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a literature review and research agenda

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Resilience in railway transport systems: a literature review and research agenda

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ABSTRACT

Critical infrastructure networks, such as transport and power networks, are essential for the functioning of a society and economy. The rising transport demand increases the congestion in railway networks and thus they become more interdependent and more complex to operate. Also, an increasing number of disruptions due to system failures as well as climate changes can be expected in the future. As a consequence, many trains are cancelled and excessively delayed, and thus, many passengers are not reaching their destinations which compromises customers need for mobility. Currently, there is a rising need to quantify impacts of disruptions and the evolution of system performance. This review paper aims to set-up a field-specific definition of resilience in railway transport and gives a comprehensive, up-to-date review of railway resilience papers. The focus is on quantitative approaches. The review analyses peer-reviewed papers in Web of Science and Scopus from January 2008 to August 2019. The results show a steady increase of the number of published papers in recent years. The review classifies resilience metrics and approaches. It has been recognised that system-based metrics tend to better capture effects on transport services and transport demand. Also, mathematical optimization shows a great potential to assess and improve resilience of railway systems. Alternatively, data-driven approaches could be potentially used for detailed ex-post analysis of past disruptions. Finally, several rising future scientific topics are identified, spanning from learning from historical data, to considering interdependent critical systems and community resilience. Practitioners can also benefit from the review to understand a common terminology, recognise possible applications for assessing and designing resilient railway transport systems.

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Introduction

Critical infrastructure networks, such as transport and power networks, are essential for the functioning of a society and economy. On their regular functioning depend millions of commuters and travellers worldwide every day. The rising transport demand increases the

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congestion in railway networks and thus they become more interdependent and more complex to operate. Therefore, urban mobility becomes more fragile to unexpected changes to the networks. Such events may range from disturbances (daily variations in operations), disruptions (due to failures of infrastructure, vehicles, engineering works and adverse weather conditions such as rain, snow storm, wind), to disasters (earthquakes, floods and hurricanes). Disruptions and disasters commonly lead to temporary line or station closures, either single or multiple, while incidents such as suicides, demonstrations or strikes may also affect the frequency of the service. In addition, Dekker et al. (2018) recognize a so called out-of-control situations, meaning that there is barely any train is running, even though the required resources (infrastructure, rolling stock and crew) are available. These situations can either be caused by large disruptions or unexpected propagation and accumulation of delays. For example, in the Netherlands, in 2018, on average 14 disruptions a day occurred lasting about 2 hours each. From these numbers, vehicle and infrastructure failures took about 70%.[1]

As a consequence, many cancelled and excessively delayed trains are observed, and thus, many passengers are not reaching their destinations which compromises customers need for mobility. In 2012, hurricane Sandy flooded several subway stations and tunnels in New York City causing severe damage to the system. Most of the major services were recovered within two weeks. It took several months for stations seriously affected to be fully functional again (Zhu, Ozbay, Xie, & Yang, 2016). The direct economic costs of the 2008 ice storm in China totalled $22.3 billion (Chen & Wang, 2019). Figure 1 shows the increasing number and duration of disruptions in the past years in the Netherlands, while increasing disruption impacts can be expected in the future due to increasing transport demand (Van Aken, Bešinovic, & Goverde, 2017a) and climate changes (Dawson, Shaw, & Roland Gehrels, 2016). Events like terrorist attacks, such as in London in 2005, have particularly far-reaching and

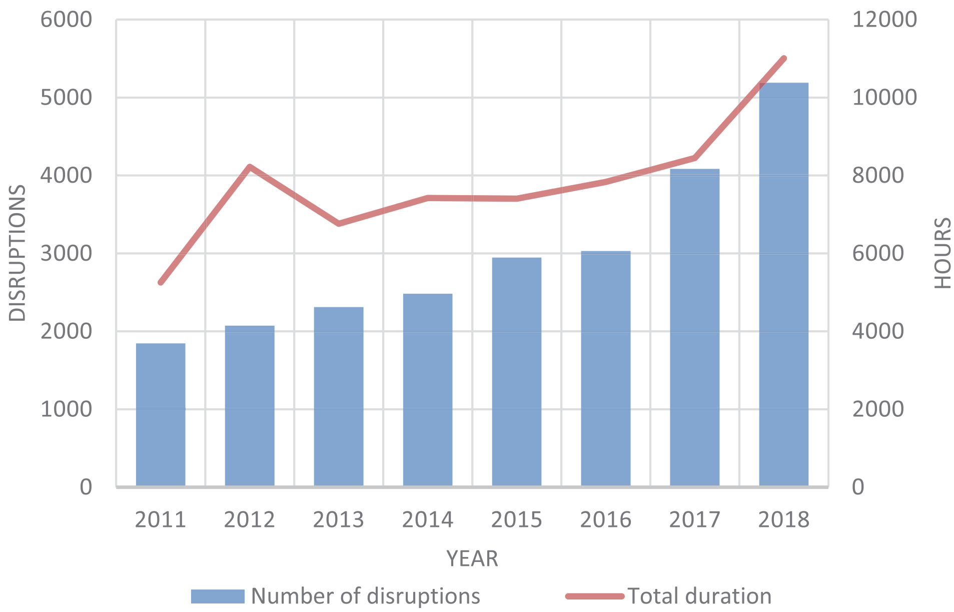

Figure 1. Number of disruptions and total duration in the Dutch railway network during 2011–2018 (source: https://www.rijdendetreinen.nl/en/statistics).

long-lasting effects on the network. Several months after the metro attack, weekdays ridership was still down between 5% and 15% (Rodríguez-Núñez & García-Palomares, 2014).

Even though it is generally recognized that transport planning and management needs to improve system performance during disturbances, as well as to reduce losses due to disruptions and disasters to the greatest extent possible, it is still challenging to address and identify appropriate implementation measures to reduce negative consequences. This is highly attributable to the lack of quantitative understanding of the effect of single and multiple infrastructure failures and adverse weather conditions and the evolution of system performance. In addition, traffic dispatchers/controllers often lack information about the incorporated flexibility in the plans and its recovery capabilities (Steenhuisen, 2009). Recently, significant attention has been given to improved protection of critical infrastructure in Europe such as energy and transport networks (IMPROVER, 2019; MOWE-IT, 2019; RailAdapt, 2019). They identified that building a resilient railway system is not only about concrete defences – it is just as much about working practices, since gaps, shortcomings and difficulties in railway operations are often a result of bad planning and preparation and lack of operational buffers. More quantitative research is needed in these directions, which needs to gain more attention in future research.

There are several review papers related to our work on engineering resilience (Hosseini, Barker, & Ramirez-Marquez, 2016) and resilience of transport systems (Mattsson & Jenelius, 2015; Wan, Yang, Zhang, Yan, & Fan, 2018; Zhou, Wang, & Yang, 2019). However, previous reviews covered only a limited number of railway studies. This review paper aims to set-up a field-specific definition of resilience in railway transport, give a comprehensive, up-to-date review of railway resilience papers, and focus on quantitative approaches.

This review paper contributes to the following. This paper:

- synthesises the literature on resilient railway transport,
- gives the definition of resilience and related concepts,
- classifies metrics and approaches of research with its advantages and disadvantages and
- determines gaps in literature and lays down fundamentals for future research.

This paper is expected to be useful to:

- junior researchers to draw attention towards open challenges in railway transport and to get familiar with the state-of-the-art methodologies,
- senior researchers to provide a multidisciplinary research agenda and generate new scientific research and
- practitioners to understand a common terminology, recognise diverse applications and build understanding toward future implementations for assessing and designing resilient railway transport systems.

The remainder of the paper is as follows. Section 2 provides a definition of resilience in railway transport and is compared with existing concepts. Section 3 describes the methodology used for literature review. Section 4 gives measures for quantifying resilience and Section 5 gives mathematical approaches for evaluating and improving resilience. Section 6 discusses main advantages and disadvantages of existing metrics and approaches. Section 7 discusses future research directions and finally, the concluding remarks are given.

Definition and concept of resilience in railway transport

In essence, resilience comes from Latin *resiliere* which means to spring back, to rebound. The widely accepted UN definition for resilience is:

> The ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions. (UNISDR, 2009)

Resilience can be found in many different domains such as engineering, organizational, economic, ecologic and social (Hosseini et al., 2016). Regarding engineering resilience and transport, in particular, it has been considerably studied in recent years. Examples can be found in air (Janić, 2015), road (Wang, Liu, Szeto, & Chow, 2016), supply chain (Ponomarov & Holcomb, 2009), waterborne (Mansouri, Sauser, & Boardman, 2009) and railway networks (Khaled, Jin, Clarke, & Hoque, 2015).

Resilience in general transport

The review of resilience definitions, both in the reviewed papers and in other transport modes given in recent review by Zhou et al. (2019), indicates that there is no unique insight on how to define resilience. However, certain similarities can be observed across these resilience definitions. The main highlights are summarised in Table 1.

We argue that resilience includes two aspects: proactive and reactive. The former covers planning for resilient system, and the latter, protecting against possible disruptions or disasters. Therefore, both aspects are equally important and should be treated as building elements of resilience in railway transport systems. These current definitions are taken into account and adapted to the context of railway transport systems.

Resilience in railway transport

Resilience of railway transport system is defined as the ability of a railway system to provide effective services in normal conditions, as well as to resist, absorb, accommodate and

Table 1. Definitions of resilience in transport systems.

Definition	Reference
Ability to recover quickly from a disruption	Bababeik, Khademi, Chen, and Nasiri (2017), Chan and Schofer (2016), Lu (2018), Saadat, Zhang, Zhang, Ayyub, and Huang (2018), Adjetey-Bahun, Planchet, Birregah, and Châtelet (2016), Jenelius and Cats (2015), Janić (2015), D'Lima and Medda (2015)
Remaining system's performance during a disruption	Khaled et al. (2015), Diab and Shalaby (2019), Ferranti et al. (2016), Dawson et al. (2016), Dorbritz (2011)
Described with four properties: robustness, redundancy, resourcefulness and rapidity (based on Bruneau et al., 2003)	Beiler, McNeil, Ames, and Gayley (2013), Bocchini, Frangopol, Ummenhofer, and Zinke (2014)
A function of system's vulnerability against potential disruption, and its adaptive capacity in recovering to an acceptable level of service within a reasonable timeframe after being affected	Mansouri et al. (2009), Saadat et al. (2018), Zhang et al. (2018)

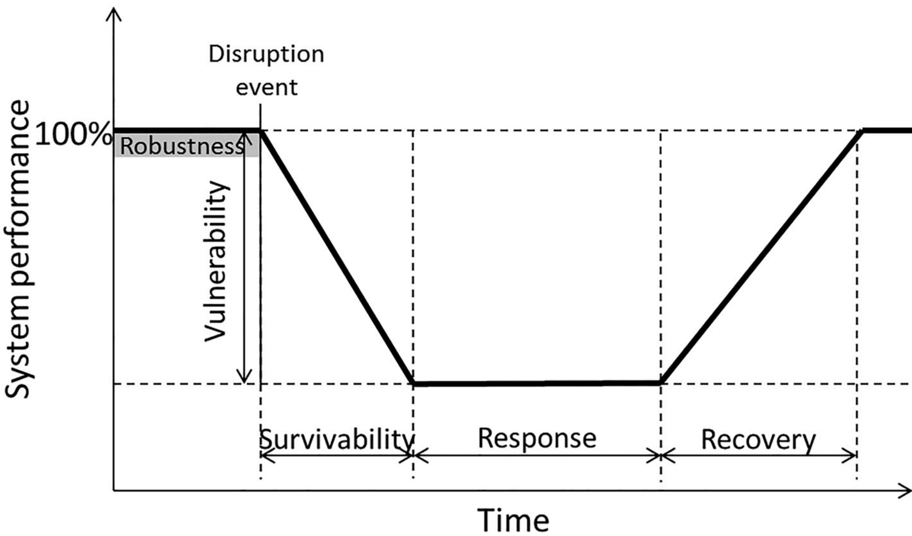

Figure 2. Resilience of railway transport system including vulnerability, survivability, response and recovery.

recover quickly from disruptions or disasters. Resilience is a comprehensive system measure and covers the following building characteristics which represent distinct system states: vulnerability, survivability, response and recovery (Figure 2). Additional proactive (preventive) characteristics to contribute to system's resilience are mitigation and preparedness.

Vulnerability is defined as how much performance remained during a disruption (Khaled et al., 2015). Similarly, Berdica (2002) defined vulnerability of a system as "susceptibility to [disruptions] that can result in considerable reductions in [..] network serviceability". Similar definition can be found in Zhou et al. (2019). Other terms related to vulnerability are resistance, flexibility, redundancy. In general transport systems, robustness can be considered as a counterpart of vulnerability, however, we make a bigger distinction between the two. In the railway context, **robustness** defines ability to mitigate from various everyday delays caused by disturbances. This definition is typical for railway transport and may differ for other transport modes.

Response is set of actions taken directly/immediately after a disruption in order to provide the best level of service possible during a disruption, ensure public safety, provide alternative travelling options to reach destinations and meet the basic subsistence needs of the people affected. This phase represents a disrupted steady-state of railway traffic. Depending on the nature of the disruption, it may last from only a few hours to multiple days. Planning responses in railways are sometimes referred as to contingency planning.

Survivability is the ability of the system to translate from the normal/planned system performance (i.e. 100%) to a disrupted state, i.e. degrade gracefully. In practice, when a disruption happens, the system can degrade differently, e.g. fail completely at once or reducing slowly the performance until finally reaching the disrupted steady-state. For example, the former can be observed with a power outage, then all trains will immediately stop and performance equals 0%. Instead, when a single link in the network fails, it may take significant time until the system translates to the disrupted steady-state.

Recovery is the ability of the system to return from the disrupted state to its original condition. Depending on a disruption, recovery may last a few hours (e.g. due to a vehicle failure) up to multiple weeks (e.g. due to severe flooding or tsunami).

During certain types of disruptions or disasters may omit some of the states of resilience. For example, after a large-scale earthquake, railway traffic can be completely interrupted, and thus no survivability occurs. Alternatively, after a smaller disruption, e.g. short power outage, a system immediately starts recovering, without the need of reaching a disrupted steady-state. Also, in some cases, survivability can be considered as part of response, while in others, response can become part of recovery phase.

Mitigation represents enhancing infrastructure, particularly the vulnerable one, with new links and nodes to improve the ability to resist the disruption.

Preparedness is considered when mitigation is too costly, and certain disruption effects are expected to occur. For example, planning response actions in advance can be assumed as part of preparedness strategies.

Literature review methodology

To give a comprehensive overview, we started with systematically searching for papers that focus on resilience of railway transport systems (van Wee & Banister, 2016). Database search was conducted on two well-known databases Web of Science and Scopus. Keywords such as "resilien*", "rail*" and "transport*" were searched in title, abstract and keywords and the scope was restricted to academic papers in English, including journal papers and conference proceedings from 2008 to 2019, as no resilience papers occur before 2008.

In the first step, terms "resilien*", "rail*" and "transport*" or "network" were searched for. In the second step, we manually checked titles, keywords and abstracts and refined the selection by removing all non-resilience and non-rail papers. In the third step, papers that refer to resilience of single railway elements were removed, such as train switches, or vehicles, as we aimed to network/system resilience in this review paper. In the fourth step, the related papers were searched following a forward snowball effect, by exploring references and citations of already selected papers. In the fifth step, papers including terms such as "vulnerability" or "disruption management" were also included to cover all building blocks of railway resilience. Finally, a final refinement was made based on full texts and sorting of all papers based on full texts. After all steps, we reviewed 59 papers.

Distribution of papers per years and scientific journals

Table 2 gives the distribution of papers regarding the year of publication. It can see a clear ascending trend which follows an increasing number of disruptions seen in Figure 1 and clarifies that research on resilience in railways becomes increasingly important.

Table 3 shows the distribution of papers among scientific journals. Majority of papers have been published in transport-related journals, such as Transportation Research Part B: Methodological, Transportation, Transportation Research Part E: Logistics and Transportation Review and Transportation Science. The resilience in railway transport has been additionally addressed in journals with the scope of safety and security, reliability and sustainability such as Reliability Engineering and System Safety, Safety Science, International Journal of Critical Infrastructure Protection, and Growth and Change.

Table 2. Distribution of papers per year of publication.

Year	References
2008	1
2009	3
2010	2
2011	2
2012	3
2014	5
2015	5
2016	9
2017	8
2018	12
2019*	9
Total	59

*until August 2019.

Classification of resilience papers

Existing resilience methodologies can be classified as qualitative and quantitative. The former typically consider developing conceptual frameworks and determining best practices without quantitative evaluations (e.g. Armstrong, Preston, & Hood, 2017; Siegel & Schraagen, 2017). Qualitative research on resilience focuses on individual human aspects such as workload, stress (Lo, Sehić, & Meijer, 2017), and organizational aspects such as team interaction and learning from experience (Siegel & Schraagen, 2017). The focus of this review paper is on quantitative methods of railway transport networks. Within quantitative methodologies, it can be further distinguished between two classifications based on metrics and approaches used. Table 4 gives an overview of the reviewed papers classified based on metrics and approach and states some examples. In addition, the application of resilience assessment can be distinguished between network-wide and scenario-specific. Network-wide studies consider assessment of the system over all disruption scenarios or a set of the most relevant ones. Scenario-specific approaches deal with assessing resilience against a specific disruption scenario.

Measuring resilience

In this section, we review metrics for evaluating resilience (one or more of its aspects) of railway transport systems. Resilience metrics are divided in two categories: topological and system-based.

Table 3. Distribution of papers per journals.

Journal title	References
Transportation Research Part B: Methodological	6
Transportation	3
Transportation Science	3
Transportation Research Part E: Logistics and Transportation Review	3
Journal of Rail Transport Planning and Management	2
Physica A: Statistical Mechanics and its Applications	2
Journal of Transport Geography	2
Transportation Research Record	2
Others (with one publication)	36
Total	**59**

Table 4. Classification of the papers in resilience in railway transport systems.

Metric	Approach	References	Examples
Topological	Topological	Derrible and Kennedy (2010a, 2010b), D'Lima and Medda (2015) Adjetey-Bahun et al. (2016), Wang et al. (2017), Saadat et al. (2018), Zhang et al. (2018), Candelieri, Galuzzi, Giordani, and Archetti (2019)	• Network-wide assessment of 30 metro networks around the world • Recovery from a short disruption in London Underground
System-based	Data-driven	Dawson et al. (2016), Ferranti et al. (2016), Zhu et al. (2016); Chan and Schofer (2016), Zhu, Xie, Ozbay, Zuo, and Yang (2017), Janić (2018), Mudigonda, Ozbay, and Bartin (2019), Diab and Shalaby (2019), Chen and Wang (2019)	• Impacts of hurricane Sandy on New York metro • Effects of an earthquake on high-speed railways in Japan
	Topological	Dorbritz (2011), Rodríguez-Núñez and García-Palomares (2014)	• Assessment of failures in the Swiss railway network
	Simulation	Cats and Jenelius (2014), Adjetey-Bahun, Birregah, Châtelet, Planchet, and Laurens-Fonseca (2014), Hong, Ouyang, Peeta, He, and Yan (2015), Jenelius and Cats (2015), Zilko, Kurowicka, and Goverde (2016), Zhu and Goverde (2017), Yap, van Oort, van Nes, and van Arem (2018), Meesit, Andrews, and Remenyte-Prescott (2019)	• Estimation of disruptions costs at Stockholm metro railway • Effects of future floodings on Chinese high-speed railways
	Optimization	Peterson and Church (2008), Babick (2009), Jespersen-Groth, Potthoff, Clausen, Huisman, and Kroon (2009), Hirai, Kunimatsu, Tomii, Kondou, and Takaba (2009), Meng and Zhou (2011), Fiondella, Rahman, Lownes, and Basavaraj (2016), Chen and Miller-Hooks (2012); Gedik, Medal, Rainwater, Pohl, and Mason (2014), Jin, Tang, Sun, and Lee (2014), Khaled et al. (2015), Azad, Hassini, and Verma (2016), Veelenturf, Kidd, Cacchiani, Kroon, and Toth (2016), Van Der Hurk, Koutsopoulos, Wilson, Kroon, and Maróti (2016), Ghaemi, Cats, and Goverde (2017), Whitman, Barker, Johansson, and Darayi (2017), Van Aken et al. (2017a), Van Aken, Bešinović, and Goverde (2017b), Bababeik et al. (2017), Bababeik, Khademi, and Chen (2018), van Lieshout, Bouman, and Huisman (2018), Ghaemi et al. (2018), Bešinović, van Aken, Looij, and Goverde (2018), Gu et al. (2017), Zhu and Goverde (2019), Liu, Zhu, Bešinović, Goverde, and Xu (2019), Bešinović et al. (2019), Szymula and Bešinović (2019), Meesit and Andrews (2019)	• Network-wide analysis of the US freight railway network • Allocate rescue trains for severe disruptions in the Iranian railway network • Passenger-centered recovery in the Dutch railway network/ Shanghai metro • Designing alternative timetables for planned disruptions • Scheduling bus replacement services for urban railways in Boston (US)/Liverpool (UK)

Topological metrics originate in complex network theory. The most common way has been to look into the topological structure of the network and assess its structural (static) characteristics assuming a failure of single component in the disrupted network while ignoring dynamic features of the system. Typically, well-known network-based metrics were used to interpret resilience such as size of a giant component, average shortest paths, betweeness centrality and connectivity (Mattsson & Jenelius, 2015; Zhou et al., 2019). Topological metrics were mostly static measures independent of services using the network (Cats & Jenelius, 2014). Wang et al. (2017) used a number of metrics emphasising on alternative paths as well as on the length of the paths. Lam and Tai (2012) defined resilience of a node in the infrastructure network as the weighted sum of all the reliable independent paths of all the nodes in the network. Adjetey-Bahun et al. (2016) used time-varying graphs to integrate time dependency of the system, and thus, betweenness centrality and average shortest path on dynamic graph.

System-based metrics have been gaining more attention, as they overcome the limitation of the graph methods and represent the demand and supply of the system as well as responses to the disruption and recovery from it.

In freight railway systems, the total generalized cost has been often used and it includes costs of rerouting and delay trains, resending of goods due to a disruption (Khaled et al., 2015) and maximizing throughput in a freight network (Chen & Miller-Hooks, 2012). Also, it can include the cost of transporting rerouting railcars, cost of itineraries using the disrupted service legs, repair scenarios, fixed cost of providing different train services, cost of repairing the disrupted service legs (Azad et al., 2016).

In passenger railway networks, performance has been evaluated based on train services adaptations and/or passenger discomfort/changes. Focusing on railway supply side, studies measured remaining transport capacity and cancelled and long-delayed transport services imposed on rail operators and passengers (Hirai et al., 2009; Janić, 2015), transport recovery in number of days, change in travel time (Mudigonda et al., 2019). Some studies quantified resilience by the summed yearly disruption duration of railway track segments (Zhu & Goverde, 2017; Yap et al., 2018) and similarly, by determining frequency and duration of disruptions per km, season, track type (Diab & Shalaby, 2019).

On demand side, more common system performance metrices capturing passenger behaviour were the number of passengers that reach their destination and the total delay of passengers after a serious perturbation (Adjetey-Bahun et al., 2014) which were occasionally followed by rerouting passengers through the remaining operating part of the network (Szymula & Bešinović, 2019). Additionally, some researchers considered a total welfare cost including passengers' dynamic travel choices, stochastic traffic conditions and rail operations. Jenelius and Cats (2015) proposed value of robustness, defined as the change in welfare during disruption compared to the baseline network, and the value of redundancy, defined as the change in welfare losses due to disruption. Lu (2018) used OD-based importance-impedance network degradation as weights of the graph by using the betweenness centrality of nodes, and geographical distances in the network, while omitting train operations.

Focussing on missed opportunity to serve customers during disruptions, several studies measured economic-related losts based on Revenue Vehicle Miles (RVM), i.e. ability to move people over distance, which depends on available rolling stock, tracks, personnel, energy (Chan & Schofer, 2016); turnstile ridership (Zhu et al., 2016, 2017) and compromised accessibility and consequent prevention of passenger trips and their contribution to the Gross Domestic Product (Janić, 2015).

Approaches for quantifying resilience

In this section, we review methods to estimate resilience of railway transport systems. Based on the classification in Table 4, the approaches can be categorized as data-driven, topological, simulation and optimization.

Data-driven approach

Data-driven methods have directly looked into recorded historical data which can reflect the change of system performance in different scenarios to assess the system's property, instead of modelling the inherent mechanisms of the system. In addition, statistical methods (e.g. descriptive statistics and statistical models) may have been used to process the data before used as performance indicators. With the advancement of data acquisition and storage, data-driven methods have become popular in different areas and typically used for assessing ex-post effects of occurred disruptions. Most commonly used data are historical traffic realization data, passenger ridership data and weather-related data.

So far, researchers mostly focused on scenario-specific studies and looked into weather-related disruptions and disasters in railway networks such as earthquakes (Janić, 2018), hurricanes (Chan & Schofer, 2016; Mudigonda et al., 2019; Zhu et al., 2016, 2017), snow- and rainfalls (Chan & Schofer, 2016; Chen & Wang, 2019; Diab & Shalaby, 2019) and climate change events like sea-level rise (Dawson et al., 2016) and heat-related failures (Ferranti et al., 2016). Studies often estimate temporal and spatial distribution of disruptions (Chen & Wang, 2019; Ferranti et al., 2016) and also the spatiotemporal variations of system recovery behaviour (Zhu et al., 2016, 2017).

Janić (2018) proposed models for assessing the resilience of a given rail network, i.e. before, during and after the impacts of disruptive events, and estimating the indicators of particular performances as the figures-of-merit for assessing the network's resilience. Zhu et al. (2016, 2017) used millions of individual ridership records per month to analyse resilience of subway trips for hurricanes Sandy and Irene and estimate resilience curves for each evacuation zone category to model time-dependent recovery patterns of the roadway and subway systems. Diab and Shalaby (2019) studied the impact of outdoor track segments of the metro system and weather conditions on the number of service disruptions and the magnitude of resulting delays. They indicated that outdoor tracks are up to four times more vulnerable to disruption, independently of season. Dawson et al. (2016) assessed the impacts of sea-level rise on the functioning of the part on the London to Penzance railway line. They identified a relationship between sea-level change and rail disruptions, and afterwards, used a model-based sea-level predictions to estimate this relationship into the future. They found that by 2100 (in a high sea-level rise scenario), the line may experience and increase to as many as 84–120 days (by up to 1170%) with line restrictions per year. Ferranti et al. (2016) analysed heat-related resilience of railway assets and proposed the concept of "failure harvesting", i.e. that once failures have been harvested, and the failed equipment replaced, the infrastructure system within that particular region become resilient for the remainder of the year at that particular temperature.

Topological approach

The topological approaches have used the metrics developed in complex network theory which are based on graph properties and most often perform network-wide assessments. They are then applied on different graph representations, mainly modelling either the infrastructure or the service network (see Mattsson & Jenelius, 2015). Typically, topological approaches for assessing resilience of railway networks follow the given procedure. For a given transport network, links are being removed either randomly or following a certain strategy. While doing so, the evolution of the metrics is tracked and the resilience is analysed. This represents an approach of complete enumeration and thus, leads to determining the critical elements in the network. The majority of studies considered a single link/

node at the time. Also, topological approaches have most often been applied on metro networks with the exception of Dorbritz (2011). Wang et al. (2017) quantified vulnerability of 30 metro networks around the world.

Topological approaches have mostly used to estimate vulnerability aspect of networks (Derrible & Kennedy, 2010a, 2010b; Dorbritz, 2011; Mattsson & Jenelius, 2015). It has been shown that that railway transport networks share the topological features of so-called scale-free networks. It means they are robust against the failure and removal of randomly chosen network elements. Simultaneously, they are highly sensitive towards tailored failures of specific important network elements (Derrible & Kennedy, 2010a, 2010b; Dorbritz, 2011). In particular, Derrible and Kennedy (2010a, 2010b) suggested that the vulnerability of subway systems corresponds to the number of cyclic paths available in the network, representing the possibility to use alternative routes under disruption. Dorbritz (2011) also generated alternative paths and assesses several metrics such as the number of additional track kilometres used or the number of vehicles needed for operating all lines.

To incorporate dynamic properties of the system, time-varying graphs were used to integrate time dynamic dependency into resilience metrics (Adjetey-Bahun et al., 2016) and evaluate the effects of disruption duration (Lu, 2018). Adjetey-Bahun et al. (2016) and Lu (2018) compared static and dynamic metrics and concluded that in normal traffic conditions in the network both resulting performances are quite the same. When a disruption occurs, interdependencies and passenger flows in the network make the static indicator less efficient and stress the importance of taking time dimension, i.e. recovery strategies into consideration. In addition, when operational aspects were considered, the importance of some edges and nodes may be changed such that some stations become important for operations that are not necessarily also important for the infrastructural network and vice versa (Adjetey-Bahun et al., 2016; Dorbritz, 2011).

Alternative applications could be found such as using a mean-reverting stochastic model to quantify system response to disruptive shocks (D'Lima & Medda, 2015) and using trip assignment model focusing on increased passenger travel time and unsatisfied passenger demand. In cases when multiple elements in the network are disrupted, best recovery strategies under minimal costs could be determined (Saadat et al., 2018; Zhang et al., 2018).

Simulation approach

Simulation models have usually used similar metrics as in the topological approach but also system/performance indicators (e.g. delay, passenger loads) to evaluate the network performance in a stochastic environment. Most commonly, simulation described the resilience evaluation based on theoretical and/or real-life disruption distributions and modelling the network impacts and reactions accordingly. Such methods were used e.g. for identifying link vulnerability from a passenger perspective (Yap et al., 2018), evaluating network performance using a discrete event simulation (Meesit et al., 2019) and assessing the supply–demand interactions in a dynamic stochastic setting given a certain disruption scenarios (Adjetey-Bahun et al., 2014; Cats & Jenelius, 2014). In addition, Cats and Jenelius (2014) estimated the value of real-time information provision (via displays at all stops) for reducing disruption impacts. While being able to catch the dynamic effects of a disruption in a better way, these approaches tend to suffer from the exponential growth of possible combinations when multi-component failures were considered. To overcome this, heuristics such as pre-selection of promising candidate-sets or the evaluation of pre-defined scenarios were applied (Cats & Jenelius, 2014; Yap et al., 2018). In addition, simulations were also used for assessing the value of new links for public transport network vulnerability (Jenelius & Cats, 2015).

Some studies applied a multi-step methodology to estimate vulnerability and mitigation strategies against possible disruptions such as floods (Hong et al., 2015) and infrastructure failures (Zhu & Goverde, 2017). The steps were as follows. First, disruption scenarios were generated based on historical statistics and then used to estimate link disruption probabilities. These are then used in a Monte Carlo simulation to calculate the average number of interrupted trains and time period. Finally, evaluated is the effectiveness of alternative strategies in selecting links for maintenance to reduce their disruption probabilities.

Optimization approach

For assessing resilience of railway transport networks, mathematical optimisation models have also been used. In addition, a significant amount of work has been performed both using both network-wide and scenario-specific approaches.

Network-wide optimization approaches have focused on quantifying or improving network resilience. Studies on quantifying resilience most commonly focused on determining the most critical network elements (Chen & Miller-Hooks, 2012; Gedik et al., 2014; Khaled et al., 2015; Peterson & Church, 2008; Szymula & Bešinović, 2019; Whitman et al., 2017). While doing so, the majority of these papers addressed a single resilience aspect being vulnerability, while Chen and Miller-Hooks (2012) emphasises recovery.

Different models could be found to model the railway network, services and disruptions within. Peterson and Church (2008), Whitman et al. (2017) used a Multi Commodity Flow (MCF) model to asses a freight railway network before and after the removal of single links to assess network resilience (i.e. vulnerability) regarding link capacities. Gedik et al. (2014) introduced an the interdiction model and used a dynamic network formulation considering capacity restrictions and congestion. Szymula and Bešinović (2019) proposed a model which combines arc- and path-based formuation to determine the links which cause the most adverse consequences to passengers and trains. Chen and Miller-Hooks (2012) proposed a stochastic mixed-integer programme for quantifying network resilience and identifying an optimal post-event actions to take.

Research on improving network-wide resilience of railway systems has been limited, e.g. Babick (2009), Fiondella et al. (2016), Azad et al. (2016), Bababeik et al. (2017). In order to improve network resilience, several alternative improvement strategies, representing preparedness and mitigation, have been considered such as network modifications (Babick, 2009), identifying an effective allocation of defence resources (Bababeik et al., 2017; Babick, 2009; Fiondella et al., 2016) and alternative train services (Azad et al., 2016).

Babick (2009) developed a three-level defender-attacker-operator framework to model mutual attacks on multiple links and defence reactions of a fictitious attacker and defender of the network. In particular, he used a modified MCF model to allocate security resources, and a Network Design Problem (NDP) approach to model network modifications. Fiondella et al. (2016) combined optimization and game theory to introduce a dynamic multiperiodic problem of allocation of finite defence resources to the infrastructure links of the incremental high-speed rail network, i.e. during network construction period. Bababeik et al. (2018) proposed a bi-level optimization model to allocate relief trains (RT) against severe disruptions in a sparse railway network that would maximize cooperative coverage of link exposure by RT stations and minimize total travel time from RT stations to all components in the network. Azad et al. (2016) aimed to meet the demand in freight railway networks by both recovering from disruptions, and mitigating against the most critical disruptions. The mitigation strategies applied were to create new itineraries by renting tracks owned by competing railroad operators.

Frequently, an additional outcome of network-wide optimization models has been a set of alternative train services during disruptions, i.e. an alternative timetable which includes rerouting and rescheduling of trains (Chen & Miller-Hooks, 2012; Khaled et al., 2015), passengers (Szymula & Bešinović, 2019), re-sending goods from the origin nodes, and using third party train services (Azad et al., 2016). In addition, Szymula and Bešinović (2019) considered cancelling trains in dense passenger networks, while Azad et al. (2016) detemined repairing the disrupted rail segments.

Network-wide optimization models most often tackled one aspect of resilience, mainly vulnerability and recovery, while several papers considered multiple aspects, e.g. recovery and preparedness (Azad et al., 2016), and mitigation and recovery (Babick, 2009). Also, network-wide models typically evaluated the reduced system performance against single link or node disruption, with an exception of Babick (2009), Gedik et al. (2014) and Szymula and Bešinović (2019) which focused on multiple simultaneous disruptions. Also, freight railway networks gained more attention, while passenger networks were addressed more recently, e.g. Szymula and Bešinović (2019). This could be explained with the fact that most of the authors researching railway resilience are US-based where freight transport dominates passenger. For solving optimization models, researchers often appllied hybrid approaches which combined e.g. augmented e-constraint and fuzzy logic (Bababeik et al., 2017), or column generation and row generation with mixed-integer linear programming (Szymula & Bešinović, 2019) and metaheuristic approaches such as genetic algorithms (Fiondella et al., 2016).

Scenario-specific optimization approaches typically focused on generating optimal rescheduling traffic actions for a given disruption scenario, consisting of single or multiple disrutions, to minimize the impact on trains and/or passengers in terms of delays and/or cancellations. These scenario-specific studies are also known in the literature as disruption management. The most common rescheduling actions during disruptions have been retiming, reordering, short-turning and cancelling, and also stop-skipping and additional stopping can be found.

Scenario-specific studies most often covered multiple aspects of resilience being survivability, response and recovery, i.e. they considered rescheduling actions from a disruption start to returning to the original state again (Ghaemi et al., 2017; Liu et al., 2019; Veelenturf et al., 2016; Zhu & Goverde, 2019;). Alternatively, some research focused exclusively on recovery, i.e. to determine the best reinsertion strategies for cancelled services into the network after a disruption finished (Jespersen-Groth et al., 2009), survivability, i.e. to find the best stop locations for trains that are cancelled due to a disruption (Hirai et al., 2009) and response in out-of-control situations, i.e. to develop a new line plan to operate in an isolated disrupted area (van Lieshout et al., 2018). Majority of papers addressed adjustments in railway lines and network, while Ghaemi et al. (2017) tackled rescheduling and rerouting trains in complex stations focusing on short-turning services. To guarantee providing feasible adjusted timetables, optimization models may need to incoroprate train circulations (Liu et al., 2019; Zhu & Goverde, 2019).

Understanding the impact of rescheduling decisions on passengers is of great importance, particularly in dense railway passenger networks like Switzerland and the Netherlands as well as busy metro lines like Beijing, London, New York City and Tokyo. Therefore, passenger assignment modelling has been used to estimate individual time-dependent passenger demand (Zhu & Goverde, 2019). Furthermore, to overcome passenger overcrowding in metro lines, an integrated disruption management has been considered to control both train services and passenger flows, i.e. passenger overcrowding in stations by controlling and limiting the inflow of passengers at station gates (Bešinović et al., 2019).

During planned maintenance, i.e. construction and maintenance work on railway tracks, infrastructure becomes unavailable and thus, planned timetables cannot operate uninterruptedly. To respond optimally to these planned disruptions, passenger railway services needed to be adjusted while minimizing delays, cancellations and short-turnings (Van Aken et al., 2017a, 2017b). In addition, simultaneously adjusting network scheduling and train routing in stations can generate operationally feasible solutions (Bešinović et al., 2018). Such precomputed alternative services represent so-called contingency plans which can be applied as a response strategy as soon as a specific disruption happens. In addition, in order to minimize the impact of a disruption, several studies suggested integration of bus services as substitutes to railway services during planned disruptions (Meesit & Andrews, 2019), and also unplanned disruptions (Gu et al., 2017; Jin et al., 2014; Van Der Hurk et al., 2016).

Majority of scenario-specific optimization papers focused on passenger railway and metro networks; while most of the authors are Europe and China-based. Typically, scenario-specific optimization approaches were modelled based on event-activity networks where events represent arrivals and departures, and activities represent running, dwelling, turning, transfer times (e.g. Ghaemi et al., 2018; Veelenturf et al., 2016; Zhu & Goverde, 2019).

Most of the current optimization models work with a given and certain information about disruption length. However, in reality, disruption length may be highly uncertain and it is difficult to tell exactly how long a disruption will last. Meng and Zhou (2011) incorporated uncertainty of the disruption duration in probabilistic disruption scenarios. Differently, Zilko et al. (2016) proposed the Copula Bayesian Network method to predict a disruption length. The impact of these railway disruption predictions and the corresponding train rescheduling on passenger delays has been estimated in Ghaemi et al. (2018).

Discussion

Resilience metrics

Using topological metrics, resilience has been assessed by analysing the structure of the systems graph model assuming a failure of a (single) component in the disrupted network and most often disregarding dynamic effects on the performance within the system. The system-based metrics have been capable of capturing operations dynamics the corresponding impacts/consequences such as the duration of disruptions, the number of affected trains and the number of affected passengers.

Therefore, system-based metrics are more appropriate to quantify resilience of railway transport systems, while topological ones would be suitable for quantifying the general network characteristics of a well-performing network. In general, researchers should strive to understand the negative effects on passengers (e.g. Ghaemi et al., 2018; Zhu & Goverde, 2019), freight (e.g. Azad et al., 2016; Khaled et al., 2015) and an overall impact on society (e.g. Jenelius & Cats, 2015).

Resilience approaches

Here we discuss the usability of topological, simulation, optimization and data-driven approaches.

Topological approaches have the main advantage that they require a limited amount of data. The methodology is built up to a mathematically solid theory. Typically, a railway transport network was presented as a graph with stations as nodes, and tracks inbetween as unidirectional links. Resilience was analysed by removing single links successively either randomly or following a certain strategy, and while doing so, re-calculating and tracking the evolution of the metric(s). This follows the approach of complete enumeration. This methodology based on topological approaches is suitable for real-life applications due to limited data needed and easy-to-use mathematical resilience indicators which allows comparisons of different railway network structures in short time. One of the disadvantages of topological approaches is, when removing multiple elements this method suffers from prohibitively high computation times due to the exponential growth of combinations with the increasing number of elements (Wang et al., 2016). Another disadvantage is that topological approaches are not capable of capturing operations dynamics and fail to realistically replicate the behaviour of the system caused by disruption. Overall, topological approaches can be very useful to describe general characteristics and indicate various conceptual weaknesses of the transport systems, they are still not very helpful for assessing operations and resilience actions of railway transport systems.

Simulation approaches have overcome the second disadvantage of topological; it models accurately train services and consequently passenger adaptations during a disruption. Simulations commonly model system behaviour, but tend not to apply optimal traffic recovery measures. In general, due to the high-complexity of detailed simulations, it is impractical and time-consuming to use such approaches for complete enumeration of all disruptions for larger railway networks. Instead, these can be suitable to obtain great details for single (or a limited number of) disruptions.

Optimization approaches represent a valuable alternative to overcome both the dynamics and combinatorial challenges of topological and simulation approaches. Current simulation and topological approaches most often dealt with single link or node disruptions. For tackling combinatorial complexity rising from multiple simultaneous disruptions, i.e. a combination of disrupted elements, optimization approaches become worthwhile considering due to their capability to determine extreme scenarios without the complete enumeration of all other scenarios.

More comprehensive optimization models have included multiple resilience aspects and typically solved one particular disruption scenario, but did not assess the network resilience over all possible (or most critical) disruptions. Passengers behaviour has become increasingly important and thus, it was introduced in modelling, particularly in dense railway and metro networks. Also, studying optimal planning of substitute services for disrupted railway systems has been on the rise. Survivability, i.e. a graceful degradation of a system, has rarely been tackled in literature explicitly.

Optimization models can address challenging tasks of capturing system dynamics such as multiple disruptions (e.g. Babick, 2009), optimal train recovery strategies (e.g. Gedik et al., 2014) and passenger behaviour (Szymula & Bešinović, 2019; Zhu & Goverde, 2019). Therefore, optimization seems particularly useful to target more complex problems and therefore, gains more attention towards resilient railway systems. In addition, optimizing real-time information provided to passengers could alleviate congestions and further improve system performance during disruptions. This may become more relevant with innovative communication means becoming available such as "location aware" and "destination aware" information services (Brakewood & Watkins, 2019).

Data-driven approaches have provided an alternative to all other model-based approaches and provided very detailed insights on resilience without modelling the system explicitly. For example, counted passenger ridership or total vehicle kilometres run can be good indicators whether the system is performing as planned or not. Therefore, these approaches could be used efficiently with limited preceding modelling effort to assess (for now) ex-post network resilience performance. The only down side is that such approaches fully rely on available good-quality and sufficient amount of historical realization data.

Overall, to accurately assess resilience of railway systems, methodological approaches shall consider specific characteristics of railways such as operations (train routes, stopping patterns, timetables) and transport demand (passenger and/or freight) together with infrastructure network topolgy. Combining all elements will be crucial for addressing proactive and reactive aspects of future resilient railway systems.

Future research directions

Based on the literature review presented in this paper, a few upcoming research directions relevant to the academic and professional community dealing with resilience have been identified as follows.

Learning from historical data

Most of the current papers have accepted the known duration of disruptions. It would be worth investing in better structuring, documenting and storing disruption-related data (Zilko et al., 2016), as well as analysing it using Artificial Intelligence applications, e.g. natural language processing, to extract information from current disruption reports (Chen & Wang, 2019). This would allow researchers to investigate nature and probability of occurrences, as well as potentially predict future disruptions.

Considering interdependency of critical systems

Interdependency of critical systems such as water, telecommunication and transport should be further supported by multidisciplinary approaches for assessing interdependent resilience. To this purpose, we could expect to combine data sources (i.e. traffic, passenger, weather, seismologic) and mathematical models (i.e. to simulate traffic, earthquakes, floods, blizzards). This would lead to developing multidisciplinary assessment methods and early warning systems for predicting disruptions and disasters.

Dealing with multiple simultaneous disruptions

In practice, multiple links tend to become disrupted simultaneously either due to intrinsic element failures or adverse weather implications, such as floods and storms. Therefore, it is important to build resilience for such cases, that determine strategies to recover from multiple disruptions as well to resist/prepare/respond to multiple disruptions. For that, optimization models become necessary due to combinatorial complexity due to a combination of critical elements on one side, and alternative operations strategies, particularly in dense and crowded railway networks on the other side.

Incorporating resilience in planning

Most of the reviewed papers have focused on recovery from a disruption or assessing resilience of an existing railway system. More importance of improving railway planning is required towards developing services that are more resilient and flexible to future disruptions. In addition, more comprehensive models for network-wide resilience are still needed, survivability is yet to gain more attention as well as investigating resilience trade-offs between vulnerability and recovery, mitigation and preparedness, and response/recovery and normal services.

Considering climate changes

Weather-related disruptions are assumed to increase due to the increasing impacts of climate change (Dawson et al., 2016) and their consequences may be more substantive lasting from multiple days to weeks. Therefore, weather-related research should gain more attention in the future. We shall investigate infrastructure adaptations and improvements, and also, allocating rescue teams and evacuation strategies. While doing so, the resilience metrics shall be suitable to quantify the overall impacts on transport demand.

Integrating demand-centered and community resilience

Resilience research more has commonly focused on assessing and optimizing usage of resources, and rather limited research was demand-centered. While doing so, demand behaviour has been usually considered as uniform, expecting that everyone behaves the same. In addition, during disruptions and disasters people may react differently to resilience strategies considered. Vodopivec and Miller-Hooks (2019) represents one of the first attempts in this direction. Thus, more research on demand-centered and community resilience shall be considered in the future.

Conclusions

This paper provided taxonomy and reviewed the approaches on resilient railway transport. The main contributions of the paper are the following. First, a comprehensive definition of resilience was defined incorporating aspects of vulnerability, survivability, response, recovery, mitigation and preparedness. Second, resilience metrics were classified to topological and system-based. Third, resilience approaches were classified as data-driven, topological, simulation and optimization. This review paper is useful for junior and senior researchers as well as practitioners and it is suitable for further research in railway systems, as well as similar systems such as public transport and air transport.

It has been concluded that, to obtain more accurate resilience assessment, system-based metrics are required to capture effects on transport services and transport demand. In particular, demand-centered resilience metrics shall be needed to precisely capture impacts on users of transport systems. Meanwhile, topological measures are more straight-forward to apply as they need less data, but also tend to provide limited information about the system.

Mathematical optimization tends to be the most suitable for determining e.g. the most critical combinations of critical links, and optimal response/recovery strategies due to its ability to tackle an increased combinatorial complexity of resilience-related challenges. In addition, with rising available historical data, data-driven approaches could become more widely used for ex-post analysis of past disruptions without explicitly modelling the system allowing quick assessments. Lastly, topological and simulation approaches could find its use for quick evaluations of certain disruption scenarios, typically including single failures. Simulations can provide relevant in-depth insights in system behaviour, however, they may be too time consuming.

Considering still a rather limited research in railway resilience, each aspect of resilience requires further investigation. Firstly, the focus shall be on operational changes that can be made in short-term and with limited costs such as investigating traffic adjustments to respond and recover quickly and effectively from both single and multiple disruptions. Secondly, research shall then address designing railway operations that are also prepared, i.e. intrinsically flexible and easily adaptable, for future disruptions. Thirdly, with an expected increasing impact of climate changes in the coming decades, long-term investments need to be tackled, and therefore, attention shall be put towards methods for improving railway infrastructure networks. Fourthly, developing multidisciplinary prediction models (disruption duration, rain/snow expectation, flooding, etc.) shall be addressed in parallel with the other research since better predictions would further contribute to extended accuracy of all future resilience-related studies.

In summary, resilience is becoming more and more important with increased needs for transport and future mobility on one side and climate changes on the other. It also gains more attention in popular literature and general public. Approaches for resilience assessment and planning in railways are still relatively unexplored. It is to expect an increase of new methodologies, in particular, optimization and data-driven approaches as well as combined approaches to address resilience of railway transport systems.

Note

1. www.rijdenoptreinen.nl, accessed on 19.08.2019.

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