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A review of rail transport system vulnerability analysis: past progress and future directions

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ABSTRACT: Analysis of the vulnerability of rail transport systems has received considerable attention in the literature over several decades. Since economic development is usually associated with increasing demand for railway transport as more and more passengers rely on railways, the consequence of disruptions to the railway system becomes unaffordable and creates significant impact on society and economies. Hence, there is a growing need for accurate estimations of the vulnerability of railway transport and for effective mitigation strategies. This paper aims to synthesize recent studies in vulnerability analysis of rail transport systems in terms of the definitions, theoretical basis, and methodology they apply through a systematic review of the literature. Several theories are introduced, and widely used approaches are categorized and demonstrated as well. The result shows that approximately one-third of studies chose to apply topological approaches, and a growing number of studies have begun to use complex networks theory. However, the findings also show that the link between research in the context of vulnerability analysis and risk analysis is weak, and practice-oriented studies are limited; this is identified as an area for future work. Overall, this review paper provides a comprehensive insight into the state-of-the-art in vulnerability analysis of rail transport systems, drawing on both research and practice and offers a guide for future studies.

KEY WORDS: ***railway, vulnerability, rail accident, disruption, resilience***

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1. Introduction

The railway network plays an essential role in the development of the economic system, such as commuting, entertainment, and tourism, with the movement of freight and lighter goods relying on a stable railway network. The demand for railway transport generally increases in line with economic development resulting in an expansion of the network. As part of a complex multi-modal transport network, the flexibility of a rail transport system can decrease while the complexity of the whole transport network is increasing, which makes it vulnerable to deal with unexpected events. For instance, the failure of a power system would result in partial or even complete suspension of the whole railway network. The temporary closure of lines or stations creates significant unsatisfied demand with the adverse effects often spreading to the whole transport network (Khademi et al., 2018).

Whilst the burden from a growing economic system on its railway network is increasing, and the cost of new railway infrastructure becomes an unaffordable choice for many Governments, the question of how to increase the stability of the existing network with limited resources has become a significant issue. To capture the impact after a disruption (such as a service suspended due to the autumn leaves) or a disturbance (such as a delay due to variations in the operation), two terms are widely discussed in disruption research: *vulnerability* and *resilience*. Previous studies usually interpret the concept of vulnerability and resilience as two sides of the same coin (Bates et al., 2014; Mattsson and Jenelius, 2015; Reggiani et al., 2015). The connotation of *vulnerability* in the context of transportation links to the reduction of capacity caused by a disruptive event, which can be estimated by any quantifiable metrics, such as total delay to passengers or the number of canceled trains. On the other hand, *resilience* is concerned with the recovery of a system or the impact a system can absorb while facing a disruption. Although some might argue that it is oversimplified to treat vulnerability as the other side of resilience (see Seeliger and Turok, 2013), such segmentation has become the mainstream.

Despite the motivation of most vulnerability studies is either to reduce the losses during disruptions or to increase performance during or after disruptions, the relationship between the nature of disruptions and vulnerability is still unclear. In other words, although previous studies have identified several measures to estimate either the consequence of disruptions or the allocation of resources before, during, and after a disruption, the sequences of a disruptive event have not been fully revealed due to the lack of data. Nevertheless, rail transport has been recognized as a system with two special characteristics: "linear interactions" and "tight coupling" (Shrivastava et al., 2009). The "linear interactions" refers to the fact that the sequences of events in an accident tend to be foreseeable and in familiar sequences according to previous accidents, and the "tight coupling" means the variability of the results between two identical processes is minor, the time lag between the execution and result is short (Perrow, 1984). The abovementioned characteristics imply that accidents in a rail transport system usually contain sequential events, and each component in such a system is interdependent due to the connection among them (Perrow, 1984; Rausand, 2013). Given such system characteristics, it has been proven that the interaction between disruptive events and components is critical; however, only limited research is devoted to discovering how and why a railway accident happened. More explicitly, more emphasis should be placed on analyzing the causes of railway accidents and the causality between hazard factors given rail transport has been proven as a linear interactions system. Such a knowledge gap might place operators at a disadvantage in terms of managing disruptions and their impact.

There are a considerable number of review papers in this context, which discuss, for example, the agenda of approaches to evaluating resilience in railway transport systems (Bešinović, 2020), the methodological insights (Zhou et al., 2019), and the relationship between vulnerability, resilience, and the connectivity (Reggiani et al., 2015). However, the analysis of the vulnerability of railway disruptions is seldom reviewed. Additionally, the definitions of elements in this context are not clearly integrated. To fill the research gap, this paper aims to not only provide a clear definition of terminology and a comprehensive literature review, but also indicate directions for further research.

To present a review of current literature addressing rail transport system vulnerability analysis, this paper is organized as follows: firstly, the review methodology is introduced (section 2). Secondly, we give a brief historical context of vulnerability in the field of transportation research (section 3). Thirdly, a review of theories in the context of vulnerability analysis is illustrated from the literature (section 4). Approaches used in the context of railway vulnerability analysis are highlighted in this section. Next, we concentrate on the empirical and methodological insights in the literature (section 5). Lastly, the outcomes of the literature review are synthesized for discussion; several gaps are identified and suggestions are made for future studies (section 6).

2. Literature review methodology

The review process in this paper adopts the method used by Bešinović (2020), which begins with a target paper, uses the related keywords to search online corpora, and remove unrelated papers through reading the titles, abstracts and full texts step by step. However, this approach has some limitations in our review due to covering multiple topics. Therefore, several combinations of keywords are applied when searching databases. Only peer-reviewed academic papers published in the last 20 years are considered, and the procedure of selecting papers consists of three steps: (1.) searching the selected online databases with the combinations of the keywords, (2.) manually checking the titles, abstracts, and keywords, removing the non-vulnerability related papers, and (3.) final refining and analyzing. The review process was conducted on two popular academic research paper databases: Web of Science (Core Collection) and Scopus.

To identify relevant papers, we searched the keywords 'Rail*', 'transport', and 'vulnerability' in the title, 72 and 63 papers were retrieved from Web of Science and Scopus respectively. The titles, keywords, and abstracts of retrieved papers were manually screened, some non-vulnerability, network without considering rail transport, and non-rail related papers were removed. Finally, 74 papers were chosen after the removal of duplicated papers.

The distribution of papers in the field of rail transport vulnerability by year of publication is shown in Figure 1. The number of published papers increases dramatically after 2015. Table 1 shows the distribution of papers per journal in the context of rail transport vulnerability. The majority of papers are published in transport-related and environment-related journals. The journals publishing the most rail transport vulnerability-related papers are *Transportation Research Part A: Policy and Practice*, which has published six papers, and *Transportation* and *Sustainability* have both published five papers. Most of the journals listed in Table 1 also have a strong background in the context of public transport and rail transport resilience analysis as well (Bešinović, 2020; Zhou et al., 2019).

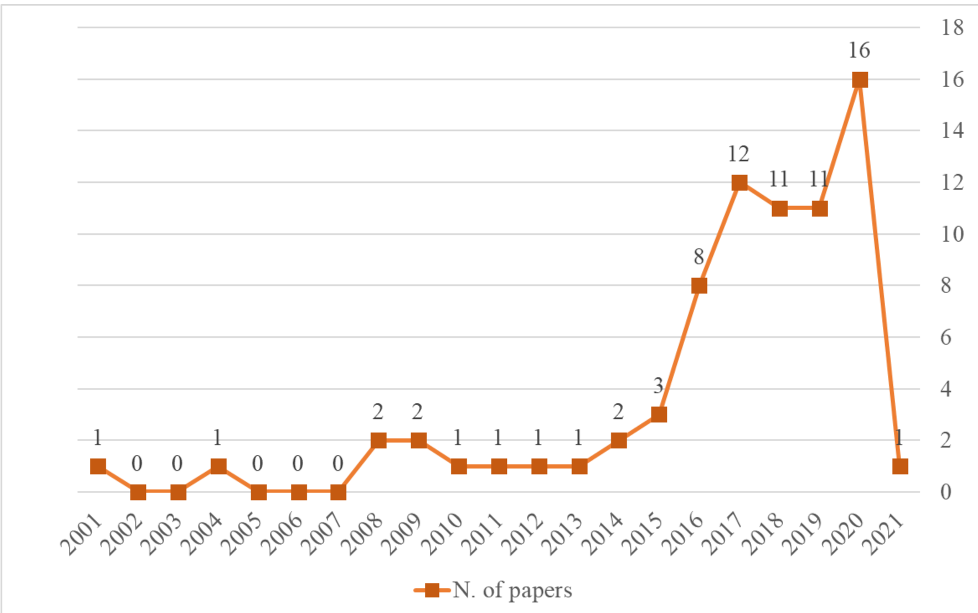

Figure 1, Distribution of papers by year of publication

Table 1, Distribution of papers per journals in the context of rail transport vulnerability

Journal title	**References**
Transportation Research Part A: Policy and Practice	6
Sustainability	5
Transportation	5
Transportation Research Part D: Transport and Environment	4
Journal of Transport Geography	3
Transportation Research Record	3
Physica A: Statistical Mechanics and its Applications	3
Journal of Advanced Transportation	3
Transportmetrica A: Transport Science	2
Reliability Engineering and System Safety	2
Public Transport	2
Natural Hazards	2
International Journal of Critical Infrastructure Protection	2
European Journal of Transport and Infrastructure Research	2
Transportation Research Part E: Logistics and Transportation Review	2
Others (with one publication)	28
Total	**74**

Before we investigate the selected papers, the critical definitions of terms used in this context and the foundational theoretical basis should be reviewed first to differentiate the review of rail transport systems from other resilience-related review articles. Additionally, the theoretical basis and methodology used in each context are distinctive in vulnerability-related and resilience-related studies. Further discussion will be presented in the following sections.

3. An overview of the concept and elements of vulnerability in the rail transport literature

The definitions of *Vulnerability*, *Resilience*, and *Robustness* in the context of railway transport are not yet consistent in the literature, and mainly depend on the topic of research. To discriminate between these terms, this review paper will introduce the definition of *vulnerability* first, followed by the comparison with other keywords.

Vulnerability is commonly defined as "*the sensitivity of a system to threats and hazards*" (Rausand, 2013), such as developing the framework for managing the risk of vulnerable infrastructure (Haimes, 2006); estimating the vulnerability of electricity delivery networks (Holmgren, 2004); and optimizing the priority of road maintenance (Jenelius et al., 2006). Additionally, works that quantitatively measure vulnerability have converged on a definition of vulnerability as the amount of performance that diminishes during disruption (Berdica, 2002; Bešinović, 2020; Yu et al., 2018; Zhang et al., 2018; Zhou et al., 2019). In practical research, the metric of performance varies depending on its topic, for instance, the cost of travel while considering a road transport network (Jenelius et al., 2006).

The definition of *vulnerability* changes in response to a specific scenario. Laurentius (1994) and Berdica (2002) deem vulnerability as susceptibility for either rare or sudden, unpredicted events; Rausand (2013), argues that the vulnerabilities are only visible when a system begins to be destroyed by minor further stress and the capacity reaches its maximum, like "Little strokes fell great oaks." On the other hand, Sarewitz et al. (2003) point to the disadvantage of considering the probability of failure while analyzing vulnerability as the estimation of probabilities in the analysis of extreme events is impractical. Sarewitz et al. (2003) then propose the use of *conditional vulnerability* (or *exposure* in D'Este and Taylor (2003) and Jenelius et al. (2006)) to calculate the aggregate result of consequences given a hazardous event occurs.

On the other hand, *resilience* also has several definitions depending on the purpose of the study. Generally, resilience is defined as "*the capability to persist and absorb a disruption without affecting performance*" in the context of general transport systems (Mattsson and Jenelius, 2015). Operationally, resilience can also be referred to as the resources which a system requires to balance demand and supply (Zhou et al., 2019). In socio-technical systems, such as a healthcare system, resilience would be the ability to prevent a disruptive event. Moreover, it can be deemed as the time a system needs to recover from shocks of disruptive events (Taysom and Crilly, 2017). Alternatively, in the research field of transport networks, resilience means the capability to maintain functionality under disruptions or the resources which are required to recover. Additionally, more research is considering *Resilience Engineering* as a paradigm for safety management, offering a broader socio-technical framework to cope with infrastructure threats and disruptions, including preparedness, response, recovery and adaptation (Worton, 2012).

A similar term to *resilience,* is *robustness*, but there is an inconsistent agreement between the definition of resilience and robustness. For instance, in the rail context, Bešinović (2020) deems that robustness is the ability to mitigate from impacts caused by disturbances, whereas resilience means the ability of a system to provide the effective service in normal conditions and the ability to resist or recover from disruptive events. However, Zhou et al. (2019) argue that the term robustness should be used when the system is still able to maintain itself in its original state regardless of the impact which the disruption creates; but once the impact makes a system unable to keep normal status, then resilience should be considered as the proper topic. Both studies support the idea that resilience research is relevant to considering the remaining capacity under disruptions. But when it comes to robustness, Bešinović (2020) assumes the performance has been affected and regular service is no longer available, whereas Zhou et al. (2019) suppose the performance remains the same whilst under disruption.

The different levels of disruption might cause an apparent contradiction in the definition. Zhou et al. (2019) argue that the difference between resilience and robustness depends on whether the network can provide the same performance while disrupted. To put this in a clear way, if an adverse event occurs and a transport network can still provide the same level of service, then the event is a *disturbance* (Nielsen, 2011), and the *robustness* means to what extent a system can defend a disturbance. On the other hand, if an adverse event degrades a transport network, the event would be referred to as a *disruption* (Nielsen, 2011), and the term *resilience* will be used to estimate the impact of the event as a result. Note that we are considering resilience from the aspect of performance or capability rather than the time a network takes to recover to normal status. In the context of time aspect, *Dynamic Resilience* (or namely *Rapidity*) is used to describe the time that a system requires to return to a state of normal function after a severe perturbation, such as after an intentional terrorist attack (Wang et al., 2016).

The terms mentioned above can be shown diagrammatically, such as McDaniels et al. (2008) proposed, in Figure 2.

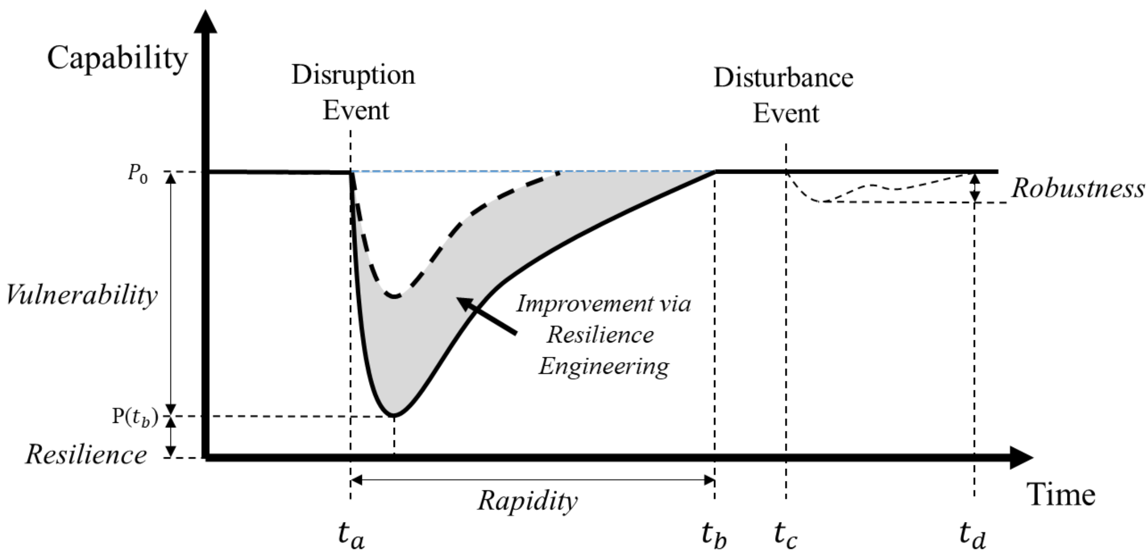

Figure 2, The relationship between Vulnerability, Resilience and Robustness (revised from McDaniels et al. 2008)

Assume P_0 is a regular capacity of a transport system network, and a disruption (e.g. terrorist attack) occurs at time t_a and reduces the capacity to the most disrupted point $P(t_b)$ at time t_b. The gap of capability between P_0 and $P(t_b)$ refers to the vulnerability of the network. In addition, the rest capacity (P_0 - $P(t_b)$) is considered as the resilience of the network. To put it in another way, the vulnerability in a network represents the susceptibility to a disruption resulting in a considerable reduction, whereas the resilience in a network stands for the rest capacity after the degradation due to a disruption (Berdica, 2002; Mattsson and Jenelius, 2015). On the other hand, when a disturbance occurs at time t_c, the network absorbs the disturbance, and the capacity remains the same as usual. The potential loss of capacity absorbed by the network is robustness. The gray area derived from the dotted line and solid line implies that if resilience engineering is conducted to help improve the network when disruption is persisting, then the degree of impact will decrease on rapidity and vulnerability. For instance, if the design of the rolling stock could absorb more impact, which is caused by explosion and prevent itself from the derailment, then the cost of time will be reduced dramatically because no heavy machinery is required to handle the disruption.

Although the concept McDaniels et al. (2008) proposed is able to explain how a disturbance and a disruption impact a network in the context of railway, the effect of varying demand during the disruption has not been considered in the definitions. Consider the demand and the supply of a railway transport in a normal business day, which is shown in Figure 3. The operators will not provide 100% volume of service for the whole day. In contrast, only the volume which is equivalent to demand would be provided in addition to a small surplus in case of the perturbation. Therefore, there would be a natural gap between demand and supply. The definitions of disruptions and disturbances should be slightly adjusted to meet such circumstance. Hence, this review paper proposes new definitions for both terms as the followings.

A *disturbance* can be divided into two types depending on whether the scheduled supply is affected. A disturbance that does not affect scheduled supply, even though an incident makes the maximum volume of a network decrease, does not have any impact on the way the operators provide service. For instance, if there is either a planned or unplanned maintenance on a two-track terminal station, which will occupy one track and leave the other track remaining to hold trains. However, the currently designed schedule will not be affected, and all trains can run on time by using the single track in that terminal station. Then we refer to this incident as a disturbance without affecting scheduled supply.

On the other hand, a disturbance, which would affect the scheduled supply, refers to an incident that means the planned supply can no longer to be reached. However, it does not create unsatisfied demand in the network. For example, a single-track operation is conducted due to a broken locomotive in a branch line, most trains cannot sustain their scheduled timetable, resulting in a decrease in supply. However, all demands can be satisfied because of the dispatching skill of the train operator. Then we refer to this incident as a disturbance affecting scheduled supply but not actual demand.

When it comes to a *disruption*, this means an incident that makes the scheduled supply unsustainable and the demand can no longer be satisfied. For instance, an earthquake resulting in a tunnel collapse shutting down specific links in a network would result in unsatisfied demands.

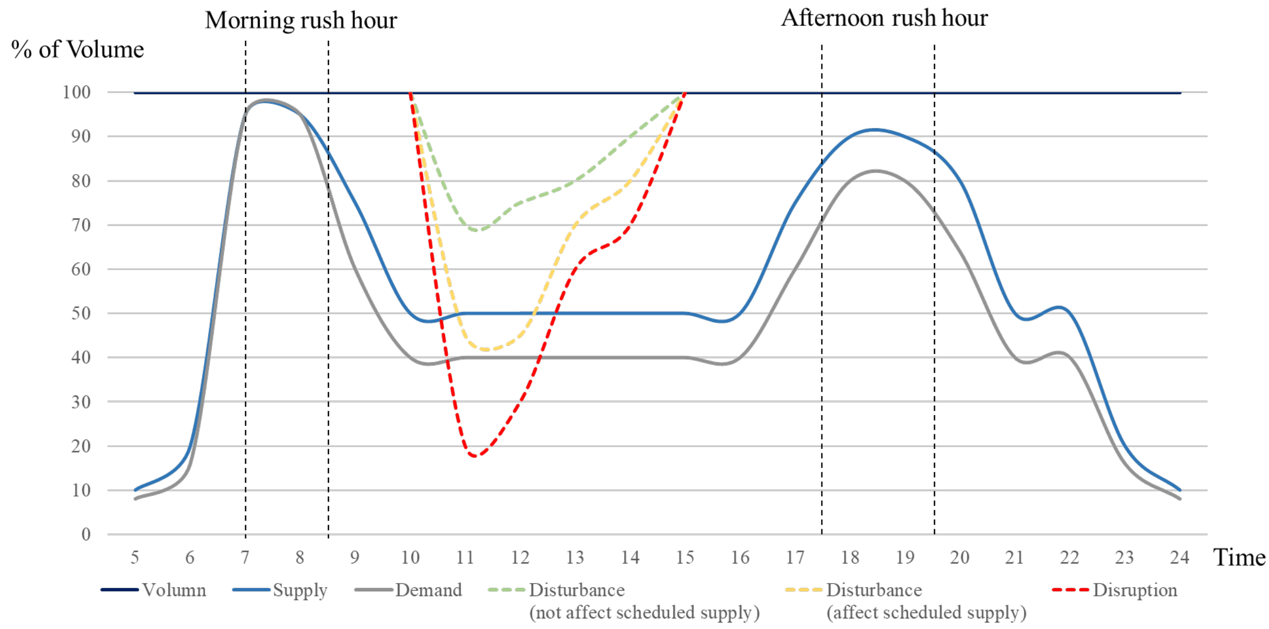

Figure 3, The relationship between supply, demand, and the effect of a disruptive event

The definitions of terms relating to research on disruption in railway systems inferred through literature are summarized in Table 1.

Table 2, Definition of terms relating to research on disruption in the railway system

Terms	**Definition**	**Source**
Vulnerability	Descriptive Definition: Sensitivity to threats and hazards, or a susceptibility to incidents that can result in considerable reductions of performance in a system.	(Berdica and Mattsson, 2007; Taylor and D'Este, 2007)
	Operational Definition: Based on descriptive definition, it refers to how much performance is taken by a disruption.	(Berdica, 2002; Bešinović, 2020; Zhang et al., 2018; Zhou et al., 2019)
Conditional vulnerability (Exposure)	The aggregate consequences a given hazardous event makes to a system.	(D'Este and Taylor, 2003; Jenelius et al., 2006)
Disruption	An event or a series of events caused by external or internal factors that leads to substantial deviations from planned operations. From the perspective of risk management, a disturbance event turns into a disruption after it begins to lead to deviations.	(Nielsen, 2011; Zhou et al., 2019)
Disturbances	A disturbance indicates an event that causes part of the railway operations to deviate from the operational plans, but the system can still provide the same level of service as usual.	(Nielsen, 2011; Zhou et al., 2019)
Resilience	Descriptive Definition: The ability of a transport system to prepare for and to withstand, absorb and adapt to shocks, and to recover from the consequences in a timely and efficient manner in the context of disruption.	(Berdica, 2002; Mattsson and Jenelius, 2015)
	Operational Definition: The rest capacity after the degradation due to a disruption.	
Dynamic Resilience	The rapidity with which a system returns to a state of normal function after a severe perturbation	(Wang et al., 2016)
Resilience engineering	A subject offering a much broader socio-technical framework to cope with infrastructure threats and disruptions, including preparedness, response, recovery, and adaptation	(Worton, 2012)
Robustness	The capability to withstand disturbances with an acceptable reduction in operating performance, measured by the potential decrease of capacity	(Pagani et al., 2019; Zhou et al., 2019)

4. A review of theories in the context of rail transport vulnerability analysis

Research on vulnerability analysis was mainly treated in a qualitative way before 1970 (Rausand, 2013). Subsequently, the quantitative approaches were popularly applied in this context after the development of *probability theory*, which allows researchers to demonstrate the risk of an accident in a specific situation event as a number between 0 and 1 (Parzen, 1960). Another advantage of using probability theory in vulnerability analysis is that the frequency and the condition of adverse events can be clearly delivered through the application of mathematical logic. For example, the nature of uncertainty of an unexpected event was well demonstrated through probability theory (see: Silva et al., 2008).

One of the most widely used theories in this context of vulnerability analysis was *Reliability Theory* (Bazovsky, 1961) which aims to apply either mathematical models or statistical approaches to managing the performance of vulnerable systems. Additionally, research in this context considers both the purpose of the system and the economic context during operation to optimize the system's performance (Barlow and Proschan, 1996). However, reliability theory is a practice-oriented theory, which concentrates on the probability and the result of a disruptive event. Compared with the identification of hazards, reliability theorists care more about how to estimate the reduction of operation (Barlow and Proschan, 1975). The interaction between hazardous elements, which might be the causes of a disruption, in a complex socio-technical system is less considered.

To gain a better understanding of the complexity of a how disruption occurs in a complicated system, the concept of system accident is argued, which is known as the *normal accident theory* (Perrow, 1984). The normal accident theory assumes that a complex system (or socio-technical system) would encounter accidents naturally. Given that disruption is inevitable, Perrow argues that the analysis should "focus on the properties of systems themselves, rather than on the errors that owners, designers, and operators make in running them" (Perrow, 1984). In doing so, normal accident theory proposes that the interaction between hazards in a complex system should be emphasized to increase the reliability. Despite normal accident theory receiving heavy criticisms due to not providing any metrics to evaluate the interactive complexity (Sammarco, 2003) and the underestimation of human error (Shrivastava et al., 2009), a distinct framework on organizational structure and situations during the period of a disruption still makes normal accident theory widely applied (Shrivastava et al., 2009).

Another popular theory used to explain the complexity of systems is *systems theory*. Systems theory argues that every system has its own purpose and structure, which might be influenced by the environment, other systems and even itself (Whitchurch and Constantine, 2008). The core assumption of systems theory is that each technology would develop independently at first, but all technologies would eventually overlap with civil systems, social systems, or technologies per se. A hierarchy is often built up to illustrate the complexity of the socio-technical system (Miles Jr, 1973). In terms of the application in the context of vulnerability analysis, the idea of the imposition of constraints and control loops in a system are widely considered to build the model. In contrast with normal accident theory and reliability theory, systems theory can interpret the etiology of accidents in modern society in a comprehensive way.

To better understand the structure of transport networks, researchers tend to describe a transport network as a topological problem, containing several nodes connected by links. The original motivation of topological analysis in the context of transportation is to find the most efficient network with a series of constraints (Alderighi et al., 2007), which means the networks are generated randomly by a specific cumulative probability distribution. However, such assumption is too strict to follow, and almost all real-world networks are governed by robust organizing principles. Therefore, the *complex networks theory* has been developed to offer researchers more flexibility to do practical analysis. In the transport analysis context, the analysis of networks has two main approaches, the unweighted networks approach and the weighted networks approach. The former is the traditional topological analysis with random networks or specific statistical distribution, and the latter designs a network with several real-world rules on the basis of complex networks theory. The rules could be the traffic congestion (Li et al., 2011), the volume of passengers (Huang et al., 2015), or the characteristics of routes of movements (Alderighi et al., 2007). Notably, both unweighted and weighted networks approaches are derived from *graph theory*, which are mathematical structures applied to model pairwise relations between objects (Erdös, 1959). The original graph theory did not consider the characteristics of society, which can simplify the research topic. In the context of rail transport vulnerability analysis, research that applies graph theory, usually assumes the links in a network are uniform, and evaluates accessibility by a metric identifying the degree of vulnerability of each node and link (Borghetti and Malavasi, 2016; Liu et al., 2017). Furthermore, complex networks theory is the foundational basis of research that considers the demand or the behavior of passengers (de Regt et al., 2019; Jiao et al., 2020; Sun et al., 2018).

5. Empirical and methodological insights

Research in rail transport vulnerability and resilience analysis is foundationally distinct. For example, the vulnerability studies concentrate on the results or impacts of a disruptive event on a rail transport system, whereas resilience studies consider either how to optimize the resources to make the systems operable or mitigate the impact of disruptions on a rail transport system. According to Table 2, the operational definition of resilience is equal to that of vulnerability, which means papers from both contexts have similar approaches.

The methodology applied in the context of rail transport vulnerability analysis mainly consists of topological analysis, simulation, statistical approach, risk analysis, and optimization. The distribution of selected articles based on research approaches and applied theoretical basis is demonstrated in Figure 4. The category “others” in Figure 4 (a) contains two literature review papers (Thaduri et al., 2020; Wang et al., 2020) and one interview paper (Lindgren et al., 2009). Articles that utilize more than one approach appear more than once in Figure 4. Most of the articles which apply more than one approach combine the topological approach and simulation. The topological analysis is popularly used in estimating the vulnerability of rail transport systems, which is followed by the simulation and statistical approaches. The statistical approach makes up 20% of the total, and articles which apply this approach commonly try to explain the critical components of a disruption. On the other hand, only 7% of articles use the optimization approach, which is inconsistent with the result which rail transport resilience review papers have observed (Bešinović, 2020). Such differences might result from the distinct research objectives. The purpose of most vulnerability analysis papers is to evaluate the severity of disruption events or find the vulnerable points in a transport network. For instance, Lu (2018) proposes a model to estimate the impacts of accumulative affected passengers due to a disruption, and Shi et al. (2019) provide an index to quantify the vulnerable nodes in a rail transport network. These purposes are relatively suitable to be solved through simulation or topological analysis. On the other hand, the topic of resilience analysis is usually concerned with either how to make the best use of resources immediately after a disruption, or how to allocate the resources properly to recover from a disruption as soon as possible. In this case, optimization would become the best choice of resilience analysis.

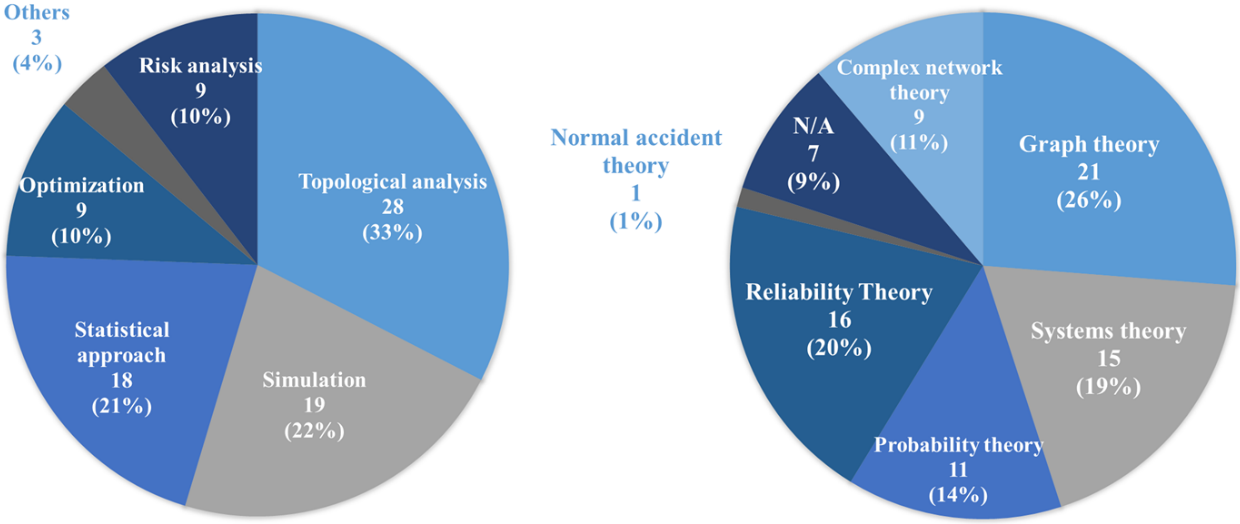

Figure 4, Distribution of selected articles based on (a) research approaches and (b) applied theorical basis.

In terms of the distribution of selected articles based on applied theoretical basis (Figure 4 (b)), the use of graph, systems and reliability theories has dominated the vulnerability research. The distinction between the use of different theories depends on the purpose and the scale of the study. For instance, if the study focuses on a micro-level aspect like the failure of specific components, the reliability theory would be considered (Gonzva et al., 2017; Khoudour et al., 2011). The probability theory is usually applied to estimate the chance of specific disruptive events as well as the impact on the rail transport system, such as identifying the tree fall hazard along railway tracks (Bíl et al., 2017) and evaluating the risk posed to railway infrastructure at level crossings (Bureika et al., 2017). The complex network theory, graph theory and systems theory are widely applied to estimate the vulnerability from a large-scale perspective, which would consider that each node is interdependent (Liu et al., 2017; Sun et al., 2015) or the use of intermodal transport (Meng et al., 2020; Miller-Hooks et al., 2012). The normal accident theory is conducted to create the conceptual framework of vulnerability, such as listing an unclassified set of attacks, which might disrupt rail traffic (Hartong et al., 2008).

Next, the approaches and the applications for rail transport vulnerability are introduced. The categories of approaches follow Figure 4. Generally, the methods used in literature can be broadly classified as statistical approach, topological analysis, simulation and optimization, and risk analysis (Bešinović, 2020; Zhou et al., 2019).

5.1 Statistical approach

Three methods are typically used in the context of statistical modeling of historical disruptions: *Data-driven approach*, *probabilistic risk assessment* and *experts' judgment system*. The *data-driven approach* directly analyses historical data to develop performance indicators (Bešinović, 2020). However, such a method requires sufficient data to conduct, so they are rare in a rail transport vulnerability context. Hong et al. (2015) applied the multi-step methodology (Monte Carlo simulation) to estimate vulnerability on the basis of 30-year flood data in China, which is popularly considered a novel approach to estimate the vulnerability of a transport network. Zuo et al. (2020) used the data from the Chinese Railway Company to estimate the component failure occurrence probability and the vulnerability of high-speed rail networks. However, the availability of disruption data is extraordinarily difficult to collect (Alexakis et al., 2014) and the statistical approach cannot accurately estimate the probability of a rare disruption.

Secondly, *probabilistic risk assessment* assumes the portability of each type of disruption follows a specific distribution, which can be found through detailed investigation. For instance, Han et al. (2020) proposed a wind risk warning model for rail transport by several kinds of wind data observation. This is a classic micro-scale vulnerability analysis, which only concentrates on a specific hazard. Most studies applying probabilistic risk assessment usually deal with the topic relating to climate impacts, such as the risk of falling trees (Bíl et al., 2017), emission from the sun and stars (Thaduri et al., 2020), and flooding and drought hazards (Hu et al., 2016).

Finally, the *experts' judgment system* assumes that the real probability of a disruption can be measured through objective data rather than subjective data based on the following reasons (An et al., 2011). Firstly, the statistical methods are not able to handle the uncertainty of information. The insufficient number of disruptive events usually leads to significant bias when estimating the probability. Secondly, the statistical data does not exist or is not recorded. Even if the data is available, it is hard to analyze due to a lack of crucial information, fragmentation, inconsistency, or a high level of uncertainty. Lastly, the existence of data relating to disruptive events can contradict the reputation of operators. Almost all disruption data is generated and recorded by operators themselves instead of third-party organizations. This makes disruption data not only confidential but also suspect. Unfortunately, there is only one paper in our review that considers experts' judgment (Green and Chmutina, 2019). However, there are many studies in the context of accident analysis which successfully estimate the probability of a disruption by conducting the expert assessment. For example, Alexakis et al. (2014) overcome the difficulty relating to the issue of probability by applying the expert assessment and the Cellular Automata Markov Model to evaluate and predict the probability of landslides in Cyprus; An et al. (2011) determine the relative importance of the risk contributions in the context of the railway industry through expert judgment.

Nevertheless, the issue relating to evaluating the probability of a disruption is gradually rising; however, there is no study tending to analyze disruption at a microscopic scale. Even though some studies consider the probability when analyzing the risk of a disruption instead of conditional vulnerability in the context of the railway industry, there is limited in-depth research analyzing the causality between infrastructure and disruption.

5.2 Topological analysis

Whilst the considered literature suffers from a lack of data to apply statistical analysis, many studies apply the concept of conditional vulnerability to evaluate a critical transport network which allows them to build an assessment model without considering the probability of disruptive events. Mattsson and Jenelius (2015) indicate that two traditional ways are topological vulnerability analysis of transport networks and system-based vulnerability analysis of transport networks, both of which allow researchers not only to assess the vulnerability in a quantitative way, but also avoid considering the probability of disruption.

The topological approach has been divided into several branches with specific characteristics to adapt the features of the transport network. For instance, air transport networks tend to be scale-free with only a few hubs but many connections. Hence, the hub-and-spoke topology is the foundational approach for air transport (Zanin and Lillo, 2013). However, private car trips usually are modeled without transfers, so transport planning uses a point-to-point network or a completely connected network.

Several studies have successfully estimated the vulnerability of the rail transport system by topological analysis. For instance, Lu and Lin (2019) provide an accessibility-based measurement for the vulnerability analysis of rail transit network through topological analysis; Liu et al. (2017) propose a critical node recognition measure to identify the vulnerable node in the rail network, and Li and Rong (2020) build a complicated two-layer network model to estimate the impact of failure effects on stations and high-speed trains.

However, traditional topological analysis usually estimates the vulnerability of a network by calculating the connectively or the affected Origin-Destination (O-D) pairs of a network after one or more nodes are removed from the network (Bababeik et al., 2019; Ye and Kim, 2019, 2021). Firstly, the traditional topological analysis applied in transport systems is commonly accepted not to consider the behavioral response of passengers during a disruption. Distinctly, the reactions of individual passengers in the network cannot be considered during the disruptive event, such as to what extent he reroutes his trip and changes his trip (Bešinović, 2020; Jenelius et al., 2006; Mattsson and Jenelius, 2015; Zhou et al., 2019). The traditional topological analysis performs well on pre-disruption planning, such as estimating the impact of climate change (Chen and Wang, 2019; Chinowsky et al., 2019; Oswald and Treat, 2013) and handling rerouting problems (Gedik et al., 2014), but is poor at predicting the flows in a network. On the contrary, recent topological studies have overcome such limitation by deeming passenger behaviors (Cai et al., 2017; Huang et al., 2015) and passenger flows (Jiang et al., 2018; Khanmohamadi et al., 2018; Pant et al., 2016; Sun et al., 2015) as independent variables in an optimal model to estimate the vulnerability of the rail network. Moreover, a growing number of studies begin to consider the economic variables around rail transport infrastructures while assessing the vulnerability of a rail transport system through topological analysis (Jiang et al., 2018; Kim and Song, 2018; Wang et al., 2017). On the other hand, topological analysis inevitably makes itself assume not only the severity and frequency of disruptions are equal, but also the condition of each node (or station when we refer to a railway network) is the same. In other words, it only considers the result of the removal of each node and link regardless of its characteristic. Nevertheless, the type of disruption varies depending on the type of a station (underground, ground, or elevated station) and the time of a year. For example, the exposure of trespass in a ground station is relatively higher than that in an underground station. The exposure of leaf fall in autumn is relatively higher than in other seasons. This implies that the vulnerability of a network would depend on various attributes, which also implies that the probability of disruptive events might be totally different from each other.

5.3 Simulation and optimization

To simplify the complexity of a system, studies in the context of vulnerability analysis of a rail transport system would try to turn the level of vulnerability into several metrics for further analysis. (Bešinović, 2020). The metrics are used as either the objective variables or independent variables in simulation and optimization models. Some articles also apply economic data to find the relationship within the rail system (Jiang et al., 2018; Kim and Song, 2018; Wang et al., 2017).

Firstly, simulation models are commonly applied in the analysis of large-scale transportation networks (Zhou et al., 2019). Due to the large-scale application, simulation models tend to use graph theory and modify the question in a topological way, which overcomes some constraints of a pure topological approach, such as the issue of operations dynamics (Bešinović, 2020). However, due to the complexity of simulation analysis, literature only concentrates on a limited number of disruption analyses in a single study. For instance, the risk of track buckling failures (Villalba Sanchis et al., 2020) and the sea level rise (Han et al., 2017). Furthermore, some simulation studies only consider the result of a disruption regardless of the failure mechanisms, such as the works of Cats and Krishnakumari (2020), Xing et al. (2017), Chang and Nojima (2001), and Fikar et al. (2016).

On the other hand, the optimization approach is less applied in vulnerability analysis compared with resilience analysis. The purpose of optimization models in transportation research is to either address the questions from the demand side or supply side (Khademi et al., 2018; Morlok and Chang, 2004), or find the balance between performance and resource allocation (Miller-Hooks et al., 2012; Zuo et al., 2020).

Both simulation and optimization approaches can provide sufficient numerical results for decision-makers to do further cost-benefit analysis. However, they cannot provide insights into the probability of events. The shortage might result from the usage of reliability theory in this context. Although the outcome of a disruption can be perfectly understood and estimated, however the real risk is still unknown without assessing the probability of the disruption.

5.4 Risk analysis

Compared with the concept of *conditional vulnerability*, *risk analysis* puts more emphasis on what could happen in the future. Despite there is no standard definition of the word "risk", literature usually associates risk with the answers to the following questions: (1.) what can go wrong? (2.) what is the probability of that occurring?, and (3.) what are the consequences? (Lemos, 2020; Rausand, 2013). A risk analysis is an application to provide the answer to these questions.

Researchers in risk analysis have devoted much work on mitigating the impact which accidents make. One popular approach is to reveal the causes of previous accidents in case of repeating itself, which is also known as sequential accident models (Rausand, 2013). Hence, many models are proposed for the purpose of understanding the causality of accidents dating back to Heinrich's domino theory (Heinrich, 1941), which argues an accident consists of a series of events and a linear one-to-one progression would eventually lead to an unexpected result (Kim and Yoon, 2013; Rausand, 2013). Subsequently, Heinrich's domino is revised by Bird and Germain (1986) and Rasmussen and Svedung (2000) and some critical components have been added. For instance, the concept of property loss (Bird and Germain, 1986); and hazardous environment (Rasmussen and Svedung, 2000).

The risk analysis applied in the railway industry usually concentrates on either the role latent conditions play in an accident (Elms, 2001), or how an accident occurs in terms of active failure (Elms, 2001; Kim and Yoon, 2013). The aim of the former is to focus on how to build a model to explore the importance of latent factors in an accident, whereas the latter aims to emphasize the sequential accident model, which can help to integrate the knowledge from historical incidents and gain an understanding on how to prevent accidents in the future.

However, the understanding on the link between the nature of the risk and vulnerability in the context of rail transport systems is limited. Most studies applying the risk analysis approach in a vulnerability context are qualitative. For instance, Hartong et al. (2008) applies the concept of risk to list an unclassified set of attacks; Khoudour et al. (2011) use the understanding of risk in the railway sector to suggest general approaches for risk analysis and threat evaluation; and Sa'adin et al. (2016) link the risk of climate change to the vulnerability of a rail transport system. Given that several hazardous factors and their possible result have been discussed in previous studies (Sa'adin et al., 2016; Pregnolato and Dawson, 2018; Sanderson et al., 2016; Song et al., 2017), implementations in real cases are required. Unfortunately, the quantitative research in vulnerability analysis is limited, and almost all studies there use the concept of conditional vulnerability, which ignores the probability of accidents. Nevertheless, the understanding of the sequence of rail accidents is still not clear, which means the vulnerability can only be analyzed under a specific disruption (Lindgren et al., 2009). The real risk that makes rail transport vulnerable cannot be revealed without further risk analysis through quantitative means.

6. Discussion and further applications

This paper has reviewed how literature deals with the problem of assessing vulnerability in the field of rail transport systems. The concept of vulnerability in the literature has been defined (section 3) and the applied theories have been discussed (section 4). We conclude that the conflict of definition in literature in the context of vulnerability assessment is due to the divergent point of view.

Subsequently, a holistic review on vulnerability analysis in the context of the rail transport system has been presented in section 5. We conclude that most studies have been completed on the basis of graph theory, reliability theory, and systems theory. Next, several approaches and their applications have been introduced. The statistical approach mainly applies historical data to demonstrate the impact of disruptions and estimate the system's vulnerability. However, such an approach is limited due to the insufficient recorded data. Hence, researchers turn to apply the concept of conditional vulnerability to handle the difficulty of acquiring data.

The concept of conditional vulnerability makes the topological approach extremely popular in vulnerability analysis due to the good accessibility of the input data and the powerful computing technology, which has even been revised to weighted networks analysis which allows researchers to impose the characteristics of passengers or the traffic flow. However, such an approach only considers the result of a disruption instead of the probability, which cannot perfectly perform the nature of risk and vulnerability. In terms of optimization and simulation, although both use the concept of conditional vulnerability, both of these practice-oriented approaches can provide direct suggestions on the issues of resource allocation to decision-makers. Lastly, the risk analysis is an approach that aims to consider the nature of the risk in vulnerability analysis. The concept of risk contains two core ideas: the probability and the consequence. Most studies have done well in exploring the latter, but only limited studies take the probability into account. Nevertheless, studies considering the probability are only in single subject areas, such as climate or a specific component in the rail transport system. No horizontal study has been done in this context, which might result in the decision-makers being disadvantaged while managing risk and mitigating the vulnerability.

In summary, this review paper identifies the following suggestions (gaps) for further studies in the context of vulnerability analysis of rail transport systems. Firstly, more attention is required on the link between vulnerability and risk analysis. The vulnerability is the result of a disruption, which has a close relation to the risk of making the system exposed to dangers. Secondly, the difficulty of acquiring disruptions data should be solved by state-of-the-art approaches. For example, literature to date usually uses statistical data instead of text data. Several studies have dealt with their research question using machine learning and text mining techniques (Hua et al., 2019; Soleimani et al., 2019). The usage of expert judgment is also worth considering. Researchers in a vulnerability context could consider putting attention towards methods for improving the vulnerability of rail transport systems. Thirdly, only limited practice-oriented studies have been done in this context, which constrains the communication between academia and the railway industry.

Although big-scale analysis can contribute a lot in the planning phase, given that railway systems around the world are gradually completed, more attention should be drawn to help decision-makers understand how to manage risk to prevent the occurrence of disruptions. Previous studies have put much emphasis on analyzing the risk of natural hazards and infrastructure failures. However, limited studies have concentrated on the vulnerability caused by human error. Given that there have been a considerable number of studies in the context of risk management, the knowledge from both sides should be aggregated to develop comprehensive and multidisciplinary prediction models. Lastly, only limited studies in our selected papers consider the vulnerability of inter-modal transportation. Both passenger and freight transportation use more than one network. Hence, research should address estimating the risk and vulnerability an inter-modal transportation system experiences; this would improve the safety of real-world transportation.

In conclusion, the continuing need for rail transport systems vulnerability analysis is increasing though the focus has transferred from planning a rail transport network to maintaining a rail transportation system. Both private and government sectors seek solutions that can reduce the vulnerability and ensure the safety of rail transportation. The link between risk and vulnerability is still weak and offers a continuing research challenge.

Reference

Alderighi, M., Cento, A., Nijkamp, P., &Rietveld, P. (2007). Assessment of new hub-and-spoke and point-to-point airline network configurations. *Transport Reviews*, *27*(5), 529–549. https://doi.org/10.1080/01441640701322552

Alexakis, D. D., Agapiou, A., Tzouvaras, M., Themistocleous, K., Neocleous, K., Michaelides, S., &Hadjimitsis, D. G. (2014). Integrated use of GIS and remote sensing for monitoring landslides in transportation pavements: The case study of Paphos area in Cyprus. *Natural Hazards*, *72*(1), 119–141. https://doi.org/10.1007/s11069-013-0770-3

An, M., Chen, Y., &Baker, C. J. (2011). A fuzzy reasoning and fuzzy-analytical hierarchy process based approach to the process of railway risk information: A railway risk management system. *Information Sciences*, *181*(18), 3946–3966. https://doi.org/10.1016/j.ins.2011.04.051

Bababeik, M., Nasiri, M. M., Khademi, N., &Chen, A. (2019). Vulnerability evaluation of freight railway networks using a heuristic routing and scheduling optimization model. *Transportation*, *46*(4), 1143–1170. https://doi.org/10.1007/s11116-017-9815-x

Barlow, R. E., &Proschan, F. (1975). *Statistical theory of reliability and life testing: probability models.* Florida State Univ Tallahassee.

Barlow, R. E., &Proschan, F. (1996). *Mathematical theory of reliability*. Society for Industrial and Applied Mathematics.

Bates, S., Angeon, V., &Ainouche, A. (2014). The pentagon of vulnerability and resilience: A methodological proposal in development economics by using graph theory. *Economic Modelling*, *42*, 445–453. https://doi.org/10.1016/j.econmod.2014.07.027

Bazovsky, I. (1961). *Reliability Theory and Practice* (Prentice-H).

Berdica, K. (2002). An introduction to road vulnerability: What has been done, is done and should be done. *Transport Policy*, *9*(2), 117–127. https://doi.org/10.1016/S0967-070X(02)00011-2

Berdica, K., &Mattsson, L. G. (2007). Vulnerability: A model-based case study of the road network in Stockholm. In *Advances in Spatial Science* (Issue 9783540680550, pp. 81–106). Springer International Publishing. https://doi.org/10.1007/978-3-540-68056-7_5

Bešinović, N. (2020). Resilience in railway transport systems: a literature review and research agenda. *Transport Reviews*, *40*(4), 457–478. https://doi.org/10.1080/01441647.2020.1728419

Bíl, M., Andrášik, R., Nezval, V., &Bílová, M. (2017). Identifying locations along railway networks with the highest tree fall hazard. *Applied Geography*, *87*, 45–53. https://doi.org/10.1016/j.apgeog.2017.07.012

Binti Sa'adin, S. L., Kaewunruen, S., &Jaroszweski, D. (2016). Heavy rainfall and flood vulnerability of Singapore-Malaysia high speed rail system. *Australian Journal of Civil Engineering*, *14*(2), 123–131. https://doi.org/10.1080/14488353.2017.1336895

Bird, J. F. E., &Germain, G. L. (1986). *Practical loss control leadership.* Loganville, Ga.

Borghetti, F., &Malavasi, G. (2016). Road accessibility model to the rail network in emergency conditions. *Journal of Rail Transport Planning and Management*, *6*(3), 237–254. https://doi.org/10.1016/j.jrtpm.2016.10.001

Bureika, G., Gaidamauskas, E., Kupinas, J., Bogdevičius, M., &Steišūnas, S. (2017). Modelling the assessment of traffic risk at level crossings of Lithuanian railways. *Transport*, *32*(3), 282–290. https://doi.org/10.3846/16484142.2016.1244114

Cai, H., Zhu, J., &Xu, T. (2017). Influence Study of Passenger Flow Capacity on the Vulnerability of the Urban Rail Transit Network. *Wuhan Ligong Daxue Xuebao (Jiaotong Kexue Yu Gongcheng Ban)/Journal of Wuhan University of Technology (Transportation Science and Engineering)*, *41*(5), 800–805. https://doi.org/10.3963/j.issn.2095-3844.2017.05.018

Cats, O., &Krishnakumari, P. (2020). Metropolitan rail network robustness. *Physica A: Statistical Mechanics and Its Applications*, *549*. https://doi.org/10.1016/j.physa.2020.124317

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. https://doi.org/10.1016/S0965-8564(00)00003-3

Chen, Z., &Wang, Y. (2019). Impacts of severe weather events on high-speed rail and aviation delays. *Transportation Research Part D: Transport and Environment*, *69*, 168–183. https://doi.org/10.1016/j.trd.2019.01.030

Chinowsky, P., Helman, J., Gulati, S., Neumann, J., &Martinich, J. (2019). Impacts of climate change on operation of the US rail network. *Transport Policy*, *75*, 183–191. https://doi.org/10.1016/j.tranpol.2017.05.007

D'Este, G. M., &Taylor, M. A. P. (2003). Network Vulnerability: An Approach to Reliability Analysis at the Level of National Strategic Transport Networks. In *The Network Reliability of Transport* (pp. 23–44). Emerald Group Publishing Limited. https://doi.org/10.1108/9781786359544-002

deRegt, R., vonFerber, C., Holovatch, Y., &Lebovka, M. (2019). Public transportation in Great Britain viewed as a complex network. *Transportmetrica A: Transport Science*, *15*(2), 722–748. https://doi.org/10.1080/23249935.2018.1529837

Elms, D. (2001). Rail safety. *Reliability Engineering and System Safety*, *74*(3), 291–297. https://doi.org/10.1016/S0951-8320(01)00085-0

Erdös, P. (1959). Graph Theory and Probability. *Canadian Journal of Mathematics*, *11*, 34–38. https://doi.org/10.4153/cjm-1959-003-9

Fikar, C., Hirsch, P., Posset, M., &Gronalt, M. (2016). Impact of transalpine rail network disruptions: A study of the Brenner Pass. *Journal of Transport Geography*, *54*, 122–131.

https://doi.org/10.1016/j.jtrangeo.2016.05.018

Gedik, R., Medal, H., Rainwater, C., Pohl, E. A., &Mason, S. J. (2014). Vulnerability assessment and re-routing of freight trains under disruptions: A coal supply chain network application. *Transportation Research Part E: Logistics and Transportation Review*, *71*, 45–57. https://doi.org/10.1016/j.tre.2014.06.017

Gonzva, M., Barroca, B., Gautier, P. É., &Diab, Y. (2017). Modeling disruptions causing domino effects in urban guided transport systems faced by flood hazards. *Natural Hazards*, *86*(1), 183–201. https://doi.org/10.1007/s11069-016-2680-7

Green, A., &Chmutina, K. (2019). Building climate resilience of UK's rail network through a multihazard approach. *Proceedings of the Institution of Civil Engineers: Engineering Sustainability*, *172*(8), 450–458. https://doi.org/10.1680/jensu.18.00031

Haimes, Y. Y. (2006). On the definition of vulnerabilities in measuring risks to infrastructures. In *Risk Analysis* (Vol. 26, Issue 2, pp. 293–296). https://doi.org/10.1111/j.1539-6924.2006.00755.x

Han, Y., Christopher Zegras, P., Rocco, V., Dowd, M., &Murga, M. (2017). When the tides come, where will we go?: Modeling the impacts of sea level rise on the greater boston, Massachusetts, transport and land use system. *Transportation Research Record*, *2653*, 54–64. https://doi.org/10.3141/2653-07

Han, Z., Tan, J., Grimmond, C. S. B., Ma, B., Yang, T., &Weng, C. (2020). An integratedwind risk warning model for urban rail transport in Shanghai, China. *Atmosphere*, *11*(1). https://doi.org/10.3390/ATMOS11010053

Hartong, M., Goel, R., &Wijesekera, D. (2008). Security and the US rail infrastructure. *International Journal of Critical Infrastructure Protection*, *1*, 15–28. https://doi.org/10.1016/j.ijcip.2008.08.006

Heinrich, H. W. (1941). Industrial Accident Prevention. A Scientific Approach. In *cabdirect.org* (Second Edition). Industrial Accident Prevention. A Scientific Approach. https://www.cabdirect.org/cabdirect/abstract/19432701767

Holmgren, Å. (2004). *Vulnerability Analysis of Electric Power Delivery Networks*. https://www.diva-portal.org/smash/record.jsf?pid=diva2:7703

Hong, L., Ouyang, M., Peeta, S., He, X., &Yan, Y. (2015). Vulnerability assessment and mitigation for the Chinese railway system under floods. *Reliability Engineering and System Safety*, *137*, 58–68. https://doi.org/10.1016/j.ress.2014.12.013

Hu, X., Hall, J. W., Shi, P., &Lim, W. H. (2016). The spatial exposure of the Chinese infrastructure system to flooding and drought hazards. *Natural Hazards*, *80*(2), 1083–1118. https://doi.org/10.1007/s11069-015-2012-3

Hua, L., Zheng, W., &Gao, S. (2019). Extraction and Analysis of Risk Factors from Chinese Railway Accident Reports. *2019 IEEE Intelligent Transportation Systems Conference, ITSC 2019*, 869–874.

https://doi.org/10.1109/ITSC.2019.8917094

Huang, A., Zhang, H. M., Guan, W., Yang, Y., &Zong, G. (2015). Cascading failures in weighted complex networks of transit systems based on coupled map lattices. *Mathematical Problems in Engineering*, *2015*. https://doi.org/10.1155/2015/940795

Jenelius, E., Petersen, T., &Mattsson, L. G. (2006). Importance and exposure in road network vulnerability analysis. *Transportation Research Part A: Policy and Practice*, *40*(7), 537–560. https://doi.org/10.1016/j.tra.2005.11.003

Jiang, R., Lu, Q. C., &Peng, Z. R. (2018). A station-based rail transit network vulnerability measure considering land use dependency. *Journal of Transport Geography*, *66*, 10–18. https://doi.org/10.1016/j.jtrangeo.2017.09.009

Jiao, J., Zhang, F., &Liu, J. (2020). A spatiotemporal analysis of the robustness of high-speed rail network in China. *Transportation Research Part D: Transport and Environment*, *89*. https://doi.org/10.1016/j.trd.2020.102584

Khademi, N., Babaei, M., Schmöcker, J. D., &Fani, A. (2018). Analysis of incident costs in a vulnerable sparse rail network – Description and Iran case study. *Research in Transportation Economics*, *70*, 9–27. https://doi.org/10.1016/j.retrec.2018.08.010

Khanmohamadi, M., Bagheri, M., Khademi, N., &Ghannadpour, S. F. (2018). A security vulnerability analysis model for dangerous goods transportation by rail – Case study: Chlorine transportation in Texas-Illinois. *Safety Science*, *110*, 230–241. https://doi.org/10.1016/j.ssci.2018.04.026

Khoudour, L., El-Koursi, E. M., Velastin, S. A., Buch, N., Lim-Thiebot, S., &Fontaine, F. (2011). An approach for protecting transport infrastructure. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *225*(4), 383–393. https://doi.org/10.1177/2041301710395076

Kim, D. S., &Yoon, W. C. (2013). An accident causation model for the railway industry: Application of the model to 80 rail accident investigation reports from the UK. *Safety Science*, *60*, 57–68. https://doi.org/10.1016/j.ssci.2013.06.010

Kim, H., &Song, Y. (2018). An integrated measure of accessibility and reliability of mass transit systems. *Transportation*, *45*(4), 1075–1100. https://doi.org/10.1007/s11116-018-9866-7

Laurentius, G. (1994). The vulnerability of the city. *Planning a High Resilience Society. Swedish Agency for Civil Emergency and Planning (ÖCB) and Umeå Universitet. Geographical Reports*, *11*.

Lemos, F. (2020). On the definition of risk. *Systems Engineering and Electronics*, *13*(3), 266–278. https://doi.org/10.3969/j.issn.1001-506X.2019.03.24

Li, S.Bin, Wu, J. J., Gao, Z. Y., Lin, Y., &Fu, B. B. (2011). The analysis of traffic congestion and dynamic propagation properties based on complex network. *Wuli Xuebao/Acta Physica Sinica*, *60*(5), 050701–

050701. https://doi.org/10.7498/aps.60.050701

Li, T., &Rong, L. (2020). A comprehensive method for the robustness assessment of high-speed rail network with operation data: A case in China. *Transportation Research Part A: Policy and Practice*, *132*, 666–681. https://doi.org/10.1016/j.tra.2019.12.019

Lindgren, J., Jonsson, D. K., &Carlsson-Kanyama, A. (2009). Climate adaptation of railways: Lessons from Sweden. *European Journal of Transport and Infrastructure Research*, *9*(2), 164–181. https://doi.org/10.18757/ejtir.2009.9.2.3295

Liu, J., Lu, H., Ma, H., &Liu, W. (2017). Network vulnerability analysis of rail transit planin Beijng-Tianjin-Hebei region considering connectivity reliability. *Sustainability (Switzerland)*, *9*(8). https://doi.org/10.3390/su9081479

Lu, Q. C. (2018). Modeling network resilience of rail transit under operational incidents. *Transportation Research Part A: Policy and Practice*, *117*, 227–237. https://doi.org/10.1016/j.tra.2018.08.015

Lu, Q. C., &Lin, S. (2019). Vulnerability analysis of urban rail transit network within multi-modal public transport networks. *Sustainability (Switzerland)*, *11*(7). https://doi.org/10.3390/SU11072109

Mattsson, L. G., &Jenelius, E. (2015). Vulnerability and resilience of transport systems - A discussion of recent research. *Transportation Research Part A: Policy and Practice*, *81*, 16–34. https://doi.org/10.1016/j.tra.2015.06.002

McDaniels, T., Chang, S., Cole, D., Mikawoz, J., &Longstaff, H. (2008). Fostering resilience to extreme events within infrastructure systems: Characterizing decision contexts for mitigation and adaptation. *Global Environmental Change*, *18*(2), 310–318. https://doi.org/10.1016/j.gloenvcha.2008.03.001

Meng, Y., Tian, X., Li, Z., Zhou, W., Zhou, Z., &Zhong, M. (2020). Comparison analysis on complex topological network models of urban rail transit: A case study of Shenzhen Metro in China. *Physica A: Statistical Mechanics and Its Applications*, *559*. https://doi.org/10.1016/j.physa.2020.125031

Miles Jr, R. F. (1973). *Systems concepts: Lectures on contemporary approaches to systems*.

Miller-Hooks, E., Zhang, X., &Faturechi, R. (2012). Measuring and maximizing resilience of freight transportation networks. *Computers and Operations Research*, *39*(7), 1633–1643. https://doi.org/10.1016/j.cor.2011.09.017

Morlok, E. K., &Chang, D. J. (2004). Measuring capacity flexibility of a transportation system. *Transportation Research Part A: Policy and Practice*, *38*(6), 405–420. https://doi.org/10.1016/j.tra.2004.03.001

Nielsen, L. (2011). *Rolling Stock Rescheduling in Passenger Railways Applications in Short-term Planning and in Disruption Management*. www.b-en-t.nl

Oswald, M. R., &Treat, C. (2013). Identifying sea level rise vulnerability using GIS: Development of a transit inundation modeling method. *International Journal of Geoinformatics*, *9*(1), 1–10.

Pagani, A., Mosquera, G., Alturki, A., Johnson, S., Jarvis, S., Wilson, A., Guo, W., &Varga, L. (2019). Resilience or robustness: Identifying topological vulnerabilities in rail networks. *Royal Society Open Science*, *6*(2). https://doi.org/10.1098/rsos.181301

Pant, R., Hall, J. W., &Blainey, S. P. (2016). Vulnerability assessment framework for interdependent critical infrastructures: Case-study for Great Britain's rail network. *European Journal of Transport and Infrastructure Research*, *16*(1), 174–194. https://doi.org/10.18757/ejtir.2016.16.1.3120

Parzen, E. (1960). *Modern probability theory and its applications*. John Wiley & Sons, Incorporated.

Perrow, C. (1984). *Normal Accidents: Living with High-Risk Technologies*. New York: Basic Books.

Pregnolato, M., &Dawson, D. A. (2018). Adaptation investments for transport resilience: Trends and recommendations. *International Journal of Safety and Security Engineering*, *8*(4), 515–527. https://doi.org/10.2495/SAFE-V8-N4-515-527

Rasmussen, J., &Svedung, I. (2000). *Proactive Risk Management in a Dynamic Society-Swedish Rescue Services Agency.* Swedish Rescue Services Agency.

Rausand, M. (2013). *Risk assessment: theory, methods, and applications* (John Wiley & Sons. (ed.); Vol. 115).

Reggiani, A., Nijkamp, P., &Lanzi, D. (2015). Transport resilience and vulnerability: The role of connectivity. *Transportation Research Part A: Policy and Practice*, *81*, 4–15. https://doi.org/10.1016/j.tra.2014.12.012

Sammarco, J. J. (2003). *A normal accident theory-based complexity assessment methodology for safety-related embedded computer systems.* West Virginia University.

Sanderson, M. G., Hanlon, H. M., Palin, E. J., Quinn, A. D., &Clark, R. T. (2016). Analogues for the railway network of Great Britain. *Meteorological Applications*, *23*(4), 731–741. https://doi.org/10.1002/met.1597

Sarewitz, D., Pielke, R., &Keykhah, M. (2003). Vulnerability and risk: Some thoughts from a political and policy perspective. In *Risk Analysis* (Vol. 23, Issue 4, pp. 805–810). John Wiley & Sons, Ltd. https://doi.org/10.1111/1539-6924.00357

Seeliger, L., &Turok, I. (2013). Towards Sustainable Cities: Extending Resilience with Insights from Vulnerability and Transition Theory. *Sustainability*, *5*(5), 2108–2128. https://doi.org/10.3390/su5052108

Shi, J., Wen, S., Zhao, X., &Wu, G. (2019). Sustainable development of urban rail transit networks: A vulnerability perspective. *Sustainability (Switzerland)*, *11*(5). https://doi.org/10.3390/su11051335

Shrivastava, S., Sonpar, K., &Pazzaglia, F. (2009). Normal Accident Theory versus High Reliability Theory: A resolution and call for an open systems view of accidents. *Human Relations*, *62*(9), 1357–1390. https://doi.org/10.1177/0018726709339117

Silva, F., Lambe, T. W., &Marr, W. A. (2008). Probability and Risk of Slope Failure. *Journal of Geotechnical and Geoenvironmental Engineering*, *134*(12), 1691–1699. https://doi.org/10.1061/(asce)1090-0241(2008)134:12(1691)

Soleimani, S., Mohammadi, A., Chen, J., &Leitner, M. (2019). Mining the highway-rail grade crossing crash data: A text mining approach. *Proceedings - 18th IEEE International Conference on Machine Learning and Applications, ICMLA 2019*, 1063–1068. https://doi.org/10.1109/ICMLA.2019.00179

Song, L., Li, Q., List, G. F., Deng, Y., &Lu, P. (2017). Using an AHP-ISM based method to study the vulnerability factors of urban rail transit system. *Sustainability (Switzerland)*, *9*(6). https://doi.org/10.3390/su9061065

Sun, D., Zhao, Y., &LU, Q. C. (2015). Vulnerability analysis of urban rail transit networks: A case study of Shanghai, China. *Sustainability (Switzerland)*, *7*(6), 6919–6936. https://doi.org/10.3390/su7066919

Sun, Huang, Y., Chen, Y., &Yao, L. (2018). Vulnerability assessment of urban rail transit based on multi-static weighted method in Beijing, China. *Transportation Research Part A: Policy and Practice*, *108*, 12–24. https://doi.org/10.1016/j.tra.2017.12.008

Taylor, M. A. P., &D'Este, G. M. (2007). Transport network vulnerability: A method for diagnosis of critical locations in transport infrastructure systems. In *Advances in Spatial Science* (Issue 9783540680550, pp. 9–30). Springer International Publishing. https://doi.org/10.1007/978-3-540-68056-7_2

Taysom, E., &Crilly, N. (2017). Resilience in Sociotechnical Systems: The Perspectives of Multiple Stakeholders. *She Ji*, *3*(3), 165–182. https://doi.org/10.1016/j.sheji.2017.10.011

Thaduri, A., Galar, D., &Kumar, U. (2020). Space weather climate impacts on railway infrastructure. *International Journal of Systems Assurance Engineering and Management*, *11*, 267–281. https://doi.org/10.1007/s13198-020-01003-9

Villalba Sanchis, I., Insa Franco, R., Martínez Fernández, P., Salvador Zuriaga, P., &Font Torres, J. B. (2020). Risk of increasing temperature due to climate change on high-speed rail network in Spain. *Transportation Research Part D: Transport and Environment*, *82*. https://doi.org/10.1016/j.trd.2020.102312

Wang, C. H., Chen, N., &Chan, S. L. (2017). A gravity model integrating high-speed rail and seismic-hazard mitigation through land-use planning: Application to California development. *Habitat International*, *62*, 51–61. https://doi.org/10.1016/j.habitatint.2017.02.009

Wang, J., Muddada, R. R., Wang, H., Ding, J., Lin, Y., Liu, C., &Zhang, W. (2016). Toward a resilient holistic supply chain network system: Concept, review and future direction. In *IEEE Systems Journal* (Vol. 10, Issue 2, pp. 410–421). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/JSYST.2014.2363161

Wang, T., Qu, Z., Yang, Z., Nichol, T., Clarke, G., &Ge, Y. E. (2020). Climate change research on transportation systems: Climate risks, adaptation and planning. *Transportation Research Part D:*

Transport and Environment, *88*. https://doi.org/10.1016/j.trd.2020.102553

Whitchurch, G. G., &Constantine, L. L. (2008). Systems Theory. In *Sourcebook of Family Theories and Methods* (pp. 325–355). Springer US. https://doi.org/10.1007/978-0-387-85764-0_14

Worton, K. E. (2012). Using socio-technical and resilience frameworks to anticipate threat. *Proceedings - 2nd Workshop on Socio-Technical Aspects in Security and Trust, STAST 2012, Co-Located with 25th IEEE Computer Security Foundations Symposium, CSF 2012*, 19–26. https://doi.org/10.1109/STAST.2012.16

Xing, Y., Lu, J., Chen, S., &Dissanayake, S. (2017). Vulnerability analysis of urban rail transit based on complex network theory: a case study of Shanghai Metro. *Public Transport*, *9*(3), 501–525. https://doi.org/10.1007/s12469-017-0170-2

Ye, Q., &Kim, H. (2019). Assessing network vulnerability of heavy rail systems with the impact of partial node failures. *Transportation*, *46*(5), 1591–1614. https://doi.org/10.1007/s11116-018-9859-6

Ye, Q., &Kim, H. (2021). Assessing network vulnerability using shortest path network problems. *Journal of Transportation Safety and Security*, *13*(1), 1–25. https://doi.org/10.1080/19439962.2019.1600626

Yu, G., Zheng, W., Wang, L., &Zhang, Z. (2018). Identification of Significant Factors Contributing to Multi-attribute Railway Accidents Dataset (MARA-D) Using SOM Data Mining. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, *2018-Novem*, 170–175. https://doi.org/10.1109/ITSC.2018.8569336

Zanin, M., &Lillo, F. (2013). Modelling the air transport with complex networks: A short review. In *European Physical Journal: Special Topics* (Vol. 215, Issue 1, pp. 5–21). Springer. https://doi.org/10.1140/epjst/e2013-01711-9

Zhang, D. ming, Du, F., Huang, H., Zhang, F., Ayyub, B. M., &Beer, M. (2018). Resiliency assessment of urban rail transit networks: Shanghai metro as an example. *Safety Science*, *106*, 230–243. https://doi.org/10.1016/j.ssci.2018.03.023

Zhou, Y., Wang, J., &Yang, H. (2019). Resilience of Transportation Systems: Concepts and Comprehensive Review. *IEEE Transactions on Intelligent Transportation Systems*, *20*(12), 4262–4276. https://doi.org/10.1109/TITS.2018.2883766

Zuo, J., Dang, J., &Lyu, M. (2020). Stochastic Risk Assessment with a Lagrangian Solution for the Optimal Cost Allocation in High-Speed Rail Networks. *Journal of Advanced Transportation*, *2020*. https://doi.org/10.1155/2020/7160681