda. In K. Hausken & J. Zhuang (Eds.), *Game theoretic analysis of congestion, safety and security: Networks, air traffic and emergency departments* (pp. 141–172). Cham, Switzerland: Springer.

Chang, L., Elnashai, A. S., Spencer, B. F., Song, J., & Ouyang, Y. (2010). *Transportations systems modeling and applications in earthquake engineering* (Report No. 10-03). Mid-America Earthquake Center.

Chang, S. E., & Nojima, N. (2001). Measuring post-disaster transportation system performance: The 1995 Kobe earthquake in comparative perspective. *Transportation Research Part A Policy and Practice, 35*(6), 475–494.

Chang, S. E., Shinozuka, M., & Moore, J. (2000). Probabilistic earthquake scenarios: Extending risk analysis methodologies to spatially distributed systems. *Earthquake Spectra, 16*(3), 557–572.

Chang, S. E., & Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. *Earthquake Spectra, 20*(3), 739–755.

Chang, S. E., McDaniels, T., Fox, J., Dhariwal, R., & Longstaff, H. (2013). Toward disaster-resilient cities: Characterizing resilience of infrastructure systems with expert judgements. *Risk Analysis, 34*(3), 416–434.

Chappell, B. (2017). Power outages persist for millions in Florida, Georgia and Carolinas after Irma, *NPR news*. Retrieved from http://www.npr.org/sections/thetwo-way/2017/09/13/550674848/power-outages-persist-for-millions-in-florida-georgia-and-carolinas-after-irma

Chen, L., & Miller-Hooks, E. (2012a). Resilience: An indicator of recovery capability in intermodal freight transport. *Transportation Science, 46*(1), 109–123.

Chen, L., & Miller-Hooks, E. (2012b). Optimal team deployment in urban search and rescue. *Transportation Research Part B: Methodological, 46*(8), 984–999.

Cheng, Y.-Y., Lee, R. K.-W., Lim, E.-P., & Zhu, F. (2015). Measuring centralities for transportation networks beyond structures. In P. Kazienko & N. Chawla (Eds.), *Applications of social media and social network analysis* (Lecture Notes in Social Networks) (pp. 23–39). Cham, Switzerland: Springer. doi:10.1007/978-3-319-19003-7_2

Chen, H., Cullinane, K., & Liu, N. (2017). Developing a model for measuring the resilience of a port-hinterland container transportation network. *Transportation Research Part E: Logistics and Transportation Review, 97*, 282–301.

Cho, H.-N., Choi, H.-H., & Kim, Y.-B. (2002). A risk assessment methodology for incorporating uncertainties using fuzzy concepts. *Reliability Engineering and System Safety, 78*(2), 173–183.

Choi, E., DesRoches, R., & Nielson, B. (2004). Seismic fragility of typical bridges in moderate seismic zones. *Engineering Structures, 26*(2), 187–199.

Choi, H. H., & Mahadevan, S. (2008). Construction project risk assessment using existing database and project-specific information. *Journal of Construction Engineering and Management, 134*(11), 894–903.

Christou, V., Bocchini, P., Miranda, M. J., & Karamlou, A. (2018). Effective sampling of spatially correlated intensity maps using hazard quantization: Application to seismic events. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 4*(1), 04017035,–13. doi:10.1061/AJRUA6.0000939

Cimellaro, G. P., Fumo, C., Reinhorn, A. M., & Bruneau, M. (2009). *Quantification of seismic resilience of health care facilities* (MCCER technical report –MCEER-09-2009). Buffalo, NY: Multidisciplinary center for earthquake engineering research.

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010). Framework for analytical quantification of disaster resilience. *Engineering Structures, 32*(11), 3639–3649.

Cimellaro, G. P., Renschler, C., Reinhom, A., & Arendt, L. (2016). PEOPLES: A framework for evaluating resilience. *Journal of Structural Engineering, 142*(10), 04016063. doi:10.1061/(ASCE)ST.1943-541X.0001514

Cimellaro, G. P., Solari, D., & Bruneau, M. (2014). Physical infrastructure interdependency and regional resilience index after the 2011 Tohoku Earthquake in Japan. *Earthquake Engineering and Structural Dynamics, 43*, 1763–1784.

Comes, T., & Van de Walle, B. (2014, May). Measuring disaster resilience: The impact of Hurricane Sandy on critical infrastructure systems. *Proceedings of the 11th International ISCRAM Conference*, University Park, PA, USA.

Cook, A., Blom, H. A. P., Lillo, F., Mantegna, R. N., Miccichè, S., Rivas, D., Vázquez, R., & Zanin, M. (2015). Applying complexity science to air traffic management. *Journal of Air Transport Management, 42*, 149–158.

Cox, A., Prager, F., & Rose, A. Z. (2009). *Transportation security and the role of resilience: A foundation for operational metrics* (CREATE Research Archive, Non-published Research Reports, Paper 77). Retrieved from http://research.create.usc.edu/cgi/viewcontent.cgi?article=1128&context=nonpublished_reports

Cox, A., Prager, F., & Rose, A. (2011). Transportation security and the role of resilience: A foundation for operational metrics. *Transport Policy, 18*, 307–317.

Croope, S., & McNeil, S. (2011). *Improving resilience of critical infrastructure systems postdisaster: Recovery and mitigation* (Transportation Research Record, 2234, pp. 3–13). Washington, DC: Transportation Research Board.

Croope, S. (2013). Improving transportation infrastructure system resilience using federal tools and customized models. *The 91th Annual Meeting of the Transportation Research Board*, Washington, DC. January 22–26, 2012.

Dall'Asta, L., Barrat, A., Barthelemy, M., & Vespingnani, A. (2006). Vulnerability of weighted networks. *Journal of Statistical Mechanics: Theory and Experiment*, P04006.

Data.Gov. (2016). *Roads*. Retrived from https://catalog.data.gov/dataset?tags=roads

Davis-McDaniel, C., Chowdhury, M., Pang, W., & Dey, K. (2013). Fault-tree model for risk assessment of bridge failure: Case study for segmental box girder bridges. *Journal of Infrastructure Systems, 19*, 326–334.

Decò, A., Bocchini, P., & Frangopol, D. M. (2013). A probabilistic approach for the prediction of seismic resilience of bridges. *Earthquake Engineering & Structural Dynamics, 42*, 1469–1487.

de Felice, G., & Giannini, R. (2010). An efficient approach for seismic fragility assessment with application to old reinforced concrete bridges. *Journal of Earthquake Engineering, 14*(2), 231–251.

de Weijer, K., & MaCandless, E. (2015). Capacity development and resilience. In H. Greijn, J. Hauck, T. Land, & J. Ubels (Eds.), *Capacity development beyond aid* (pp. 81–92). The Hague: SNV; Maastricht: ECDPM.

Dehghani, M. S., Flintsch, G., & McNeil, S. (2014). Impact of road conditions and disruption uncertainties on network

vulnerability. *Journal of Infrastructure Systems, 20*(3), 04014015.
Department of Homeland Security (DHS). (2008, September). *DHS risk lexicon*. Risk Steering Committee. Retrieved from https://www.dhs.gov/xlibrary/assets/dhs_risk_lexicon.pdf
Department of Homeland Security (DHS). (2011a). *Buildings and infrastructure protection series: Integrated rapid visual screening of mass transit stations, BIPS 02*. Retrieved from https://www.wbdg.org/FFC/DHS/bips_02.pdf
Department of Homeland Security (DHS). (2011b). *Buildings and Infrastructure protection series: Integrated rapid visual screening of tunnels, BIPS 03*. Retrieved from https://www.wbdg.org/FFC/DHS/bips_03.pdf
Department of Homeland Security (DHS). (2014a). *State disaster recovery planning guide*. Retrieved from http://coastalhazardscenter.org/dev/wp-content/uploads/2012/05/State-Disaster-Recovery-Planning-Guide_2012.pdf
Department of Homeland Security (DHS). (2014b). *Homeland security advanced research projects agency*. Retrieved from https://www.dhs.gov/science-and-technology/hsarpa
Department of Homeland Security (DHS). (2016). *Integrated rapid visual screening series (IRVS) software package*. Retrieved from https://www.dhs.gov/high-performance-and-integrated-design-resilience-program
Department of Homeland Security (DHS). (2017). *(U) Hurricane Irma: Infrastructure impact assessment South Florida: Transportation – 2030 EDT September 7, 2017*: National Protection and Programs Directorate, Office of Cyber and Infrastructure Analysis (OCIA).
Derrible, S., & Kennedy, C. (2010). The complexity and robustness of metro networks. *Physica A: Statistical Mechanics and its Applications, 389*, 3678–3691.
D'Este, G. M., Zito, R., & Taylor, M. A. P. (1999). Using GPS to measure traffic system performance. *Computer-Aided Civil and Infrastructure Engineering, 14*(4), 255–265.
Diestel, R. (2016). *Graph theory* (Springer Graduate Texts in Mathematics, 5th ed., Vol. 173, pp. 12). London: Springer-Verlag.
Di Muro, M. A., La Rocca, C. E., Stanley, H. E., Havlin, S., & Braunstein, L. A. (2016). Recovery of interdependent networks. *Science Report, 6*, 22834.
D'Lima, M., & Medda, F. (2015). A new measure of resilience: An approach to the London Underground. *Transportation Research Part A: Policy and Practice, 81*, 35–46.
Dojutrek, M. S., Labi, S., & Dietz, J. E. (2015). A fuzzy approach for assessing transportation infrastructure security. In F. Boulanger, D. Krob, G. Morel, & J.-C. Roussel (Eds.), *Proceedings of the Fifth International Conference on Complex Systems Design & Management* (pp. 207–224). doi:10.1007/978-3-319-11617-4_15
Dong, Y., & Frangopol, D. M. (2015a). Performance-based seismic assessment of conventional and base-isolated steel buildings include environmental impact and resilience. *Earthquake Engineering & Structural Dynamics, 45*(5), 739–756.
Dong, Y., & Frangopol, D. M. (2015b). Risk and resilience assessment of bridges under mainshock and aftershocks incorporating uncertainties. *Engineering Structures, 83*, 198–208.
Dong, Y., & Frangopol, D. M. (2016). Performance-based seismic assessment of conventional and base-isolated steel buildings including environmental impact and resilience. *Earthquake Engineering & Structural Dynamics, 45*, 739–756.
Dong, Y., & Frangopol, D. M. (2017). Probabilistic assessment of an interdependent healthcare-bridge network system under seismic hazard. *Structure and Infrastructure Engineering, 13*(1), 160–170.
Dottle, R., King, R., & Koeze, E. (2017). Hurricane Harvey's impact – And how it compares to other storms. *FiveThirtyEight*. Retrieved from https://fivethirtyeight.com/features/hurricane-harveys-impact-and-how-it-compares-to-other-storms/
Duan, M., Wu, D., Dong, B., & Zhang, L. (2016). Quantitatively measuring transportation network resilience under earthquake uncertainty and risks. *American Journal of Civil Engineering, 4*(4), 174–184.
Dudenhoeffer, D. D., Permann, M. R., & Manic, M. (2006). CIMS: A framework for infrastructure interdependency modeling and analysis. In L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, & R. M. Fujimoto (Eds.), *Proceeding of the 2006 Winter Simulation Conference* (pp. 478–485). Monterey, CA: Winter Simulation Conference.
Dueñas-Osorio, L., & Kwasinski, A. (2012). Quantification of lifeline system interdependencies after the 27 February 2010 M_w 8.8 Offshore Maule, Chile. *Earthquake Spectra, 28*, S581–S603.
Dunn, M., & Wigert, I. (2004). Critial Information Infrastructure Protection (CIIP). In A. Wegner & J. Metzger (Eds.), *International CIIP handbook 2004: An inventory and analysis of protection policies in fourteen countries* (pp. 345). Zürich, Switzerland: Swiss Federal Institute of Technology Zurich (ETH).
Ehlen, M. A., & Scholand, A. J. (2005, June 12–16). Modeling interdependencies between power and economic sectors using the N-ABLE™ agent-based model. IEEE Power Engineering Society General Meeting 2005 (pp. 2842–2846). San Francisco, CA: IEEE.
El Rashidy, R. A. H. (2014). *The resilience of road transportation networks: Redundancy, vulnerability and mobility characteristics* (Ph.D. dissertation). The University of Leeds.
Enjalbert, S., Vanderhaegen, F., Pichon, M., Ouedraogo, K. A., & Millot, P. (2011). Assessment of transportation system resilience. In P. C. Cacciabue, M. Hjälmdahl, A. Luedtke, & C. Riccioli (Eds.), *Human modelling in assisted transportation* (pp. 335–341). Milan: Springer. doi: 10.1007/978-88-470-1821-1_36
Ezell, B. C., Farr, J. V., & Wiese, I. (2000). Infrastructure risk analysis model. *Journal of Infrastructure Systems, 6*(3), 114–117.
Fantini, P., Cimellaro, G. P., & Mahin, S. A. (2014 December). "Measuring lifeline emergency response using temporal network models." *Proceedings of 15th U.S.-Japan workshop on the improvement of structural engineering and Resiliency, Applied Technology Council (ATC) and Japan Structural Consultants Association (JSCA),* Island of Hawai.
Federal highway Administration (FHWA) (2016). *National highway system*. Retrived from https://www.fhwa.dot.gov/planning/national_highway_system/

Faturechi, R. (2013). *Resilience of transportation infrastructure systems: Quantification and optimization* (Ph.D. dissertation). University of Maryland, College Park, MD.

Faturechi, R., & Miller-Hooks, E. (2014). Travel time resilience of roadway networks under disaster. *Transportation Research Part B: Methodological, 70*, 47–64.

Faturechi, R., & Miller-Hooks, E. (2015). Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review. *Journal of Infrastructure System, 21*(1), 0414025.

Federal Emergency Management Agency (FEMA). (2010). *Hazus MH MR5 technical manual*. Washington, DC: Author.

Federal Emergency Management Agency (FEMA). (2012). *Seismic performance assessment of buildings, Volume 2 – Implementation guide* (FEMA P58). Washington, DC: Author.

Federal Emergency Management Agency (FEMA). (2016a). *Mitigation Framework Leadership Group (MitFLG) draft concept paper: Draft interagency concept for community resilience indicators and national-level measures*. Retrieved from https://www.fema.gov/media-library/assets/documents/117607

Federal Emergency Management Agency (FEMA). (2016b). *HAZUS*. Retrieved from http://www.fema.gov/hazus

Ferreira, A., de Picado-Santos, L., Wu, Z., & Flintsch, G. (2011). Selection of pavement performance models for use in the Portuguese PMS. *International Journal of Pavement Engineering, 12*(1), 87–97.

Fotouhi, H., Moryadee, S., & Miller-Hooks, E. (2017). Quantifying the resilience of an urban traffic-electric power coupled system. *Reliability Engineering and System Safety, 163*, 79–94.

Francis, R. A., & Bekera, B. B. (2014). A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering System Safety, 121*, 90–103.

Frangopol, D. M., & Bocchini, P. (2011). *Resilience as optimization criterion for the rehabilitation of bridges belonging to a transportation network subject to earthquake*. SEI-ASCE 2011 Structures Congress, Las Vegas, NV, pp. 2044–2055.

Franchin, P., & Cavalieri, F. (2015). Probabilistic assessment of civil infrastructure resilience to earthquakes. *Computer-Aided Civil and Infrastructure Engineering, 30*, 583–600.

Freckleton, D., Heaslip, K., Louisell, W., & Collura, J. (2012, January 22–26). Evaluation of transportation network resiliency with consideration for disaster magnitude. *The 91th Transportation Research Board Annual Meeting*, Washington, DC.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry, 40*, 35–41.

Gallopín, G. C. (2006). Linkages between vulnerability, resilience, and adaptive capacity. *Global Environmental Change, 16*(3), 293–303.

Garbin, D. A., & Shortle, J. F. (2007). *Critical thinking: Moving from infrastructure protection to infrastructure resiliency* (Critical Infrastructure Protection Program. Discussion Paper Series). George Mason University. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=C359CF09E0E785A43C91C0A1871A9B4E?doi=10.1.1.169.9384&rep=rep1&type=pdf

Gardoni, P., & Murphy, C. (2008). Recovery from natural and man-made disasters as capabilities restoration and enhancement. *International Journal of Sustainable Development and Planning, 3*(4), 1–17.

Gardoni, P., & Murphy, C. (2010). Gauging the societal impacts of natural disasters using a capability approach. *Disasters, 34*(3), 619–636.

Gehl, P., Seyedi, D., Douglas, J., and Khiar, M. (2009, June). Introduction of fragility surfaces for a more accurate modeling of the seismic vulnerability of reinforced concrete structures. *COMPDYN 2009 – ECCOMAS Thematic Conference on Computational Methods in Structural Dynamics and Earthquake Engineering*, Greece. Paper # 228. <hal-005605523>

Gheorghe, A. V., Birchmeier, J., Vamanu, D., Papazoglou, I., & Kröger, W. (2005). Comprehensive risk assessment for rail transportation of dangerous goods: A validated platform for decision support. *Reliability Engineering & System Safety, 88*(3), 247–272.

Ghosh, J., & Padgett, J. E. (2010). Aging considerations in the development of time-dependent seismic fragility curves. *Journal of Structural Engineering, 136*(12), 1497–1511.

Ghosh, J. & Padgett, J. E. (2011). Probabilistic seismic loss assessment of aging bridges using a component-level cost estimation approach. *Earthquake Engineering & Structural Dynamics, 40*(15), 1743–1761.

Godschalk, D. R. (2003). Urban hazard mitigation: Creating resilient cities. *Natural Hazards Review, 4*(3), 136–143.

Goh, C. Y., Dauwel, J., Mitrovic, N., Asif, M. T., Oran, A., & Jaillet, P. (2012, September 16–19). Online map-matching based on Hidden Markov model for real-time traffic sensing applications. *15th International IEEE Conference on Intelligent Transportation Systems*, Anchorage, AK, USA, 776–781.

Gomez, C., Baker, J. W., Castiblanco, D., & Faber, M. H. (2015, May 6–9). Coupled pre- and post-disaster decisions in the context of infrastructure resilience. *8th International Forum on Engineering Decision Making*, Kyoto, Japan.

González, A. D., Dueñas-Osorio, L., Sánchez-Silva, M., & Medaglia, A. L. (2016). The interdependent network design problem for optimal infrastructure system restoration. *Journal of Computer-Aided Civil and Infrastructure Engineering, 31*(5), 334–350.

Goodchild, A., Jessup, E., McCormack, E., Andreoli, D., Rose, S., Ta, C., & Pitera, K. (2009). *Development and analysis of a GIS-based statewide freight data flow network* (Washington State Department of Transportation research report, WA-RD 730.1).

Gordon, P., Richardson, H. W., & Liao, Y. (1997). A note on travel speeds debate. *Transportation research part A: Policy and practice, 31*(3), 259–262.

Gordon, P., Moore, J. E., II, Park, J. Y., & Richardson, H. W. (2007). The economic impacts of a terrorist attack on the U.S. commercial aviation system. *Risk Analysis, 27*(3), 505–512.

Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., McAllister, T., & van de Lindt, J. (2016). Modeling the resilience of critical infrastructure: The role of network dependencies. *Sustainable and Resilient Infrastructure, 1*(3–4), 153–168.

Guidotti, R., Gardoni, P., & Chen, Y. (2017). Network reliability analysis with link and nodal weights and auxiliary nodes. *Structural Safety, 65*, 12–26.

Guikema, S. D. (2009). Natural disaster risk analysis for critical infrastructure systems: An approach based on statistical learning theory. *Reliability Engineering & System Safety, 94*(4), 855–860.

Gunderson, L. H., & Pritchard, L., Jr. (2002). *Resilience and the behavior of large-scale systems* (SCOPE Series, Vol. 60). Washington, DC: Island Press.

Gürcanli, G. E., & Müngen, U. (2009). An occupational safety risk analysis method at construction sites using fuzzy sets. *International Journal of Industrial Ergonomics, 39*(2), 371–387.

Haggett, P., & Chorley, R. (1969). *Network analysis in geography*. London: Edwald Arnold.

Haimes, Y. Y., Horowitz, B. M., Lambert, J. H., Santos, J. R., Lian, C., & Crowther, K. G. (2005a). Inoperability Input-output model for interdependent infrastructure sectors. I: Theory and methodology. *Journal of Infrastructure Systems, 11*(2), 67–79.

Haimes, Y. Y., Horowitz, B. M., Lambert, J. H., Santos, J. R., Crowther, K. G., & Lian, C. (2005b). Inoperability input-output model for interdependent infrastructure sectors. II: Case studies. *Journal of Infrastructure Systems, 11*(2), 80–92.

Hamad, K., & Kikuchi, S. (2002). Developing a measure of traffic congestion: Fuzzy inference approach. *Transportation Research Record: Journal of the Transportation Research Board, 1802*, 77–85.

Han, Y., & Davidson, R. A. (2012). Probabilistic seismic hazard analysis for spatially distributed infrastructure. *Earthquake Engineering & Structural Dynamics, 41*, 2141–2158.

Heaslip, K, Louisell, W., Collura, J., & Serulle, N. U. (2010, January 10–14). A sketch level method for assessing transportation network resiliency to natural disasters and man-made events. *The 89th Annual Meeting of the Transportation Research Board*, Washington, DC.

Holden, R., Val, D. V., Burkhard, R., & Nodwell, S. (2013). A network flow model for interdependent infrastructures at the local scale. *Safety Science, 53*, 51–60.

Holling, C. S. (1973). Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics, 4*(1), 1–23.

Holling, C. S. (1986). The resilience of terrestrial ecosystems: Local surprise and global change. In W. C. Clark & R. E. Munn (Eds.), *Sustainable development of the biosphere* (pp. 292–317). Cambridge: Cambridge University Press.

Horowitz, A. J. (1991). *Delay/volume relations for travel forecasting, based on the 1985 highway capacity manual* (FHWA report). Washington, DC.

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety, 145*, 47–61.

Hu, F., Yeung, C. H., Yang, S., Wang, W., & Zeng, A. (2016). Recovery of infrastructure networks after localised attacks. *Scientific Reports, 6*, 509.

Huang, H., & Zhang, D. (2016). Resilience analysis of shield tunnel lining under extreme surcharge: Characterization and field application. *Tunnelling and Underground Space Technology, 51*, 301–312.

Huynh, N., Cao, V. L., Wickramasuriya, R., Berryman, M. M., Perez, P., & Barthelemy, J. (2014, May 5–9). An agent based model for the simulation of transportation demand and transportation demand in a Sydney metropolitan area. In *Proceedings of the Eighth International Workshop on Agents in Traffic and Transportation*, Paris, France, pp. 1–7.

Hyun, K.-C., Min, S., Choi, H., Park, J., & Lee, I.-M. (2015). Risk analysis using fault-tree analysis (FTA) and analytic hierarchy process (AHP) applicable to shield TBM tunnels. *Tunnelling and Underground Space Technology, 49*, 121–129.

Ip, W. H., & Wang, D. W. (2011). Resilience and friability of transportation networks: Evaluation, analysis and optimization. *IEEE Systems Journal, 5*, 189–198.

Intergovernmental Panel on Climate Change (IPCC). (2014). Climate change 2014: Mitigation of climate change. *Contribution of Working Group III to the 5th Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press.

Jacques, C. C., McIntosh, J., Giovinazzi, S., Kirsch, T. D., Wilson, T., & Mitrani-Reiser, J. (2014). Resilience of the Canterbury Hospital System to the 2011 Christchurch earthquake. *Earthquake Spectra, 30*, 533–554.

Jayaram, N., & Baker, J. W. (2010). Efficient sampling and data reduction techniques for probabilistic seismic lifeline risk assessment. *Earthquake Engineering & Structural Dynamics, 39*, 1109–1131.

Jenelius, E., Peterson, T., & Mattsson, L. (2006). Importance and exposure in road network vulnerability analysis. *Transportation Research: Part A, 40*(1), 537–560.

Jia, G., Tabandeh, A., & Gardoni, P. (2017). Life-cycle analysis of engineering systems: Modeling deterioration, instantaneous reliability, and resilience. In P. Gardoni (Ed.), *Risk and reliability analysis: Theory and applications* (pp. 465–494). Cham, Switzerland: Springer.

Jordan, F. (2008). Predicting target selection by terrorists: A network analysis of the 2005 London underground attacks. *International Journal of Critical Infrastructures, 4*(1/2), 206–214.

Jeong, S. H., & Elnashai, A. S. (2007). Probabilistic fragility analysis parameterized by fundamental response quantities. *Engineering Structures, 29*(6), 1238–1251.

Jin, J. G., Tang, L., Sun, L., & Lee, D.-H. (2014). Enhancing metro network resilience via localized integration with bus services. *Transportation Research Part E: Logistics and Transportation Review, 63*, 17–30.

Johansson, J., & Hassel, H. (2010). An approach for modelling interdependent infrastructures in the context of vulnerability analysis. *Reliability Engineering and System Safety, 95*(12), 1335–1344.

Johansson, J., & Hassel, H. (2012). Chapter 6 Vulnerability analysis of interdependent technical infrastructures. In P. Hokstad, I. B. Utne, & J. Vatn (Eds.), *Risk and interdependencies in critical infrastructures: A guideline for analysis* (pp. 49-65). London, UK: Springer.

Johansen, C., Horney, J., & Tien, I. (2016). Metrics for evaluating and improving community resilience. *Journal of Infrastructure Systems, 23*(2), 04016032. doi:10.1061/(ASCE)IS.1943-555X.0000329

Julliard, R., Yun, P. J., & Rado, R. (2015). Robustness of transportation networks: The case of Madagascar's road network. *International Journal of Advancements in Research & Technology, 4*(5), 1–4.

Kansky, K. (1963). *Structure of transportation networks: Relationships between network geometry and regional*

characteristics (Doctoral dissertation). Chicago, IL: University of Chicago.
Karamlou, A., & Bocchini, P. (2015). Computation of bridge seismic fragility by large-scale simulation for probabilistic resilience analysis. *Earthquake Engineering & Structural Dynamics, 44*, 1959–1978.
Karamlou, A., & Bocchini, P. (2016a). Sequencing algorithm with multiple-input genetic operators: Application to disaster resilience. *Engineering Structures, 117*, 591–602.
Karamlou, A., & Bocchini, P. (2016b). From component damage to system-level probabilistic restoration function for damaged bridges. *Journal of Infrastructure Systems, 23*(3), 04016042.
Karamlou, A., & Bocchini, P. (2017). Functionality-fragility surfaces. *Earthquake Engineering & Structural Dynamics, 46*(10), 1687–1709.
Karamlou, A., Bocchini, P., & Christou, V. (2016, June 26–30). Metrics and algorithm for optimal retrofit strategy of resilient transportation networks. *The 8th International Conference on Bridge Maintenance, Safety and Management (IABMA 2016)*, Foz do Iguacu, Brazil.
Karamlou, A., Ma, L., Sun, W., & Bocchini, P. (2017). Generalized probabilistic restoration prediction, *12th Int. Conf. on Structural Safety and Reliability (ICOSSAR 2017)*, TU Wien, Vienna, Austria, #7247.
Kendra, J. M., & Wachtendorf, T. (2003). Elements of Resilience After the World Trade Center Disaster: Reconstituting New York City's Emergency Operations Centre. *Disasters, 27*(1), 37–53.
Kim, H., & Anderson, R. (2013). An experimental evaluation of robustness of networks. *IEEE Systems Journal, 7*(2), 179–188.
Kirwan, B., Gibson, W. H., & Hickling, B. (2008). Human error data collection as a precursor to the development of a human reliability assessment capability in air traffic management. *Reliability Engineering & System Safety, 93*(2), 217–233.
Kotzanikolaou, P., Theoharidou, M., & Gritzalis, D. (2013). Assessing n-order dependencies between critical infrastructures. *International Journal of Critical Infrastructures, 9*(1/2), 93–110.
Krishnamurthy, V., Kwasinski, A., & Dueñas-Osorio, L. (2016). Comparison of power and telecommunications dependencies and interdependencies in the 2011 Tohoku and 2010 Maule earthquakes. *Journal of Infrastructure Systems, 22*(3), 04016013.
Kwon, O.-S., & Elnashai, A. S. (2009). Fragility analysis of a highway over-crossing bridge with consideration of soil–structure interactions. *Structure and Infrastructure Engineering, 6*(1–2), 159–178.
Latora, V., & Marchiori, M. (2001). Efficient behavior of small-world networks. *Physical Review Letters, 87*(19), 440.
Latora, V., & Marchiori, M. (2002). Is the Boston subway a small-world network? *Physica A: Statistical Mechanics and its Applications, 314*, 109–113.
Latora, V., & Marchiori, M. (2004). How the science of complex networks can help developing strategies against terrorism. *Chaos, Solitons and Fractals, 20*, 69–75.
LeBeau, K. H., & Wadia-Fascetti, S. J. (2007). Fault tree analysis of schoharie creek bridge collapse. *Journal of Performance of Constructed Facilities, 21*(4), 320–326.
Lee, A., Vargo, J., & Seville, E. (2013). Developing a tool to measure and compare organizations' resilience. *Natural Hazards Review, 14*, 29–41.
Lee, S., Kim, J., Lee, S., & Chang-Richards, Y. (2014, May 20–22). Development of resilience index in transportation systems. *10th International Conference of the International Institute for Infrastructure Resilience and Reconstruction (I3R2)*, Purdue University, West Lafayette, IN, USA.
Lemoine, P. D., Cordovez, J. M., Zambrano, J. M., Sarmiento, O. L., Meisel, J. D., Valdivia, J. A., & Zarama, R. (2016). Using agent based modeling to assess the effect of increased Bus Rapid Transit system infrastructure on walking for transportation. *Preventive Medicine, 88*, 39–45.
Leontief, W. W. (1951). Input-output economics. *Scientific American, 185*, 15–21.
Leu, L., Abbass, H., & Curtis, N. (2010, September 29–October 1). Resilience of ground transportation networks: A case study on Melbourne. *The 33rd Australasian Transport Research Forum Conference*, Canberra.
Leviäkangas, P., Molarius, R., Könönen, V., Zulkarnain, Z., & Hietajärvi, A.-M. (2013). Devising and demonstrating an extreme weather risk indicator for use in transportation systems. *Transportation Research Record, Journal of the Transportation Research Board, 2329*, 45–53.
Leviäkangas, P., & Aapaoja, A. (2015). Resilience of transport infrastructure systems. *CSID Journal of Sustainable Infrastructure Development, 1*, 80–90.
Lhomme, S., Serre, D., Diab, Y., & Laganier, R. (2011). A methodology to produce interdependent networks disturbance scenarios. *Vulnerability, Uncertainty, and Risk: Analysis, Modeling, and Management,* 724–731.
Lhomme, S., Serre, D., Diab, Y., & Laganier, R. (2013). Analyzing resilience of urban networks: A preliminary step towards more flood resilient cities. *Natural Hazards and Earth System Science, 13*, 221–230.
Lian, C., & Haimes, Y. V. (2006). Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input–output model. *Systems Engineering, 9*(3), 241–258.
Lindley, J. A. (1987). Urban freeway congestion: Quantification of the problem and effectiveness of potential solutions. *ITE journal, 57*(1), 27–32.
Mabrouki, C., Bentaleb, F., & Mousrij, A. (2014). A decision support methodology for risk management within a port terminal. *Safety Science, 63*, 124–132.
Macababbad, R. J. R. M., & Regidor, J. R. F. (2011). A study on travel time and delay survey and traffic data analysis and visualization methodology. *Proceedings of the Eastern Asia Society for Transportation Studies*, 8. Retrieved from https://www.jstage.jst.go.jp/article/eastpro/2011/0/2011_0_318/_pdf
MacKenzie, C., & Barker, K. (2013). Empirical data and regression analysis for estimation of infrastructure resilience with application to electric power outages. *Journal of Infrastructure Systems, 19*, 25–35. doi:10.1061/(ASCE)IS.1943-555X.0000103
Mackie, K., & Stojadinovic, B. (2004, August 1–6). Fragility curves for reinforced concrete highway overpass bridges. *13th World Conference on Earthquake Engineering*, Vancouver, BC, Canada, Paper No. 1553.
Mackie, K. R., Wong, J.-M., & Stojadinovic, B. (2008). *Integrated probabilistic performance-based evaluation of benchmark reinforced concrete bridges*. Berkeley, CA: Pacific Earthquake Engineering Center.

MAECENTER. (2016). *Mid-America Earthquake Center seismic loss assessment system: MAEviz*. Retrieved from http://mae.cee.illinois.edu/software_and_tools/maeviz.html

Mendonça, D., & Wallace, W. (2006). Impacts of the 2001 World Trade Center attack on New York City critical infrastructures. *Journal of Infrastructure Systems, 12*(4), 260–270. doi:10.1061/(ASCE)1076-0342

Mileti, D. (1999). *Disasters by design: A reassessment of natural hazards in the United States (Natural Hazards and Disasters)*. Washington, DC: National Academy Press.

Miller-Hooks, E., Zhang, X., & Faturechi, R. (2012). Measuring and maximizing resilience of freight transportation networks. *Computers & Operations Research, 39*(7), 1633–1643.

Mishra, S., Welch, T. F., & Jha, M. K. (2012). Performance indicators for public transit connectivity in multi-modal transportation networks. *Transportation Research Part A: Policy and Practice, 46*(7), 1066–1085.

Mohmand, Y. T., & Wang, A. (2013). Weighted complex network analysis of Pakistan highways. *Discrete Dynamics in Nature and Society*. *2013*, Article ID: 862612.

Molarius, R., Könönen, V., Leviäkangas, P., Zulkarnain, J., Rönty, J., & Hietajärvi, A.-M. (2014). The extreme weather risk indicators (EWRI) for the European transport system. *Natural Hazards, 72*(1), 189–210.

Murray-Tuite, P. M., & Mahmassani, H. (2004). Methodology for determining vulnerable links in a transportation network. *Transportation Research Record: Journal of the Transportation Research Board, 1882*, 88–96.

Morlok, E. K., & Chang, D. J. (2004). Measuring capacity flexibility of a transportation system. *Transportation Research Part A, 38*, 405–420.

Murray-Tuite, P. M. (2006). A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions. In L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, & R. M. Fujimoto (Eds.), *Proceedings of the 2006 Winter Simulation Conference* (pp. 1398–1405). Monterey, CA: Winter Simulation Conference.

Murray-Tuite, P. M. (2010). Bayesian analysis for transportation risk. M. Bell, S. H. Hosseinloo, & U. Kanturska (Eds.), *Security and environmental sustainability of multimodal transport: Proc. of NATO Advanced Research Workshop on Security and Environmental Sustainability of Multimodal Transport*. Springer, Netherland.

Nagurney, A., & Qaing, Q. (2007, May 4–7). A transportation network efficiency measure that captures flows, behaviors, and costs with applications to network component importance identification and vulnerability. *Proceedings of the POMS 18th Annual Conference*, Dallas, TX, USA. Retrieved from https://supernet.isenberg.umass.edu/articles/POMS2007NagurneyQiang.pdf

Nair, R., Avetisyan, H., & Miller-Hooks, E. (2010). Resilience framework for ports and other intermodal components. *Transportation Research Record: Journal of the Transportation Research Board, 2166*, 54–65.

Nan, C., & Sansavini, G. (2017). A quantitative method for assessing resilience of interdependent infrastructures. *Reliability Engineering and System Safety, 157*, 35–53.

National Institute of Building Sciences (NIBS) (2004). *HAZUS-MH: Users' manual and technical manuals*. Report prepared for the Federal Emergency Management Agency, Washington, DC.

National Institute of Standard and Technology (NIST). (2013). *NIST Technical Note 1795: Developing guidelines and standards for disaster resilience of the built environment: A research needs assessment*. doi:10.6028/NIST.TN.1795&gt

National Institute of Standard and Technology (NIST). (2016a). *Community resilience planning guide for buildings and infrastructure systems* (NIST Special Publication 1190). Retrieved from https://doi.org/10.6028/NIST.SP.1190v1

National Institute of Standard and Technology (NIST). (2016b). *Community resilience planning guide for buildings and infrastructure systems* (NIST Special Publication 1190). Retrieved from https://doi.org/10.6028/NIST.SP.1190v2

Nielson, B. G., & DesRoches, R. (2007). Seismic fragility methodology for highway bridges using a component level approach. *Earthquake Engineering & Structural Dynamics, 36*(6), 823–839.

National Oceanic and Atomspheric Administration (NOAA). (2015). *Inundation mapping interface*. Retrieved from http://water.weather.gov/ahps/inundation.php

National Research Council (NRC). (2011). *National earthquake resilience: Research, implementation, and outreach*. Washington, DC: The National Academies Press.

Office of Cyber and Infrastructure Analysis (OCIA). (2017). Executive summarity: OCIA Hurricane Irma Products. *Critical Infrastructure Security and Resilience Note*. Department of Homeland Security. Retrieved from https://www.aba.com/Tools/Function/Fraud/Documents/irma-dhs-ocia-hurricane-products.pdf

Omer, M. (2013). *The resilience of networked infrastructure systems: Analysis and measurement*. Singapore, Singapore: World Scientific.

Omer, M., Mostashari, A., & Nilchiani, R. (2011). Measuring the resiliency of the Manhattan points of entry in the face of severe disruption. *American Journal of Engineering and Applied Sciences, 4*(1), 153–161.

Omer, M., Mostashari, A., & Nilchiani, R. (2013). Assessing resilience in a regional road-based transportation network. *International Journal of Industrial and System Engineering, 13*(4), 389–408. doi:10.1504/IJISE.2013.052605

O'Reilly, G. P., Jrad, A., Kelic, A., & LeClaire, R. (2007). Telecom critical infrastructure simulations: Discrete event simulation vs. dynamic simulation how do they compare? *Proceedings of the IEEE Global Telecommunications Conference*, Washington, DC, p. 2597–2601.

O'Rourke, T. D. (2007). Critical infrastructure, interdependencies, and resilience. *Engineering for the Threat of Natural Disasters, 37*(1), 22–29.

Osei-Asamoah, A., & Lownes, N. (2014). Complex network method of evaluating resilience in surface transportation networks. *Transportation Research Record: Journal of the Transportation Research Board, 2467*, 120–128.

Oswald, M., McNeil, S., Ames, D., & Gayley, R. (2013). Identifying resiliency performance measures for megaregional planning: A case study of the Boswash transportation corridor. *The 92th Annual Meeting of the Transportation Research Board*, Washington, DC.

Oswald, M., & Treat, C. (2013). Assessing public transportation vulnerability to sea level rise: A case study application. *Journal of Public Transportation, 16*(3), 59–77.

Outkin, A., Flaim, S., Seirp, A., & Gavrilov, J. (2008). FinSim: A framework for modeling financial system interdependencies.

In Y. Shan & A. Yang (Eds.), *Applications of complex adaptive systems* (pp. 257–277). London: IGI Global
Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety, 121*, 43–60.
Ouyang, M., & Dueñas-Osorio, L. (2011). Efficient approach to compute generalized interdependent effects between infrastructure systems. *Journal of Computing in Civil Engineering, 25*(5), 394–406.
Ouyang, M., Dueñas-Osorio, L., & Min, X. (2012). A three-stage resilience analysis framework for urban infrastructure systems. *Structural Safety, 36–37*, 23–31.
Ouyang, M., & Wang, Z. (2015). Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis. *Reliability Engineering & System Safety, 141*, 74–82.
Padgett, J. (2007). *Vulnerability assessment of retrofitted bridges using probabilistic methods* (PhD thesis). Georgia Institute of Technology, Atlanta, GA.
Padgett, J. E., & DesRoches, R. (2007). Sensitivity of seismic response and fragility to parameter uncertainty. *Journal of Structural Engineering, 133*(12), 1710–1718.
Pant, S. B. (2012). *Transportation network resiliency: A study of self-annealing* (Ph.D. dissertation). Utah State University, All Graduate Theses and Dissertations. Paper 1434. Retrieved from http://digitalcommons.usu.edu/etd/1434
Pant, R., Barker, K., & Zobel, C. W. (2014). Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. *Reliability Engineering & System Safety, 125*, 90–102.
Parthasarathi, P., Levinson, D., & Hochmair, H. (2013). Network structure and travel time perception. *PLoS ONE, 8*(10), e77718.
Perrault, M., Gueguen, P., Aldea, A., & Demetriu, S. (2013). Using experimental data to reduce the single-building sigma of fragility curves: Case study of the BRD tower in Bucharest, Romania. *Earthquake Engineering and Engineering Vibration, 12*, 643–658.
Pimm, S. L. (1991). *The balance of nature? Ecological issues in the conservation of species and communities*. Chicago, IL: University Of Chicago Press.
Pinnaka, S., Yarlagadda, R., & Centinkaya, E. K. (2015, March 24–27). Modelling robustness of critical infrastructure networks. *The 11th International Conference on the Design of Reliable Communication Networks (DRCN)*, Kansas City, KS, USA, pp. 95–98.
Pinto, A., Ribeiro, R. A., & Nunes, I. L. (2012). Fuzzy approach for reducing subjectivity in estimating occupational accident severity. *Accident Analysis and Prevention, 45*, 281–290.
Pitilakis, K. (2011). *D2.9 State-of-the-art literature review of methodologies to assess the vulnerability of a "system of systems"* (SYNER-G 244061).
Pitilakis, K., Crowley, H., & Kaynia, A. M. (2013a). SYNER-G: Typology definition and fragility functions for physical elements at seismic risk. *The series Geotechnical, Geological and Earthquake Engineering, 27*, 47–93.
Pitilakis, K., Crowley, H., & Kaynia, A. M. (2013b). Introduction. In K. Pitilakis, P. Franchin, B. Khazai, & H. Wenzel (Eds.), *SYNER-G: Systemic seismic vulnerability and risk assessment of complex urban, utility, lifeline systems and critical facilities: Methodology and applications* (pp. 1–21). Dordrecht, Netherlands: Springer.
PPD-21. (2013, February 12). *Presidential policy directive/ PPD-21 – Critical infrastructure security and resilience*. Washington, DC: The White House. Retrieved from https://www.dhs.gov/sites/default/files/publications/ISC-PPD-21-Implementation-White-Paper-2015-508.pdf
Ramachandran, V., Long, S. K., Shoberg, T., Corns, S. M., & Carlo, H. J. (2016). Post-disaster supply chain interdependent critical infrastructure system restoration: A review of data necessary and available for modeling. *Data Science Journal, 15*(1), 1–13. doi:10.5334/dsj-2016-001
Reed, D. A., Kapur, K. C., & Christie, R. D. (2009). Methodology for assessing the resilience of networked infrastructure. *IEEE Systems Journal, 3*(2), 174–180.
Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. (2001). Identifying, understanding and analyzing critical infrastructure interdependencies. *IEEE Control Systems Magazine, 21*(6), 11–25.
Rokneddin, K., Ghosh, J., Dueñas-Osorio, L., & Padgett, J. E. (2013). Bridge retrofit prioritisation for ageing transportation networks subject to seismic hazards. *Structure and Infrastructure Engineering, 9*(10), 1050–1066.
Rose, A. (2004a). Economic principles, issues, and research priorities of natural hazard loss estimation. In Y. Okuyama & S. Chang (Eds.), *Modeling of spatial economic impacts of natural hazards* (pp. 13–39). Heidelberg: Springer.
Rose, A. (2004b). Defining and measuring economic resilience to disasters. *Disaster Prevention and Management: An International Journal, 13*, 307–314.
Rose, A., & Liao, S. Y. (2005). Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions. *Journal of Regional Science, 45*(1), 75–112.
Rose, A. (2007). Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. *Environmental Hazards, 7*(4), 383–398.
Rose, A. (2009). *Economic resilience to disasters*. Published Articles & Papers. Paper 75. Retrieved from http://create.usc.edu/sites/default/files/publications/economicresiliencetodisasters_2.pdf
Rose, A., & Krausmann, E. (2013). An economic framework for the development of a resilience index for business recovery. *International Journal of Disaster Risk Reduction, 5*, 73–83.
Santos, J. R. (2006). Inoperability input-output modeling of disruptions to interdependent economic systems. *Systems Engineering, 9*(1), 20–34.
Santos, J., Pagsuyoin, S., Herrera, L., Tan, R., & Yu, K. (2014). Analysis of drought risk management strategies using dynamic –inoperability input–output modeling and event tree analysis. *Environment Systems and Decisions, 34*, 492–506. doi:10.1007/s10669-014-9514-5
Schintler, L. A., Kulkarni, R., Gorman, S., & Stough, R. (2007). Using raster-based GIS and graph theory to analyze complex networks. *Networks and Spatial Economics, 7*(4), 301–313.
Schoon, M. (2005). A short historical overview of the concepts of resilience, vulnerability, and adaptation. *Workshop in Political Theory and Policy Analysis, W05–4*, Indiana University, Retrived from https://michaelschoon.files.wordpress.com/2011/05/historical_critique-of-resilience-workingpaper.pdf.
Schrank, D., & Lomax, T. (1997). *Urban roadway congestion: 1982–1994, Volume 1 &2* (Research Report 1131–9). Texas Transportation Institute.

Schrank, D., Turner, S., & Lomax, T. (1990). *Estimation of urban roadway congestion in major urban areas: 1982–1987* (Research Report 1131-2). Texas Transportation Institute.

Selva, J., & Argyroudis, S. (2013). Impact on loss/risk assessments of inter-model variability in vulnerability analysis. *Natural Hazards, 67*(2), 723–746.

Selva, J., & Sandri, L. (2013). Probabilistic seismic hazard assessment: combining cornell-like approaches and data at sites through bayesian inference. *Bulletin of the Seismological Society of America, 103*(3), 1709–1722.

Sempier, T. T., Swann, D. L., Emmer, R., and Schneider, M. (2010). Coastal community resilience index: A community self-assessment. *MASGP-08-14*. Retrieved from https://toolkit.climate.gov/tool/coastal-resilience-index

Serulle, N. U. (2010). *Transportation network resiliency: A fuzzy systems approach* (All Graduate Theses and Dissertations, Paper 769, Utah State University). Retrieved from http://digitalcommons.usu.edu/etd/769

Serulle, N. U., Heaslip, K., Brady, B., Louisell, W. C., & Collura, J. (2011). Resiliency of transportation network of Santo Domingo, Dominican Republic: Case study. *Transportation Research Record: Journal of the Transportation Research Board, 2234*, 22–30.

Setola, R., De Porcellinis, S., & Sforna, M. (2009). Critical infrastructure dependency assessment using the input–output inoperability model. *International Journal of Critical Infrastructure Protection, 2*, 170–178.

Shah, S. S., & Babiceanu, R. F. (2015). Resilience modeling and analysis of interdependent infrastructure systems. *IEEE Systems and Information Engineering Design Symposium*, Charlottesville, VA: IEEE, 15202155.

Sharkey, T. C., Nurre, S. G., Nguyen, H., Chow, J. H., Mitchell, J. E., & Wallace, W. A. (2015). Identification and classification of restoration interdependencies in the wake of Hurricane Sandy. *Journal of Infrastructure Systems, 22*(1), 04015007.

Sheridan, T. B. (2008). Risk, human error, and system resilience: Fundamental ideas. *Psychology, 50*(3), 418–426.

Shimizu, H., Moritou, Y., & Kobayashi, M. (2010, August 18–21). An estimation of link travel time in urban road networks. *Proceedings of SICE Annual Conference 2010*, Taipei, Taiwan, pp. 2901–2905.

Shinozuka, M., Murachi, Y., Dong, X., Zhou, Y., & Orlikowski, M. J. (2003). Effect of seismic retrofit of bridges on transportation networks. *Earthquake Engineering and Engineering Vibration, 2*(2), 169–179.

Spizziri, L. (2011). *Justification and application of eigenvector centrality*. Retrieved from https://www.math.washington.edu/~morrow/336_11/papers/leo.pdf

Stanton, N. A., Harris, D., Salmon, P. M., Demagalski, J. M., Marshall, A., Young, M. S., Dekker, S. W. A., & Waldmann, T. (2006). Predicting design induced pilot error using HET (human error template) – A new formal human error identification method for flight decks. *The Aeronautical Journal, 110*(1104), 107–115.

Sudakov, B., & Vu, V. H. (2008). Local resilience of graphs. *Random Structures and Algorithms, 33*, 409–433.

Sultana, S., & Chen, Z. (2009). Modeling flood induced interdependencies among hydroelectricity generating infrastructures. *Journal of Environmental Management, 90*(11), 3272–3282.

Sun, D., & Guan, S. (2016). Measuring vulnerability of urban metro network from line operation perspective. *Transportation Research Part A: Policy and Practice, 94*, 348–359.

Svendsen, N. K., & Wolthusen, S. D. (2005). Graph models of critical infrastructure interdependencies. In A. K. Bandara & M. Burgess (Ed.), *Inter-domain management. First International Conference on Autonomous Infrastructure, Management and Security*. Oslo, Norway, June 21–22, 2007.

Tahmasebi, E. (2016). *Damage analysis of steel concentrically braced frame systems under seismic conditions* (Ph.D. dissertation, Lehigh University).

Tampère, C., Stada, J., & Immers, B. (2007). Methodology for identifying vulnerable sections in a national road network. *Transportation Research Record: Journal of the Transportation Research Board, 2012*, 1–10.

Tatano, H., & Tsuchiya, S. (2008). A framework for economic loss estimation due to seismic transportation network disruption; a spatial computable general equilibrium approach. *Natural Hazards, 44*(2), 253–265.

Taylor, M. A. P. (1992). Exploring the nature of urban traffic congestion: Concepts, parameters, theories and models. *Proceedings of 16th Australian Road Research Board Conference*, 16(5), pp. 83–105. Perth: ARRB.

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

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

The Lifeline Council (TLC). (2014). *Lifelines interdependency study* (The City and County of San Francisco).

The White House. (2014). *An economic analysis of transportation infrastructure investment*. Retrieved from https://obamawhitehouse.archives.gov/sites/default/files/docs/economic_analysis_of_transportation_investments.pdf

Tierney, K., & Bruneau, M. (2007, May–June). Conceptualizing and measuring resilience: A key to disaster loss reduction. *TR News*, 250.

Titi, A., & Biondini, F. (2013). Resilience of concrete frame structures under corrosion. In G. Deodatis, B. R. Ellingwood, & M. Frangopol (Eds.), *Safety, reliability, risk and life-cycle performance of structures and infrastructures* (pp. 597–604). London: Taylor & Francis Group.

TRansportation ANalysis and SIMulation System (TRANSIMS). (2016). Retrieved from https://www.fhwa.dot.gov/planning/tmip/resources/transims/

Trucco, P., Minato, N., & Careri, N. (2013, December 10–13). Resilience of transport systems under disaster: Simulation-based analysis of 2011 tsunami in Japan. *2013 IEEE International Conference on Industrial Engineering and Engineering Management*, pp. 487–491.

Tsionis, G., & Fardis, M. N. (2013). Fragility functions of road and railway bridges. In K. Pitilakis, P. Franchin, B. Khazai, & H. Wenzel (Eds.), *SYNER-G: Systemic seismic vulnerability and risk assessment of complex urban, utility, lifeline systems and critical facilities: methodology and applications*. Springer.

Tu, Y., Yang, C., & Chen, X. (2012). Road network topology vulnerability analysis and application. *Proceedings of the Institution of Civil Engineers, 166*(2), 95–104.

United States Department of Commerce (USDOC). (2013). *Economic impact of Hurricane Sandy: Potential economic activity lost and gained in New Jersey and New York*.

Economics and Statistics Administration Office of the Chief Economist. Retrieved from http://www.esa.doc.gov/sites/default/files/sandyfinal101713.pdf

United States Department of Transportation (USDOT). (2016). *National transportation statistics*: Bureau of Transportation Statistics. Retrieved from http://www.bts.gov/publications/national_transportation_statistics/

Utne, I. B., Hokstad, P., & Vatn, J. (2011). A method for risk modeling of interdependencies in critical infrastructures. *Reliability Engineering & System Safety, 96*(6), 671–678.

Volkanovski, A., Čepin, M., & Mavko, B. (2009). Application of the fault tree analysis for assessment of power system reliability. *Reliability Engineering and System Safety, 94*, 1116–1127.

Voltes-Dorta, A., Rodríguez-Déniz, H., & Suau-Sanchez, P. (2017). Passenger recovery after an airport closure at tourist destinations: A case study of Palma de Mallorca airport. *Tourism Management, 59*, 449–466.

Vugrin, E. D., Warren, D. E., Ehlen, M. A., & Camphouse, R. C. (2010). A framework for assessing the resilience of infrastructure and economic systems. In K. Gopalakrishnan & S. Peeta (Eds.), *Sustainable and resilient critical infrastructure systems* (pp. 77–116). Berlin Heidelberg: Springer.

Vugrin, E. D., Warren, D. E., & Ehlen, M. A. (2011). A resilience assessment framework for infrastructure and economic systems: Quantitative and qualitative resilience analysis of petrochemical supply chains to a hurricane. *Process Safety Progress, 30*, 280–290.

Vugrin, E. D., Verzi, S. J., Finley, P. D., Turnquist, M. A., Griffin, A. R., Ricci, K. A., & Wyte-Lake, T. (2015). Modeling hospitals' adaptive capacity during a loss of infrastructure services. *Journal of Healthcare Engineering, 6*(1), 85–120.

Wang, F., Ding, L., Luo, H., & Love, P. E. D. (2014). Probabilistic risk assessment of tunneling-induced damage to existing properties. *Expert Systems with Applications, 41*(4), 951–961.

Wang, H., Hernandez, J. M., & Van Mieghem, P. V. (2008). Betweenness centrality in a weighted network. *Physical Review E, 77*, 046105.

Wang, Jiaoe, Mo, H., Wang, F., & Jin, F. (2011). Exploring the network structure and nodal centrality of China's air transport network: A complex network approach. *Journal of Transport Geography, 19*(4), 712–721.

Wang, Y., & Elhag, T. (2007). A fuzzy group decision making approach for bridge risk assessment. *Computers & Industrial Engineering, 53*(1), 137–148.

Wang, Z., Dueñas-Osorio, L., & Padgett, J. E. (2015). A new mutually reinforcing network node and link ranking algorithm. *Scientific Reports, 5*, 39.

Werner, S. D., Taylor, C. E., Cho, S., Lavoie, J.-P., Huyck, C. K., Eitzel, C., Eguchi, R. T., & Moore, J. E., II (2005). New developments in seismic risk analysis of highway systems. In M. Bruneau (Ed.) *Research Progress and Accomplishments 2003–2004* (pp. 221–238). Buffalo, NY: Multidisciplinary Center for Earthquake Engineering Research (MCEER).

Woods, D., & Wreathall, J. (2003). *Managing risk proactively: The emergence of resilience engineering* (p. 2003). Columbus, GA: Ohio University.

Xu, X., Chen, A., Jansuwan, S., & Heaslip, K. (2012, January 22–26). Road network redundancy measures: Route diversity and network spare capacity. *The 91st Annual Meeting of the Transportation Research Board*, Washington, DC.

Xu, X., Chen, A., Jansuwan, S., & Heaslip, K. (2015). Modeling transportation network redundancy. *Transportation Research Procedia, 9*, 283–302.

Zhang, L., Chiaradia, A., & Zhuang, Y. (2014). Chapter 13 A configurational accessibility study of road and metro network in Shanghai, China. In Q. Pan & J. Cao (Eds.), *Recent developments in Chinese urban planning. 8th International Association for China Planning Conference* (pp. 219–245). Guangzhou, China.

Zhang, P., & Peeta, S. (2011). A generalized modeling framework to analyze interdependencies among infrastructure systems. *Transportation Research Part B: Methodological, 45*(3), 553–579.

Zhang, P., Peeta, S., & Friesz, T. (2005). Dynamic game theoretic model of multi-layer infrastructure networks. *Networks and Spatial Economics, 5*, 147–178.

Zhang, D., Centinkaya, E. K., & Sterbenz, J. P. G. (2013, September 10–12). Robustness of mobile ad hoc networks under centrality-based attacks. *The 5th International Workshops on Reliable Networks Design and Modeling*, Almaty, AZ, pp. 229 –435.

Zhang, X., & Miller-Hooks, E. (2015). Scheduling short-term recovery activities to maximize transportation network resilience. *Journal of Computing in Civil Engineering, 29*(6), 04014087.

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.

Zhang, W., Wang, N., & Nicholson, C. (2017). Resilience-based post-disaster recovery strategies for road-bridge networks. *Structural and Infrastructure Engineering, 13*(11), 1404–1413. doi:10.1080/15732479.2016.1271813

Zhou, H., Wang, J., Wan, J., & Jia, H. (2010a). Resilience to natural hazards: A geographic perspective. *Natural Hazards, 53*(1), 21–41.

Zhou, Y., Banerjee, S., & Shinozuka, M. (2010b). Socio-economic effect of seismic retrofit of bridges for highway transportation networks: A pilot study. *Structure and Infrastructure Engineering, 6*, 145–157.

Zimmerman R. (2004). Decision-making and the vulnerability of interdependent critical infrastructure. *Proceedings of the 2004 IEEE International Conference on Systems, Man and Cybernetics*, pp. 4059–4063. Hague, Netherlands: IEEE.

Zio, E., & Ferrario, E. (2013). A framework for the system-of-systems analysis of the risk for a safety-critical plant exposed to external events. *Reliability Engineering and System Safety, 114*, 114–125.

Zoumpoulaki, A., Avradinis, N., & Vosinakis, S. (2010). A multi-agent simulation framework for emergency evacuation incorporating personality and emotions. In S. Konstantopoulos S. Perantonis, V. Karkaletsis, C. D. Spyropoulos, & G. Vouros (Eds.) *Artificial Intelligence: Theories, Models and Applications* (Volume 6040 of the series Lecture Notes in Computer Science, pp. 423–426). Greece: SETN2010.