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Resilience assessment of railway networks: Combining infrastructure restoration and transport management

Nikola Bešinović [a,*], Raphael Ferrari Nassar [a], Christopher Szymula [b]

[a] Department for Transport and Planning, Delft University of Technology, Delft, The Netherlands
[b] "Friedrich List" Faculty of Transportation and Traffic Science, Technische Universität Dresden, Dresden, Germany

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ABSTRACT

During railways operations, unplanned events might occur which can result in rail traffic being heavily impacted. The paper proposes a passenger-centred resilience assessment for disruption scenarios which consist of multiple simultaneous disruptions. It combines train traffic operations, passenger flows and network restoration. To evaluate resilience, an optimization-based approach has been developed for solving the new infrastructure restoration and transport management (IRTM) problem. Additionally, this approach develops mitigation plans for the best infrastructure restoration and traffic recovery and it captures the time-dependent transport network performance during disruptions. The approach is general with respect to types of disruptions, and can be applied for evaluation against short disruptions (1–2 h) as well as more substantial ones (multiple days or weeks). The performance of the proposed approach has been demonstrated on a Dutch railway network. Furthermore, the resilience of the system is assessed against the critical infrastructure disruption scenarios in the network. This optimization-based approach shall enable decision makers to quantify accurately impacts of multiple disruptions by considering the created inconveniences to passengers in the railway operation due to these disruptions.

1. Introduction

In many countries, including the Netherlands, railway plays a major role in people's daily mobility. However, during railways operations, unplanned events, i.e. disruptions, might occur which can result in traffic being impacted, and as such can cause significant implications on train operations as well to passengers ability to travel. In particular, more severe impacts are typically experienced when multiple simultaneous disruptions are spread widely in the network. A day with severe disruptions is referred as to a Black day, it can happen due to adverse weather, e.g. a storm,[1] or a serious failure in the network, e.g. a broken catenary wire.[2]

The growth in number of trains and number of passengers progresses faster than constructing new railway infrastructure, entailing denser operations in the railway network (NS, 2019). It can also be seen that the number of disruptions increased as well.[3] Disruptions can lead to partial or complete track blockages of the network. In the Netherlands, on average in 2019, 16 disruptions per day occur and the average duration of a disruption in the network is two and a half hours. Thus, simultaneous multiple disruptions may frequently occur. Since they represent a grand challenge for railway operations, operators should be particularly aware of the impacts of future disruptions, able to quantify them, and most importantly prepare the response strategies.

It is vital to have clear strategies to contain and mitigate disruptions, and then work to restore normal service as quickly as possible. Decision-support could improve the potential outcome of train traffic planning by presenting viable options given the current disruption context (Schipper and Gerrits, 2018). During incidents there are a number of re-planning activities to keep the train service running around the affected area and then to bring the affected area back into service after the incident has closed. Currently, support for re-planning is often limited, reactive and dependent on the dispatchers' skills (Golightly et al., 2013). When dealing with multiple disruptions in particular, the available restoration equipment and/or teams may be limited and then their management and coordination may further define the duration of the overall disruptions. However, these elements (train services, infrastructure restoration) are often addressed independently. When things

* Corresponding author.
E-mail address: n.besinovic@tudelft.nl (N. Bešinović).

[1] https://nltimes.nl/2018/01/18/code-orange-flights-scrapped-trains-delayed-traffic-jammed
[2] https://nltimes.nl/2019/04/09/randstad-train-traffic-disrupted-broken-overhead-line
[3] www.rijdendetreinen.nl/en/statistics

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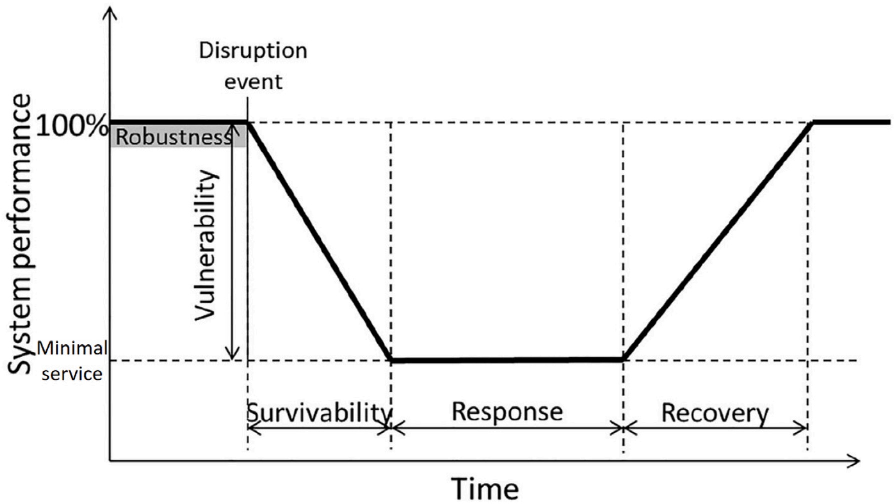

Fig. 1. Resilience of railway system.

go wrong, however, the inter-relation between these elements plays an important role and thus, with close linkages between (seemingly) independent roles becoming apparent.

Resilience of railway transport system has been originally introduced as the ability to absorb disruptions, and to rapidly recover from perturbations (Adjetey-Bahun et al., 2016). Recently, Bešinović (2020) extended it to the present form to incorporate performance in normal conditions and state the individual phases of resilience. Resilience of railway transport systems is defined as the ability of a railway system to provide effective services in normal conditions, as well as to resist, absorb, accommodate and recover quickly from disruptions (Bešinović, 2020). Fig. 1 depicts the stages of the system resilience, so called the resilience curve. This system performance presentation is also referred as a bathtub model (Ghaemi et al., 2017). In theory, the system is expected to return to 100%. In practice, depending on a disruption type and/or severity, the performance could reach less than 100% within a considered period, e.g. a day.

This paper presents a new approach for assessing resilience of railway networks taking into account traffic management and infrastructure restoration and it illustrates a scenario-specific approach, i.e. for given disruption scenarios. Railway system combines multiple subsystems including infrastructure, rolling stock, passengers and restoration teams. The paper introduces an infrastructure restoration and traffic management (IRTM) problem and proposes a new optimization-based approach for optimal recovery from multiple disruptions in a railway network from the passengers perspective. The aim is to jointly determine the best sequence for restoring disrupted elements, generate traffic rescheduling during disruptions and minimize total impacts on passengers such as rerouting and denied boardings. To do so, a heuristic framework has been developed that combines a mixed integer linear program (MILP) for disruption management and enumeration of possible restoration sequences. Essentially, the presented approach models explicitly response and recovery phases in Fig. 1, with response starting right after disruption occurrence, and thus, survivability is not modelled explicitly, as the system deteriorates instantaneously to the minimum level with the occurrence of disruptions. The scope of the research is estimating resilience against disruptions that commonly occur on a regular basis, daily/weekly, and dispatchers need to address them frequently; and, it considers a single restoration team, so the links are visited sequentially. In particular, resilience is assessed against critical (i.e. worst-case) disruption scenarios to determine the expected worst possible performance of the system. The experimental results in the Dutch railway network show the capability to estimate efficiently the system resilience and find the corresponding optimal recovery plans including restoration sequences and traffic management.

The current paper exhibits the following main contributions:

- Models a railway transport system with multiple network interdependencies including infrastructure, trains, passengers, and restoration activities.
- Determines resilience for railway network after simultaneous multiple disruptions by combining infrastructure restoration and transport management.
- Exploits resilience metrics that accounts for passenger-related and train-related costs during disruptions.
- Provides the resilience optimal sequence of restoration activities.
- Demonstrates the proposed approach on a real-life cases in the Dutch railway network.

The remainder of the paper is as follows. Section 2 presents the existing literature on resilience in railway networks and states the scientific gaps. Section 3 introduces the problem formulation of IRTM, and Section 4 gives mathematical modelling and the solution approach. Section 5 shows the results and Section 6 gives the concluding remarks. Finally, Appendix presents a detailed summary of the possible restoration scenarios from the example disruption scenario (presented in Section 5.2).

2. Literature review

In this section, an overview of the current literature is shown. First, Section 2.1 presents the state-of-the-art on optimization approach on traffic management. Second, Section 2.2 gives the state-of-the-art on restoration of infrastructure. Third, the gaps in current research are identified together with the proposed idea of our research. For a detailed review of resilience in railway transport systems, we refer to Bešinović (2020).

2.1. Dealing with disruptions: Transport management perspective

Most of disruption-related research has been done in which optimization approaches were used to provide input to decision-makers on how to better recover from disrupted networks for a given disruption scenario. The main focuses of disruption-related research from transport perspective are train rescheduling (e.g. Meng and Zhou (2011), Zhan et al. (2015),), determining critical links (e.g. Gedik et al. (2014)) and recently passenger rerouting (e.g. Zhu and Goverde

(2019)). We refer to Cacchiani et al. (2014) for an overview of real-time railway rescheduling problems as well as the solutions.

Meng and Zhou (2011) proposed a stochastic programming approach to incorporate different probabilistic scenario in the time horizon in order to minimize the expected additional delay under different forecast operational conditions. Their model was able to provide the order of trains to proceed after the disruption with the last delay. Narayanaswami and Rangaraj (2013) described the problem of rescheduling trains due a disruption on a single-track railway line. The authors developed a mixed integer linear program (MILP) model to minimize the weighted delay of all trains at their destination. The model does not allow trains to be cancelled, and it does not consider the capacities of the stations. Zhan et al. (2015) provided a MILP model that considers a single disruption in the high-speed train railway that led to total blockage of the network. The trains that are blocked due to the disruption does not leave their stations, and the order in which the remaining trains have to enter the network, after the disruption is finished is determined.

Veelenturf et al. (2017) proposed a heuristic approach for a partially integrated rescheduling model for both timetable and rolling stock. They considered the passenger perspective on scenarios in which large disruptions with partially blockage occurred in the network and aimed on minimizing delays and cancellation due to lack of rolling stock and using additional stops to the timetable services as to improve the overall passengers experience. Zhu et al. (2018) proposed two approaches when dealing with multiple disruptions. The first one is the sequential approach, in which single-disruption rescheduling model is used to solve each of the disruptions in a sequential order. The second one is the combined approach, in which a multiple-disruption model is used to handle each extra disruption with all ongoing disruptions being considered.

Zhu and Goverde (2019) proposed a Mixed Integer Linear Programming (MILP) model to handle timetable rescheduling in the railway system in case of a complete blockage. The model aims at minimizing passengers' delays by considering re-timing, reordering, cancelling, flexible stopping (i.e. adding or removing stops) and flexible short turning as dispatch decisions. Zhu and Goverde (2021) developed two approaches for rescheduling the timetable in a dynamic environment: the sequential approach and the combined approach. Adjetey-Bahun et al. (2016) proposed a simulation based model to quantify the resilience of mass railway transport systems under disruption by measuring passenger delay and passenger load. They considered four interrelated subsystems: transportation, power, organization, and telecommunication.

Alternatively, research on contingency planning aimed at creating predetermined adjusted timetables for a given disruption scenario (e.g. Van Aken et al. (2017)). These contingency plans would typically speed up tackling the disruptions once they occur in real-time. Van Aken et al. (2017) proposed a Mixed Integer Linear Programming (MILP) model to solve Train Timetable Adjustment Problems (TTAP) in case of multiple possessions occurring in the Dutch Railway network. The goal is to minimize the deviation from the original timetable.

Zhang and Ng (2022) developed a model to formulate the cascading failure based on the disaster spreading theory and network theory to investigate robustness of the urban rail transit network. Tang et al. (2021) assessed resilience focusing on passenger flows after multiple random or malicious disruptions, and considered disrupting platforms at stations. Their work focused on recovery phase, and proposed two heuristic approaches. Xu and Chopra (2022) focused on resilience analysis based on spatial–temporal flow patterns from a passenger-centric perspective using network theory approach. They addressed random and targeted disruptions based on node importance. Tang et al. (2021) and Xu and Chopra (2022) considered network theory approaches and only passenger flows, while not determining optimal train service adjustments nor an optimal maintenance sequence.

For network-wide approaches for railway resilience, the current research is limited. Gedik et al. (2014) proposed a two-stage Mixed Integer Programming (MIP) to maximize the total disruption in the network by finding the most critical combination of disruptions, i.e. to evaluate vulnerability of the network. Then it looks for the optimal rerouting of the freight trains in the network by using a discrete dynamic network flow problem. The model aims at minimizing costs and delays on the disrupted network and considers the capacity constraints and congestion of the network. Babick (2009) proposed a modified Multi-Commodity-Flow (MCF) aiming at minimizing shipping costs (and penalties for non-delivery) in a freight transport network. He developed a tri-level framework to model multiple disruptions in the Western U.S railroad network in case of mutual attacks on various links in the network and defence reactions of a fictitious attacker and defender of the network. Bababeik et al. (2018) proposed a heuristic approach for increasing the resilience level of a critical rail network by applying the strategy of location and allocation of emergency relief trains. Szymula and Bešinović (2020) proposed a new Railway Network Vulnerability Model (RNVM) as to find a combination of links which cause the worst consequences for passengers and trains in the Dutch railway network. They used column generation and row generation with a MILP to model the passengers' flow and infrastructure constraint as to minimize passengers travel cost. The dispatch modes considered in the paper are rerouting, short-turning and cancellation.

2.2. Dealing with disruptions: Infrastructure restoration perspective

To increase resilience of the network, it is important to investigate and optimize the strategies for infrastructure restoration as they may have a significant implications on the overall system performance. However, in railway context, a limited work has been performed. Zhang et al. (2018) proposed a framework based on complex network theory to recover from multiple disruptions. They considered infrastructure network (modelled as an undirected graph) and evaluated based on metrics connectivity of stations and links for each disrupted/recovery state. While doing so, neither train services nor passengers were considered.

Janić (2018) proposed analytical models for assessing the resilience of a given rail network using the figures-of-merit, and evaluated ex-post impacts of the large-scale disruptive event—the Great East Earthquake in 2011 and of the recovering the high-speed railway Tohoku line. Recently, Büchel et al. (2020) and Knoester (2021) proposed data-driven approaches for an ex-post resilience assessment of railway networks, using historical traffic realization data, for given disruption in Switzerland and the Netherlands, respectively. In addition, Knoester (2021) analysed a large heterogeneous set of single disruptions, and determined representative resilience curves dependent on disruption type (e.g. switch/signal/track failure, vehicle breakdown and collision). Yin et al. (2022) analysed historical realized traffic data and focused on train services. To evaluate resilience, they proposed a hybrid knowledge-based and data-driven Bayesian network.

Majority of research lies in maintenance planning on tactical level to determine optimal scheduling for infrastructure improvements activities. While doing so, typically, assets life-cycle has been in the main focus. Furuya and Madanat (2013) presented a decision-making framework that focuses on designing optimal maintenance policies of railway infrastructures, while minimizing costs and applying clustering of activities where possible. The relevant cost savings are generated if two or more adjacent facilities are maintained simultaneously. Fecarotti and Andrews (2017) developed intervention programs for an entire network by selecting the intervention strategy based on the conditions of assets combining Petri-Net simulations and knapsack-based MIP model.

Pargar (2015) used an integer linear program to determine the optimal time point for executing interventions on different track components considering dependencies between different components through component and location specific setup costs, and between different track sections through a system dependent setup cost. Burkhalter and Adey (2018) proposed a model for determining optimal intervention programs, i.e. optimal planned closures of infrastructure sections for its maintenance. They approximated impacts on train traffic of a single infrastructure closure, where the cost represents the total increased train travel time per unit time due to disrupted conditions. It focuses on a detailed line including track sections and interlocking, and thus its application is limited to short railway lines. While doing so, optimal train rescheduling and passenger rerouting were not considered. Bressi et al. (2021) proposed a probabilistic railway track degradation models using the theory of Markov chains. Then, they formulated a multi-objective optimization problem is formulated and solved using a Genetic Algorithm.

More broadly, restoration strategies and approaches on (interdependent) critical networks have been used to improve resilience of the system by finding optimal sequence of restoring elements (e.g. Almoghathawi et al., 2019), scheduling restoration tasks (e.g. Nurre et al., 2012), determining the best subset of links to recover (e.g. Fang et al., 2016), assigning and routing single and multiple restoration teams (e.g. Morshedlou et al., 2018; Iloglu and Albert, 2018; Li et al., 2019) and integrated restoration planning and crew routing (e.g. Morshedlou et al. 2021). Commonly, the resilience-based impacts are modelled at the level of (interdependent) infrastructure network and they are based on the ability to provide paths/flows in the network. However, operational services were not considered explicitly on top of such infrastructure networks. Examples of such services could be service schedule-based operations (e.g. trains, buses) or customers (e.g. passengers of freight) were not considered explicitly. We refer to Çelik (2016), Liu and Song (2020) Sharkey et al. (2021) for an overview of the literature on network restoration and recovery infrastructure.

2.3. Gaps

Table 1 summarizes the reviewed papers and highlights the contributions of the current paper. It shows the focus and considered elements in the railway-focused papers including consideration of resilience assessment type (network-wide/scenario-specific), number of disruptions (single/multiple), infrastructure restoration, train traffic rescheduling, passenger demand, and type of the model proposed.

When dealing with disruptions, gaps can be identified. Disruptions have been tackled from two exclusive perspectives, either transport management or infrastructure management.

- In traffic management, multiple disruptions have been tackled only recently (e.g. Veelenturf et al., 2017, Van Aken et al., 2017; Szymula and Bešinović, 2020; Zhu and Goverde, 2021). While doing so, a given disruption scenario assumes both start and end time are known and all disruptions resolve at the same time. However, none of the papers considered the recovery phase based on determining the sequence of blockages to be recovered.
- In infrastructure restoration, most of the restoration approaches typically considered only the costs and benefits of executing preventive maintenance of infrastructure components, i.e. planned maintenance (e.g. Fecarotti and Andrews, 2017, Burkhalter and Adey, 2018, Bressi et al., 2021), while dealing with disruptions has not been tackled. Also, these infrastructure restoration approaches commonly do not consider impacts to the train services as well as passengers.
- Current network theory-based railway resilience assessment approaches consider random failures and passengers flows only (e.g. Xu and Chopra, 2022; Tang et al., 2021, while they do not model critical disruption scenarios, optimal train service adjustments nor an optimal maintenance sequence.
- The existing data-driven resilience assessment approaches (e.g. Büchel et al., 2020; Knoester, 2021; Yin et al., 2022) provide a valuable insight into performance during a specific disruption scenario. However, these cannot be used to evaluate various infrastructure recovery alternatives for each disruption scenario, nor suggest optimal decisions towards most resilient operations.
- Papathanasiou and Adey (2020) stressed the importance of quantifying effects on rail service when comparing intervention strategies and determining the optimal ones and highlighted the need for further research in these topics. Similarly, Liu and Song (2020) stressed the need for addressing demand-driven resilience assessment of critical infrastructures.

To the best of our knowledge, the problem of jointly optimizing the routing of restoration teams (i.e. sequencing the restoration of links), the rescheduling of train services and the rerouting of passenger flows has not been appropriately studied for disrupted railway networks.

3. Problem definition

The paper proposes a passenger-centred resilience assessment for disruption scenarios which consist of multiple infrastructure disruptions. It combines infrastructure elements, train services and passengers. Time-dependent transport network performance during disruptions is captured. The approach determines resilience of the system (i.e. response and recovery strategy) including optimal infrastructure restoration sequence, i.e. routing the restoration team, optimal traffic rescheduling and passenger routing during the disrupted period; and the objective is to minimize the passenger and train costs due to rerouting and cancellations. Railway transport resilience can be described as the loss of transported passengers and operated train services in a network. Finally, we quantify the resilience curve as shown in Fig. 1.

To model network resilience, we combine four levels of networks as shown in Fig. 2. The first level refers to the infrastructure network which includes the disrupted links. The second level presents the train service network, the third level presents the passenger flows throughout the network and the fourth level is road network used by the restoration team to visit the disrupted links.

We propose to perform resilience assessment against the critical disruption scenarios in the network. A disruption scenario, including single or a number of multiple disruptions, which has the most severe impacts on passengers in the network for the given number of simultaneously disrupted links is referred as critical (Szymula and Bešinović, 2020). For example, we can have the critical scenarios with 1, 2 or 3 disruptions. Such scenarios may also be referred as to worst-case or extreme. This way, one can understand the lowest possible performance and thus, the worst expected impacts on the system.

3.1. Notation

Infrastructure Network. The physical railway infrastructure network is modelled as a graph $G^I = (N, A)$. Set of nodes N represents the stations and the set of undirected arcs A represents the links between two stations. To represent the infrastructure restrictions in the network, parameter $h_{ij}^{t,m}$ is defined as a minimum headway time on arc $(i,j) \in A$ between two successive trains $t, m \in T$. Parameter m_{ij} defines whether an arc (i,j) is disrupted ($m_{ij} = 1$) or not ($m_{ij} = 0$). The set of all

Table 1
Summary of the reviewed papers on railway system resilience under disruptions.

Paper	Assessment	Disruptions	Infrastructure restoration	Train traffic	Passenger flows	Model
Meng and Zhou [7]	scenario	single	–	+	–	stochastic program
Narayanaswami and Rangaraj [12]	scenario	single	–	+	–	MILP
Veelenturf et al. [13]	scenario	single	–	+	–	MILP, heuristic
Zhu et al. [14]	scenario	multiple	–	+	–	MILP, sequential
Zhan et al. [8]	scenario	single	–	+	–	MILP
Van Aken et al. [16]	scenario	multiple	–	+	–	MIP
Gedik et al. [9]	network-wide	multiple	–	+	–	MIP
Babick [20]	network-wide	multiple	–	+	–	MIP
Bababeik et al. [21]	network-wide	multiple	–	+	–	heuristics
Szymula and Bešinović [22]	network-wide	multiple	–	+	+	MIP
Zhu and Goverde [10]	scenario	single	–	+	+	MILP
Zhu and Goverde [15]	scenario	multiple	–	+	–	MILP-based, rolling-horizon
Adjetey-Bahun et al. [4]	scenario	double	–	+	+	simulation-based
Zhang et al. [23]	scenario	multiple	+	–	–	complex network model
Zhang and Ng [17]	scenario	multiple	–	–	–	network theory
Tang et al. [18]	scenario	multiple	+	–	+	network theory, heuristic
Xu and Chopra [19]	scenario	multiple	+	–	+	network theory
Janić [24]	scenario	multiple	+	+	–	analytic, ex-post
Büchel et al. [25]	scenario	single	–	+	–	analytic, ex-post
Knoester [26]	scenario	single/multiple	–	+	–	analytic, ex-post
Yin et al. [27]	scenario	single	+	+	–	knowledge based, Bayesian network, ex-post
Furuya and Madanat [28]	scenario	multiple	+	–	–	two-stage optimization
Fecarotti and Andrews [29]	scenario	multiple	+	–	–	Petri-nets, MIP
Pargar [30]	scenario	multiple	+	–	–	ILP
Burkhalter and Adey [31]	scenario	multiple	+	+-	–	MIP
Bressi et al. [32]	scenario	multiple	+	–	–	Markov chain, Genetic Algorithm
This paper	**scenario/network-wide**	multiple	+	+	+	MIP-based approach

disrupted arcs in the network is defined as $A' \subset A$ and is given as input of the problem, and only complete closures are considered.

Train Service Network. Set of trains T includes all trains running in the infrastructure network G^I. For train $t \in T$, subsets A^t and N^t represent the route that each of the trains is originally scheduled route. A route of the train $t \in T$ contains the origin $N(O_t)$ and destination $N(D_t)$ nodes, which are connected via traversed arcs and nodes in A^t and N^t, respectively. An arc-based formulation is used to model trains in the network. The binary decision variable x^t_{ij} represents the flow of each train $t \in T$ on arc $(i,j) \in A$. Thus, $x^t_{ij} = 1$ if the train is using the corresponding arc, and $x^t_{ij} = 0$ otherwise. In other words, the train route of a train $t \in T$ is defined as the set of arcs $(i,j) \in A$ with $x^t_{ij} = 1$.

For some train types it is more important to operate between their origin and destination, e.g. freight trains, while the others is more important to provide services on scheduled routes. Therefore, the set of trains T consists of two disjoint subsets representing the trains that can be rerouted $T^{RR} \subset T$ and the trains that can be short-turned $T^{ST} \subset T$ and run on scheduled routes. Set T^{RR} is composed of international and freight trains and the T^{ST} of intercity and local trains. Correspondingly, the decision variables x^t_{ij} are modelled on the complete network $(i,j) \in A$ for trains in T^{RR}, to allow for rerouting in the network. While, for trains in T^{ST}, x^t_{ij} are modelled only for $(i,j) \in A^t$.

For routing and short-turning, the binary decision variables o^t_i and d^t_i are used to model the actual origins and destinations of a train $t \in T$. If a train t originates (terminates) in node $i \in N^t$, o^t_i (d^t_i) is 1, otherwise is 0. In particular, for all trains in T, the scheduled origins and destinations (from the scheduled timetable) are fixed to 1. For trains in T^{ST}, these decision variables are used in N^t to ensure that the train origin and destination are only in nodes of the original route. And for trains in T^{RR}, all intermediate nodes are fixed to 0, to prevent short-turning of these trains.

A scheduled timetable TT is given to ensure the feasibility of trains operation. The timetable TT provides the scheduled departure (and passing through) times $T^t_{D,i}$ and arrival times $T^t_{A,i}$ of train $t \in T$ at node $i \in N$. The dwell time of train $t \in T$ at station $i \in N$ is represented as t^t_i. Additionally, parameter τ^t_{ij} represents the minimum running time of train $t \in T$ between nodes i and j, and is computed taking into account train characteristics like max speed, train type and engine characteristics. The decision variables $T^t_{\overline{D},i}$ and $T^t_{\overline{A},i}$ represent the retimed departure and arrival time of train $t \in T$ in node $i \in N$ respectively. The disrupted timetable is referred as DT consisting of $T^t_{\overline{D},i}$ and $T^t_{\overline{A},i}$ (or cancellations) for all trains T.

Passenger Network. The passenger demand in the railway network is represented by the Origin–Destination (OD) matrix K, where k represents a single OD pair. Parameter d_k represents the passenger demand (i.e. number of passengers) for the flow k. A path-based formulation approach is used to model passenger flows. A passenger path p_k is defined as a sequence of nodes $n \in N$ between the origin and destination of the passenger flow $k \in K$. Set of paths $p \in P^k$ is defined in the network for each k. The determination of alternative paths in P^k allows for passenger detours from the shortest path, taking into account the train capacity. To calculate the service capacity in train $t \in T$, the parameter s^t defines the number of seats. To model the actual passenger flow in the network, the decision variable f^k_p represents the demand share of the total demand of path $p \in P^k$ of the OD pair k. The shortest path algorithm is applied when routing the passenger flow, this is done in order to model a realistic response from the railway operators. Normally, operators aim at ensuring that the passengers flow that are influenced by the disruption can be rerouted within the shortest path available, considering the operational and capacity constraints.

Restoration network. The restoration team uses road network to reach disrupted links. Instead of modelling the road network explicitly, we introduce a restoration network $G^R = (D, A^R)$. Set D presents the disrupted network components, and is referred as to a disruption scenario. Let us denote a single disruption component as d_i, where $d_i \in D$. The number of components in the disruption scenario is $|D|$. A restoration scenario R is defined as an ordered sequence of disruptions in D. For example, for a disruption scenario consisting of three disruptions $D = \{d_1, d_2, d_3\}$, a possible restoration scenario can be $R = d_3 \rightarrow d_1 \rightarrow d_2$, meaning that d_3 is restored first, followed by d_1 and finally d_2. These components can be either nodes or arcs. In our

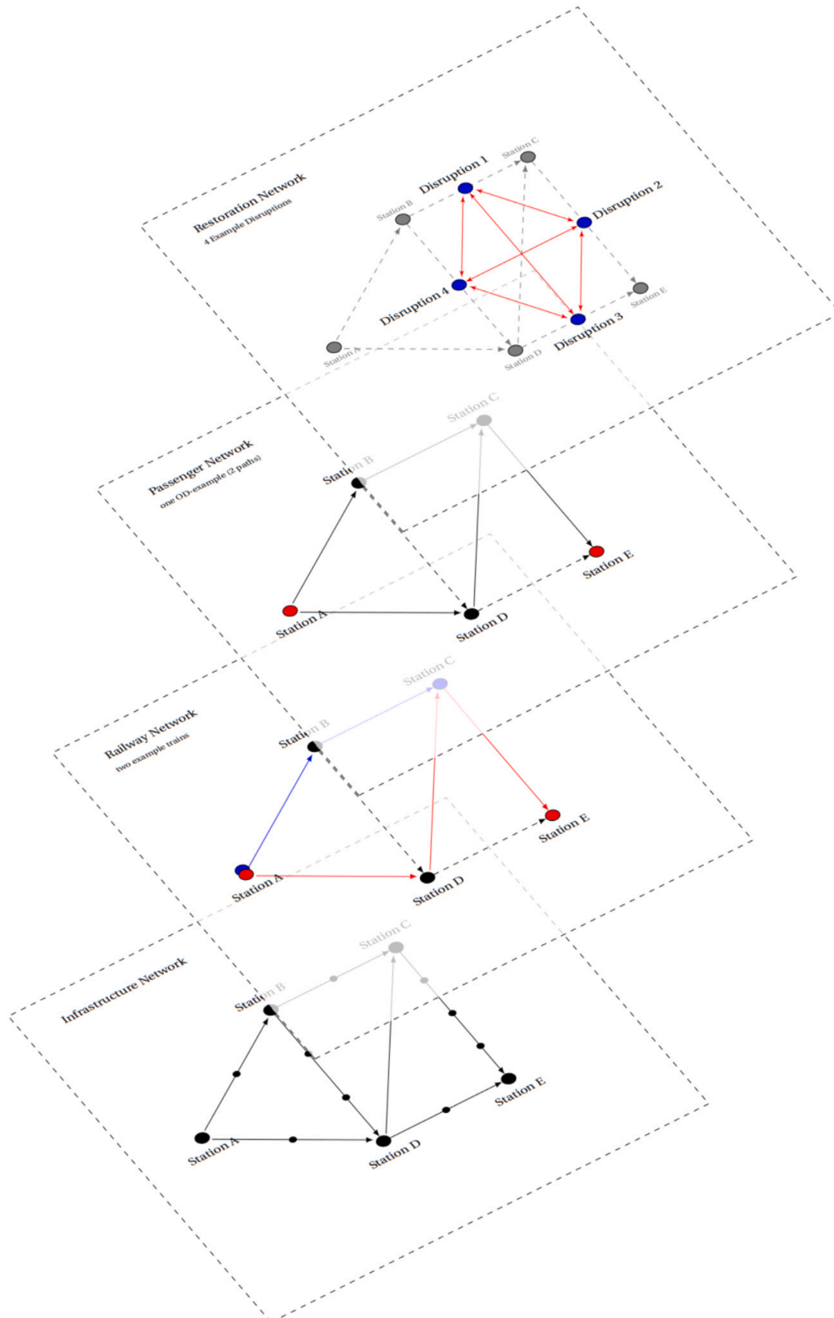

Fig. 2. Overall multi-level network view of the problem.

case, only links are considered to be disrupted. In essence, the nodes D in restoration network G^R correspond to links A' in infrastructure network G^I, where each node $d_i \in D$ is mapped to the specific arc $(i,j) \in A'$. To provide an exact location of d_i on the disrupted link (i,j), it is assumed that the disruption is located in the middle of the corresponding disrupted railway link. Set of links A^R between disrupted nodes represent road connections between any two disrupted components in D, i.e. the shortest paths in the original road network.

4. Methodology

To assess resilience of the railway network under multiple disruptions, we develop an optimization-based approach that combines a disruption management model (DMM) for determining optimal traffic management strategies for a given fixed set of disruptions, the enumeration procedure of possible routing sequences of the restoration team, and a computation of the overall costs and impacts on railway transport. We refer to this problem as **infrastructure restoration and transport management (IRTM)** problem. The resilience-based impacts include total (remaining) number of passengers transported and number of train services altered, e.g. rerouting, partial or complete cancellations. The DMM is modelled as a mixed integer program and computes a steady-state adjusted (response) timetable for a single phase during the fixed disruptions.

Thus, the DMM is solved multiple times for each subset of disrupted links, representing a sequential restoration of links, and the incumbent results are combined in the total impact for each restoration sequence. While doing so, the DMM captures the interdependencies between the multiple disruptions in the network within each phase. The corresponding resilience curve is characterized by multiple response phases until the network is recovered, i.e. each phase for a fixed subset of disrupted links. Note that traffic transitions between any two disrupted phases, i.e. periods with fixed number of disruptions, are not considered. Therefore, the outcome can be considered as an approximation of the expected impacts, and thus it could be referred as to resilience "stairway", instead of "curve". The resilience cost $resCost$ of the system is computed as:

$$resCost = \sum_{i=0}^{|D|-1} \frac{F_0 - F(R_i)}{F_0} \cdot (t_{i+1} - t_i), \tag{1}$$

where F_0 represents the performance of the undisrupted system, R_i represents a subset of (remaining) disrupted links within a disruption scenario D for the ith link being restored, R_0 is equal to a case with all links D being disrupted. Then, $F(R_i)$ is the performance incurred at a single disrupted phase and is obtained by solving DMM for a fixed set of disrupted links. Finally, the impact is multiplied by the duration of the phase $(t_{i+1} - t_i)$, from the end of phase i to the end of phase $i + 1$. The performance $F_{(R_i)}$ can be quantified in number of transported passengers, running trains or passenger-minutes. The **resCost** represents the area above the resilience curve and is calculated as the sum of the unmet performances over the independent periods, i.e. adjusted response timetables. The resCost can be quantified as percentage of e.g. unsatisfied demand (non-transported passengers), not-provided supply (cancelled trains) or extra incurred travel times(pax-minutes). Note that such normalized $resCost$ is preferable in order to allow for comparisons with different railway networks. Section 4.1 gives the modelling assumptions, Section 4.2 presents the mathematical formulation of DMM, and Section 4.3 defines the algorithm for solving IRTM and computing $resCost$.

4.1. Assumptions

There are several assumptions and considerations for the proposed optimization-based approach for resilience assessment:

- Considered disruptions are complete infrastructure closures of open tracks only, i.e. links. Disrupted links could be either completely disrupted or fully operated after its restoration.
- For restoring the network, exactly one restoration team is available, and therefore the links need to be fixed sequentially.
- Restoration durations for disrupted links are fixed, where all disrupted links are assumed to have the same restoration duration of one time unit, i.e. hour, for each disrupted link.
- Travel times for restoration team between two locations is assumed equal, and thus w.l.o.g. it is not explicitly considered as part of the **resCost**.[4]
- A train can short-turn at any station, i.e. enough station capacity is available.
- Trains are short-turned only if they are directly affected by a disruption,
- Passengers are routed along the shortest paths within the network.
- Passenger demand is assumed equal for the complete disrupted period.
- Transport capacity for each train is fixed.

[4] Note that the equal travel times do not impact the optimal sequence of the solution, they can only contribute to the total cost.

4.2. Disruption management for fixed disruptions

The DMM model for determining optimal disruption management strategies for trains and passengers for a fixed set of disruptions is introduced. The DMM formulation combines arc-based and path-based formulations to model network infrastructure, train services and passenger flows. First, the train services and the underlying infrastructure are closely related and highly interdependent; therefore, they are modelled together using an arc-based formulation where trains are modelled as flows in an infrastructure network. Such arc-based formulation enables easy implementation of short-turning and rerouting in the railway network. Second, the passenger flows depend on the resulting provided capacities (i.e. trains running in the network); thus, they are modelled using a path-based formulation. This formulation can be solved more efficiently, when expecting a large number of alternative passenger paths for real-life problem instances. A similar modelling approach was taken by e.g. Szymula and Bešinović (2020).

The DMM model contains three sets of constraints including (1) train routing and cancelling, (2) train rescheduling and (3) passenger routing. The goal of the DMM model is to minimize the inconveniences in railway operations due to the simultaneous disruptions. More formally, the objective of the DMM is to maximize transported passengers over the shortest paths, and minimize their total time spending in the network, as well as to minimize train cancellations, train rerouting, and train delays, i.e. deviations from the original timetable, as given in Eq. (2). To do so, the specific costs are defined. The travel cost c_p^k accounts for the travel times over traversed arcs of the path p for the OD pair k, and is calculated using averaged travel cost over all passenger trains running on each arc. In this paper, only the travel time is considered, while waiting and transfer times are neglected. The term $1/c_p^k$ is used to favour using the shortest paths. The rescheduling cost c_{delay}^t is applied for the trains that deviate from the original time for each arrival event. To avoid double counting of delays at a single station then only delays at arrival events are considered. The cancellation cost c_{cancel}^t is applied to penalize train cancellations. The generalized rerouting cost $C_x^{i,j,t}$ is defined using the train-related travel times per arc τ_{ij}^t and the corresponding cost per time unit c_r^t, and is computed as $C_x^{i,j,t} = c_r^t \cdot \tau_{ij}^t$. Finally, to keep as many running services as possible, no operation cost regarding short-turning is applied.

The mathematical formulation of the DMM model is given as:

$$\begin{aligned} \max \sum_{k\in K} \sum_{p\in P^k} 1/c_p^k \cdot d_k \cdot f_p^k - \sum_{t\in T^{RR}} \sum_{(i,j)\in A} c_{cancel}^t \cdot x_{ij}^t \\ - \sum_{t\in T^{RR}} \sum_{(i,j)\in A} C_x^{i,j,t} \cdot x_{ij}^t - \sum_{t\in T} \sum_{i\in N} c_{delay}^t \cdot (T_{\bar{A},i}^t - T_{A,i}^t) \end{aligned} \tag{2}$$

such that

$$\sum_{j\in N} x_{ij}^t - \sum_{j\in N} x_{ji}^t = \begin{cases} -o_i^t, & \text{if node i is a starting node} \\ d_i^t, & \text{if node i is an ending node} \\ 0, & \text{otherwise} \end{cases} \quad \forall t \in T, i \in N^t \tag{3}$$

$$\sum_{i\in N^t} o_i^t = \sum_{i\in N^t} d_i^t \qquad \forall t \in T \tag{4}$$

$$o_i^t = 1 \qquad \forall t \in T, i = N(O_t) \tag{5}$$

$$d_i^t = 1 \qquad \forall t \in T, i = N(D_t) \tag{6}$$

$$o_i^t = 0 \qquad \forall t \in T^{RR}, i \neq N(O_t), N(D_t) \tag{7}$$

$$d_i^t = 0 \qquad \forall t \in T^{RR}, i \neq N(O_t), N(D_t) \tag{8}$$

$$o_j^t \geq m_{ij} \qquad \forall t \in T^{ST}, i \in N^t, (i,j) \in A^t \tag{9}$$

$$d_i^t \geq m_{ij} \qquad \forall t \in T^{ST}, j \in N^t, (i,j) \in A^t \tag{10}$$

$$\sum_{i\in N^t} o_i^t \leq \sum_{(i,j)\in A^t} m_{ij} + 1 \qquad \forall t \in T^{RR} \cup T^{ST} \tag{11}$$

$$\sum_{i\in N^t} d^t_j \le \sum_{(i,j)\in A^t} m_{ij} + 1 \qquad \forall t \in T^{RR} \cup T^{ST} \tag{12}$$

$$T^t_{D,i} + \tau^t_{ij} \le T^t_{A,j} + M(1 - x^t_{ij}) \qquad \forall t \in T^{RR}, (i,j) \in A \tag{13}$$

$$T^t_{D,i} + \tau^t_{ij} x^t_{ij} \le T^t_{A,j} \qquad \forall t \in T^{ST}, (i,j) \in A^t \tag{14}$$

$$T^t_{D,i} \ge \sum_{j\in N} T^t_{D,i} x^t_{ij} \qquad \forall t \in T, i \in N^t \tag{15}$$

$$T^t_{D,i} - T^t_{A,i} \ge t^t_i - M(1 - x^t_{ij}) \qquad \forall t \in T^{RR}, (i,j) \in A \tag{16}$$

$$T^t_{D,i} - T^t_{A,i} \ge t^t_i x^t_{ij} \qquad \forall t \in T^{ST}, (i,j) \in A \tag{17}$$

$$T^t_{D,i} \ge T^m_{D,i} + h^{t,m}_{i,j} - M(1 - x^t_{ij}) - M(1 - x^m_{ij}) \qquad \forall t \in T, m \in T, i \in N^t, m \ne t \tag{18}$$

$$T^t_{A,i} - T^t_{D,i} \ge 0 \qquad \forall t \in T, i \in N^t \tag{19}$$

$$\sum_{p\in P^k} \delta^p_{ij} d_k f^k_p \le \sum_{t\in T} s^t x^t_{ij} \qquad \forall (i,j) \in A \tag{20}$$

$$\sum_{p\in P^k} f^k_p \le 1 \qquad \forall k \in K \tag{21}$$

$$x^t_{ij}, o^t_i, d^t_i \in \{0,1\} \qquad \forall t \in T, n \in N^t \tag{22}$$

$$f^k_p = [0,1] \qquad \forall k \in K, p \in P^k \tag{23}$$

Train routing. Constraint (3) ensures the flow continuity and that the trains are only allowed to start or end at origin and destination nodes o^t_i and d^t_i, respectively. Constraint (4) guarantees that the number of origins and destinations on each train route is the same. Constraints (5) and (6) ensure that the original scheduled origins and destinations at the terminals of the trains are always kept as sources/sinks for the train flows in order to maintain the original train services as in the undisrupted case. Constraints (7) and (8) guarantee that rerouted trains are not being short-turned and it is routed from its origin to destination. Constraints (9) and (10) link the short-turn location selection to a disrupted link. If a link is disrupted, the trains originally using this link are forced to short-turn at the station right next to the disrupted link, and thus "new" origin and destination are introduced. These constraints deals with short-turning due to disrupted links in the original train route only. Constraints (11) and (12) ensure that originally scheduled trains are only short-turning according to the number of disrupted links at the original route, in order to prevent unnecessary short-turning, e.g. on an undisrupted part of the network. Additionally, it allows the existence of at least one origin and destination to represent the undisrupted state.

Train rescheduling. Constraints (13) and (14) ensure the minimal running times between two stations for rerouting and short-turning trains in case of train operations on link (i,j). Constraint (15) guarantees that the rescheduled departure time cannot be earlier than the one originally planned. Constraint (16) relates to the dwell time for rerouting, and similarly, constraint (17) guarantees the dwell time for short-turned trains. Both constraint (16) and (17) only need to hold if there are trains running. Constraint (18) ensures the minimal headway times in the case of both involved trains are operating. Constraint (19) guarantees the non-negativity of all time instances.

Passenger routing. Constraint (20) limits the cumulative passenger flows at each arc. Here, the parameter δ^p_{ij} is used to determine whether the path $p \in P^k$ of passenger flow $k \in K$ traverses the arc (i,j). Constraint (21) restricts the passenger flow shares for each OD pair k to be at most as large as the overall demand of that pair. Lastly, constraint (22) sets the range of the train-related decision variables of the problem, and constraint (23) restricts the range of the passenger-related decision variables.

4.3. Solution approach

We introduce an optimization-based approach for resilience assessment by jointly restoring links, managing train traffic and routing passengers in the network. Algorithm 1 gives the pseudocode for assessing resilience of a railway network based on the IRTM. The algorithm takes the railway network G^I, original timetable TT, OD demand matrix K and disruption scenario D. Note that the duration for restoring each link and travelling between two links are assumed equal, and thus, time is not explicitly required in the algorithm. The outcome is constituted of resilience cost $resCost$, the optimal restoration sequence R^*, and the disrupted timetable DT^*, i.e. represents a set of timetable variants for each disrupted phase.

Algorithm 1: Algorithm for railway resilience assessment

1 function Resilience assessment (G^I, TT, K, D);
Input : infrastructure G^I, timetable TT, passenger OD matrix K, set of disruptions D,
Output: optimal sequence R^*, disrupted timetable DT, resilience cost $resCost^*$
2 Initialize $resCost = 0$, $DT = 0$
3 Compute F_0 ←DMM(0)
4 Generate all restoration scenarios $\mathscr{R}$
5 Compute $F(D)$ ←DMM(D)
6 **for** $s = 1$ **to** $|\mathscr{R}|$ **do**
7     $D_s = R_s$
8   set $resCost(R_s) = \frac{F_0 - F(D)}{F_0}$, $DT(R_s) = DT(D)$
9   **while** $D_s \ne \emptyset$ **do**
10         $D_s = D_s \setminus D_s\{1\}$
11   Compute $F(D_s)$ ←DMM(D_s)
12   Update $resCost(R_s) = resCost(R_s) + \frac{F_0 - F(D_s)}{F_0}$, $DT(R_s) = DT(R_s) + DT(D_s)$
13   **end**
14 **end**
15 Optimal resilience cost: $resCost^* = \min\{resCost(R_1), ..., resCost(R_{|\mathscr{R}|})\}$
16 Optimal restoration sequence: $R^* = \{R_s | resCost(R_s) = resCost^*, s = 1, ..., |\mathscr{R}|\}$
17 Optimal disrupted timetable: $DT^* = DT(R^*)$

The algorithm starts with initializing $resCost$ and DT, and computing the system performance for undisrupted scenario F_0 by running DMM with no disruptions, which essentially finds the optimal routing for passengers. In step 4, all restoration scenarios are generated, i.e. sequences, $\mathscr{R}$, where $R \in \mathscr{R}$. The number of possible scenarios $|\mathscr{R}|$ is equal to the number of all combinations of disruptions in D. The sth restoration scenario is denoted R_s, and the optimal scenario is denoted R^*. Then, the DMM is solved once for all disrupted links in D (step 5). The output performance of the DMM for the single phase is $F(D)$. Note that this first disrupted phase is equal for all scenarios in $\mathscr{R}$. For each restoration scenario, a new auxiliary set D_s consisting of the remaining (non-restored) disruptions is introduced (step 7). Also, an initial resilience cost for the sth scenario R_s is set to $(F_0 - F(D))/F_0$ and the corresponding disrupted timetable DT for this phase is saved (step 8). Then iteratively, the first disruption in sequence D_s is removed, denoted $D_s\{1\}$, which represents this link being restored (step 10). The DMM is resolved for the remaining disruptions in D_s (step 11), and the $resCost(R_s)$ ($DT(R_s)$) is updated with the cost (disrupted timetable) of the new reduced D_s (step 12). In essence, the $DT(D_s)$, representing a timetable for this new disrupted period, is added ("glued") to the existing $DT(R_s)$. The sequence of steps 10–12 is repeated until all disruptions are restored and the corresponding partial costs are computed and therefore also the total resilience cost and disrupted timetable for sequence R_s is obtained. The number of iterations of the while-loop is equal $|D| - 1$. That is due to the case that all recovery scenarios have equal cost in the first period after a disruption happened, i.e. when the number of actual disruptions equal $|D|$. Therefore, the DMM is solved only once for all links in D.

In step 15, the resilience of the system $resCost^*$ is determined as the minimal value of $resCost$ among the previously computed resilience costs over all scenarios in $\mathscr{R}$. Such $resCost^*$ represents the maximal remaining system performance. Also, the corresponding restoration sequence R^* and the disrupted timetable DT^* are taken as final, in steps 16 and 17, respectively .

For solving larger real-life instances by the DMM, some computation challenges may arise. First, the model may theoretically have an extreme number of possible travelling path alternatives P_k for each pair k. Considering them all in the model at once may render the problem impossible to solve (e.g. Gentile et al., 2016). However, many of such paths may not be used in practice, since they are long detours. Second, a problem could be a great number of headway constraints to satisfy infrastructure dependencies to guarantee operational feasibility of computed solutions. However, as we start with an existing timetable that satisfies all headway constraints already, when adjusting train services due to disrupted critical links, only a limited number of extra headway constraints may be considered additionally. To solve the DMM efficiently, we use a heuristic approach proposed by Szymula and Bešinović (2020) which combines (1) a column generation for introducing useful alternative passenger paths and (2) row generation for introducing the headway constraints to train routes that are in conflict.

The adopted enumeration approach of all possible restoration sequences may theoretically lead to an excessive amount of required computations of the DMM. However, in practice, this approach remains to be acceptable for a small number of simultaneous disruptions in a disruption scenario. For example, the number of simultaneous disruptions in the Dutch railway network typically remains under five disruptions, while in urban railway networks, e.g. Copenhagen metro, it rarely reaches three simultaneous disruptions.

5. Experimental results

The resilience assessment IRTM approach is demonstrated on a Dutch passenger railway network. First, we show the working of the proposed approach on an exemplary case study for a given realistic disruption scenario in the eastern part of the Dutch network. Second, we analyse railway resilience against the critical disruption scenarios in the complete Dutch network, and also, recognize the change (deterioration) in system resilience with the number of disrupted links. Section 5.1 gives the experimental setup, Section 5.2 performs a detailed specific analysis for an exemplary case study, and Section 5.3 presents a more general analysis - a network resilience assessment against different number of disruptions.

5.1. Setup

Fig. 3 shows the Dutch passenger railway network used in the experiments. The red circle highlights the eastern part for the first experiment, while the complete network is used in the second one. The infrastructure network consists of more than 500 (848) infrastructure arcs and 250 (398) stations in which approximately 330 (507) trains operate per hour for the first (second) experiment.

The traffic data is the General Transit Feed Specification (GTFS) data of the operating timetable from a working day in 2019 and includes the operated lines, routes and the scheduled arrival and departure times. The passenger demand per origin and destination (OD) pairs is based on real demand data from the Dutch railway network, and only the passenger flows with demands higher than 100 passengers per hour are considered. A train capacity is set to 500 seats for example case study and 1000 seats for network resilience assessment. The model and the solution approach are implemented in Matlab and solved using CPLEX version 12.9.0.

For the restoration process in all experiments, it is assumed that the repair time of any disrupted link is equal to 60 min. Such disruptions could relate to e.g. fixing a broken switch, removing a failed train, or clearing a fallen tree. The model is directly applicable to disruptions lasting multiple hours/days, and it would require only multiplying the obtained costs with the duration (time needed) to restore a link. Regarding train operations, intercity and local trains operate on their planned routes, while the international trains can be also rerouted.

In the example case study (experiment 1), the disruption scenario consists of three link disruptions: Echt-Roermond, Arnhem Zuid-Elst and Utrecht Lunetten-Utrecht Vaartsche Rijn. These links are chosen because of their importance in the overall performance of the Dutch railway network. Disrupting these multiple locations simultaneously is expected to cause a higher level of severity to railway operations. This disruption scenario resembles a Black day, similar to e.g. 10 December 2017.[5] To better understand the size of the network, we report characteristic distances between the main stations in the eastern part of the Netherlands. The distance between Utrecht Centraal and Eindhoven Centraal is approximately 76 km, Anrhem Centraal and Nijmegen is 18 km and Nijmegen and Roermond is 84 km. Additionally, Utrecht-Nijmegen is 57 km, Utrecht-Zwolle is 81 km, Zwolle-Groningen is 85 km, and Groningen-Leeuwarden 51 km. This information helped us understanding the dimension of the area impacted by these disruptions.

In the network-wide resilience assessment (experiment 2), to generate the critical scenarios for the given number of disruptions, we used the Railway Network Vulnerability Model (RNVM) developed in Szymula and Bešinović (2020). In particular, scenarios with 1 to 5 disruptions are considered. We do not consider more than 5 disruptions, as more simultaneously occurring disruptions are rare to happen. Table 2 gives an overview of the critical disruptions.

In the experiments, we (1) find the most resilient restoration scenario and traffic management for the given disruption scenarios including resilience costs the number of transported passengers, their travel costs and number of impacted train services, and (2) draw the corresponding resilience curves. Also, we uncover the added value of using a passenger-centred metric for resilience assessment (compared to train-centred ones). To do so, we report performance in the number of transported passengers and define the relation between transported passengers and the running trains. In order to have a benchmark on transport performance in undisrupted network, i.e. the number of passengers that can be transported in the network, the DMM model is run without any disrupted links, and thus represents 100% of network performance. This resulted to $F_0 = 57{,}912$ passengers for the example case study, and $F_0 = 333,855$ passengers for the network-wide resilience assessment.

5.2. Example case study

In total, six restoration scenarios are generated presenting all possible sequences of combining the three given disruptions (see Table 3). For each restoration scenario, Algorithm 1 is run to assess resilience.

Table 4 presents network performance for each scenario in terms of the total number of transported passengers, the total number of disconnected passengers, the total number of affected train (partially/completely cancelled or rerouted), the objective function value, computed by DMM

[5] https://nltimes.nl/2017/12/11/multiple-train-traffic-disruptions-trains-zaandam

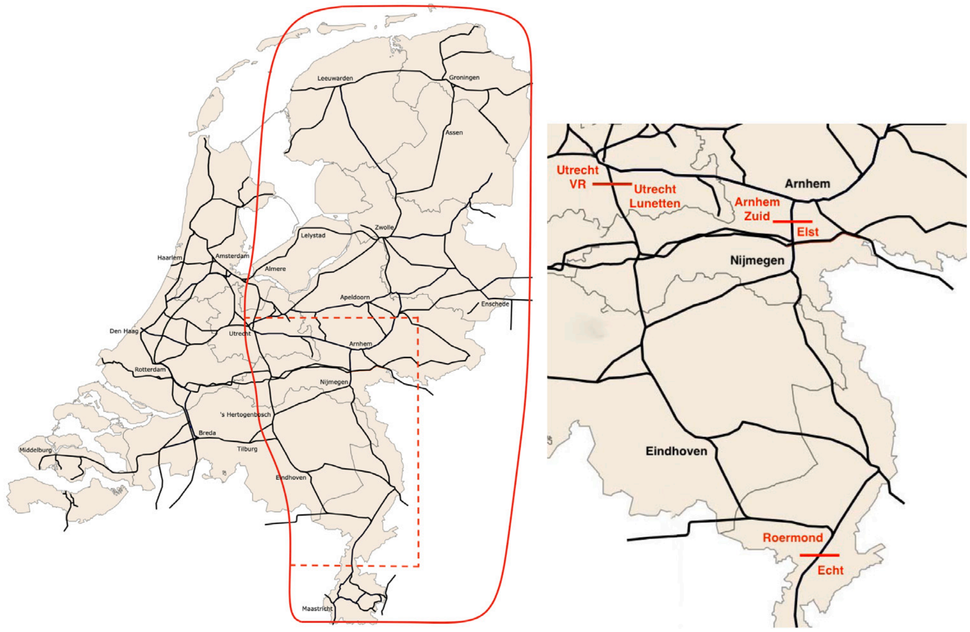

Fig. 3. Complete case study network (left) and the zoomed part of the network with highlighted disruptions for the exemplary experiment (right).

Table 2
The critical disruption scenarios.

Critical disruption scenarios				
1 disruption	2 disruptions	3 disruptions	4 disruptions	5 disruptions
Sittard-Susteren	Sittard-Susteren Cuijk-Mook Molenhoek	Sittard-Susteren Nijmegen Lent-Nijmegen Nijmegen Goffert-Nijmegen	Sittard-Susteren Rotterdam Centraal-Rotterdam Blaak Gouda-Gouda Goverwelle Amsterdam RAI-Duivendrecht	Utrecht Centraal-Utrecht Vaartsche Rijn Sittard-Susteren Rotterdam Centraal-Rotterdam Blaak Weesp-Almere Poort Hoevlaken-Barneveld Noord

Table 3
All possible combinations for the restorations with three disrupted links.

	First arc restored	Second arc restored	Third arc restored
Scenario 1	Echt - Roermond	Elst - Arnhem Zuid	Utrecht Lunetten - Utrecht Vaartsche Rijn
Scenario 2	Echt - Roermond	Utrecht Lunetten - Utrecht Vaartsche Rijn	Elst - Arnhem Zuid
Scenario 3	Elst - Arnhem Zuid	Echt - Roermond	Utrecht Lunetten - Utrecht Vaartsche Rijn
Scenario 4	Elst - Arnhem Zuid	Utrecht Lunetten - Utrecht Vaartsche Rijn	Echt - Roermond
Scenario 5	Utrecht Lunetten - Utrecht Vaartsche Rijn	Elst - Arnhem Zuid	Echt - Roermond
Scenario 6	Utrecht Lunetten - Utrecht Vaartsche Rijn	Echt - Roermond	Elst - Arnhem Zuid

(2)–(23), and the resilience cost $resCost(R_s)$, computed using Eq. (1)). These values present summations over the disrupted phases, from a disruption start until the last disruption was fixed. The table highlights that Scenario 5 is the best solution as it leads to the highest number of passengers transported and the lowest number of affected trains. Also, the highest value on the objective function is in line with the goal of the problem, as it helps to minimize the inconveniences in the network. In this scenario, the first step was to assign the restoration of the disruption between Utrecht Lunetten and Utrecht Vaartsche Rijn. This would make sense since many passengers (i.e. OD pairs) originate/end at station Utrecht. This is then followed by the link between Elst and Arnhem Zuid and Lastly Echt-Roermond. Finally, as the last link to be restored is Echt-Roermond, which is more at a periphery of the network and lesser number of passengers traverse this link.

Fig. 4 shows the resilience curve, from disruption occurrence to recovery, based on the number of transported passengers for best recovery scenario - Scenario 5. The performance is given as the ratio of transported passengers during disruption, compared to the nominal conditions (i.e. 100%) and given in %. The time instance (state) 0 represents the state before the disruptions occur. Then, in the following three states (hours) the three disrupted links are restored sequentially, one per each state. In the fourth state, all train services and disruptions are restored. Here, 100% represents normal operations and equals 57,912 transported passengers. When all three links are closed (state 1), the percentage of transported passengers drops to about 79.7% and then gradually increases as links are being fixed. In the third state, with one remaining disruptions, only 1.8% of passengers were not able to travel.

Table 5 presents the detailed results from the optimal restoration and train recovery plan (Scenario 5). In Appendix, the detailed results for all remaining scenarios are shown. Each row reports the disrupted states with the corresponding disrupted links. It includes the total cost of the objective function, the total number of transported passengers among the three-hour restoration and recovery process, the total number of disconnected passengers and the total number of affected train lines. It shows that the number of disconnected passenger when all 3 links (state 1) are disrupted is as much as 11,730 passengers, while it drops to only 1,058 passengers for the last remaining disrupted link (state 3). It can also be seen that no trains were rerouted (only international trains could be rerouted), and no trains were additionally

Table 4
Comparison of the different restoration scenarios. The best scenario is highlighted - Scenario 5.

	Number of transported passengers	Number of disconnected passengers	Number of affected trains	Objective function	resCost
Scenario 1	146,576	27,160	118	217,408	46.9
Scenario 2	150,144	23,592	107	219,946	40.7
Scenario 3	149,644	24,092	107	224,016	41.6
Scenario 4	154,351	19,385	91	228,501	33.5
Scenario 5	**156,954**	**16,782**	**86**	**230,863**	**29.0**
Scenario 6	155,815	17,921	91	228,916	30.9

Table 5
Detailed results for Scenario 5.

Disrupted state	Disrupted links	Objective function	Transported passengers	Disconnected passengers	Rerouted trains	Cancelled trains	Short-turned trains	Duration [h]	resCost [-]
1	Lunetten - Vaartsche Rijn Arnhem Zuid - Elst Echt - Roermond	68,894	46,182	11,730	0	0	48	1	20.3
2	Arnhem Zuid - Elst Echt - Roermond	78,901	53,918	3,994	0	0	27	1	6.9
3	Echt - Roermond	83,068	56,854	1,058	0	0	11	1	1.8
Total		230,863	156,954	16,782	0	0	86	3	29.0

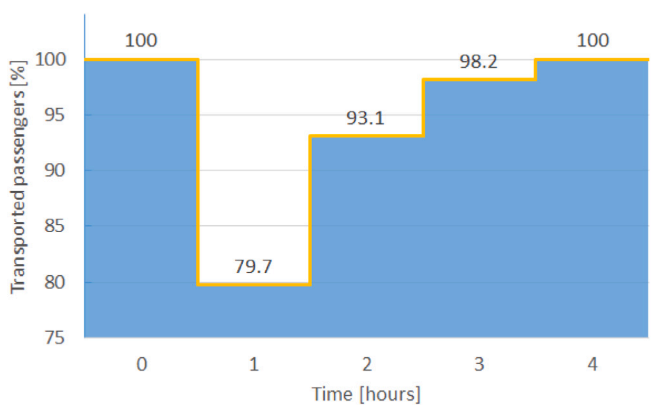

Fig. 4. Resilience curve for the best restoration scenario - Scenario 5.

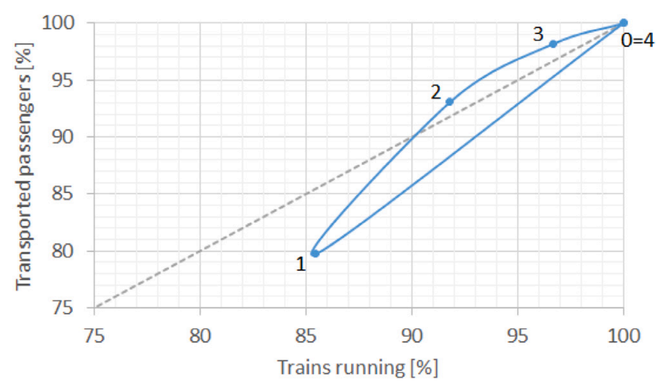

Fig. 5. Relation between transported passengers and running trains - Scenario 5.

cancelled during disruptions. Looking at the running train services, it can be seen that for the first state as many as 48 trains needed to be short-turned. The first restored link Utrecht Lunetten-Vaartsche Rijn by itself is responsible for 21 short-turned trains in the network. The disruption of this link led to 7,7336 disconnected passengers (i.e. equal to the difference between disrupted states 1 and 2).

At state 2, the number of short-turned trains nearly halved; it went to 27. The blockage of the second link Arnhem Zuid - Elst contributes to 16 trains having to be short-turned. By restoring this link the number of short-turned trains decreases to only 11 and the number of passengers increased to 56,854 in state 3. It is interesting to observe that, in other restoration scenarios in which this link Arnhem Zuid-Elst is the first link to be fixed (i.e. scenarios 3 and 4), the amount of new passengers that are enabled to travel again is higher than in scenario 5 (5,113 in scenario 3 and 4 and only 2,936 in scenario 5). This can be explained by the fact that, after the restoration of Utrecht Lunetten - Utrecht Vaartsche Rijn, some of the passengers that were disconnected because of the disruption between Elst and Arnhem Zuid were reassigned to other alternative routes in order to reach their destination. Finally, for the third link Echt-Roermond, even though this corridor is the main connection between the eastern and the southern part of the network, it is responsible for only 11 of the 48 trains being short-turned in this experiment and it contributed to 1,058 passengers not being transported.

We now investigate the relation between train-centred and passenger-centred impacts of resilience assessment. Fig. 5 visualizes the relation between transported passengers and number of running trains during the disrupted period. Each point represent one state during a disruption. The diagonal represents an equal impact on passengers and trains respectively. Points above the diagonal indicate a heavier impact on trains, while points below indicate a heavier impact on passengers. For example, the point 1 (79.7;85) represents the first state with all three disruptions. The state 0 (4) represents the system before (after) the disruptions. It can be seen that the relation between affected trains and passengers is not linear. In fact, when more disruptions are present a more significant impact is observed on passengers; fewer passengers are able to travel and do not have rerouting alternatives. Instead, for limited disruptions (states 2 and 3), passengers tend to have the alternative routes to choose from, and thus more possibilities to perform their journeys. Therefore the impact on passengers is lower. It can be seen that the number of affected trains (due to infrastructure restoration) may have non-linear implications on the transported passenger flows, and thus tend to lead to inaccurate estimation of the system resilience.

Regarding possible influences of inter-station distances, disrupting a long link may lead to an excessive passengers detour, particularly for passenger demand that originates/ends near such disruptions. Thus, their alternative routes may not be attractive, due to significantly increased travel time, and the passengers could decide not to travel. An example of such link would be between Leeuwarden and Groningen in

Table 6
Results overview of the resilience assessment for 5 critical scenarios.

Scenario	Disruption duration [h]	Number of transported passengers	Number of disconnected passengers	Number of affected trains	Objective function	resCost [-]
1 disruption	1	326,809	20,869	11	4,943,958.71	2.1
2 disruptions	2	659,143	41,707	19	10,289,111.13	2.6
3 disruptions	3	963,951	79,349	63	10,401,488.17	11.3
4 disruptions	4	1,225,224	146,782	281	17,576,081.85	33.0
5 disruptions	5	1,416,779	164,118	357	20,182,691.81	75.6

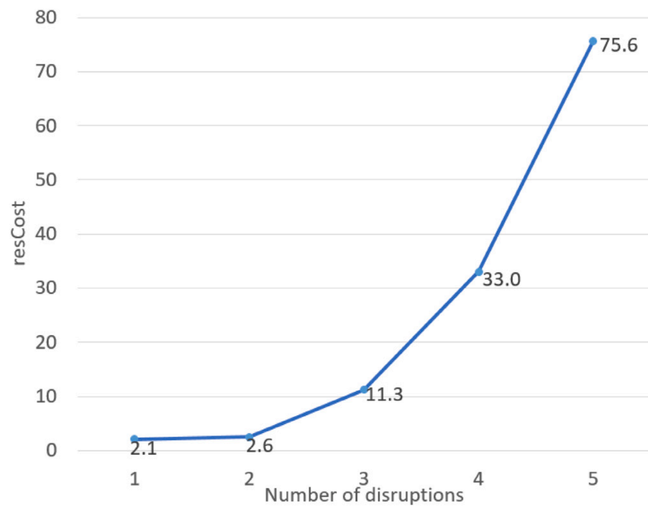

Fig. 6. Resilience costs for the 5 critical scenarios.

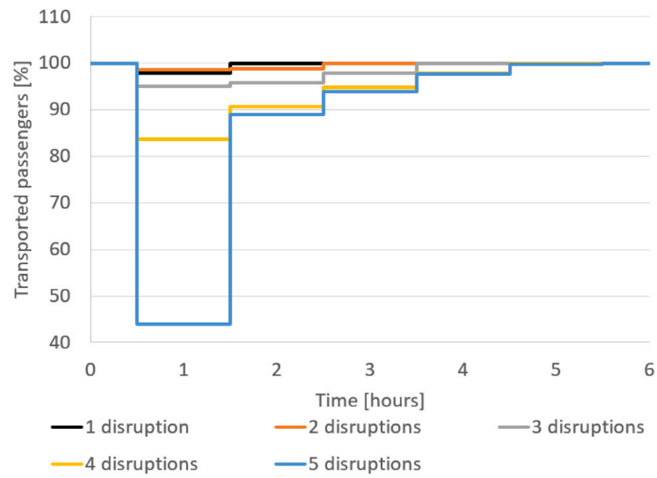

Fig. 7. Resilience curves for the 5 critical scenarios.

the northern part of the country (see Fig. 3). Additionally, to have such long link critical from the passenger perspective, it also has to serve a high volume of passengers in normal conditions. Thus, the criticality of links depends on complex relations between distances, passenger demand and alternative passenger routing options.

5.3. Resilience assessment against the critical disruption scenarios

This section presents the results of the resilience assessment for the critical disruption scenarios with 1 up to 5 disrupted links computed using the **IRTM** approach. Table 6 gives the assessment overview showing the duration of disruptions, number of transported/disconnected passengers, number of affected trains (short-turned and cancelled), objective function and resilience cost $resCost$ due to the disruptions. It expectedly demonstrates the increasing number of disconnected passengers and affected trains when increasing the number of disruptions in scenarios. Similarly, the OF increases as well. Note that the number of transported passengers increases, with longer periods of disruption, however, it changes with a less than a linear rate, suggesting that scenarios with more disruptions create significantly higher impacts. Looking at $resCost$, scenarios with 1 and 2 disruptions lead to only minor implications to the network, i.e. having $resCost$ of 2.1 and 2.6, respectively. Instead $resCost$ rise sharply for 3, 4 and 5 disruptions, increasing 3 times from 3 to 4 disruptions, and then again 2.3 times from 4 to 5 disruptions. Fig. 6 visualizes the resilience costs $resCost$ for the 5 critical scenarios. It clearly shows the exponential impact of disruptions to the railway network. And, any other disruption scenario with the same number of disruptions is expected to have lower $resCost$ that the selected ones.

Fig. 7 shows resilience curves for the 5 critical scenarios for the corresponding optimal recovery strategies. Each curve shows a gradual increase in performance, measured as transported passengers, with restoration of each link. Typically, more significant improvements are seen after restoring the first links, while they reduce at the later stages. Most strikingly, for 5 disruptions, in the first period (when all disruptions are active), the network performance drops to as low as 44% of the normal. Luckily, it springs back to 89% after recovering the first disruption. For scenarios with up to 3 disruptions, the impact is limited to above 95% (Note that this is the performance on the network level, while in Section 5.2 the eastern part of the railway network was considered. Thus, the values between the two experiments are not directly comparable since different networks were used.).

Fig. 8 depicts relations between transported passengers and running trains for 5 critical scenarios (for optimal restoration sequences). It clearly shows the discrepancy represented in a non-linear relation between the two metrics. Moreover, it does not show a recognizable trend over different disruption scenarios. On one hand, for some disruption scenarios, train-related resilience measure tend to generate an underestimation (a higher impact on passengers than on trains) of disruptions effects over all phases, e.g. scenario with 3 disruptions. On the other hand, scenarios with 2 and 4 disruptions show the overestimation of train-related measure over all phases. However, for 5 disruption scenario, the it is an overestimate in phases with no more than four disruptions and underestimate when all links are broken. Most notably, in the last case, it shows that passengers are significantly more impacted than trains, leaving only 44% of transported passengers vs 77% of running trains of the total numbers in the undisrupted phase. These results highlight the relevance of using passengers-related metrics for evaluating resilience of railway transport systems in order to obtain more accurate and more relevant performance estimates.

6. Conclusions

The paper presented a new optimization-based approach for quantifying resilience of railway networks while integrating infrastructure restoration, traffic management and passenger management. The system resilience was measured based on the (remaining) ability to transport passengers during the disruptions. The model is able to find

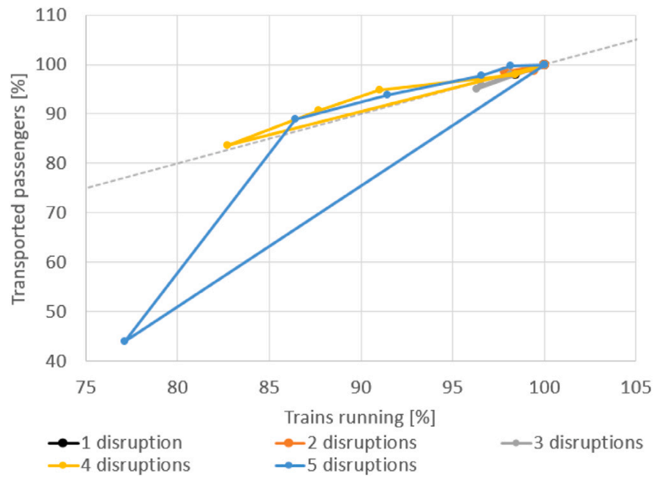

Fig. 8. Relation between transported passengers and running trains for 5 critical scenarios.

the most resilient restoration strategies for a given disruption scenario consisting of multiple link disruptions. The approach combines an optimization model for disruption management (DMM) to jointly reschedule train services and reroute passenger flows in the network and an enumerative procedure to evaluate various restoration scenarios, which are combined into an integrated Infrastructure Restoration and Transport Management (IRTM) framework.

The experiments showed high potential for assessing resilience of the Dutch railway network. At the same time, the proposed IRTM approach identifies jointly the optimal link restoration sequence the corresponding train timetable, and passenger flows in the network. The resilience curves were generated showing the system performance during disruption. In addition, it demonstrated the added value of using a passenger-centred metrics for assessing resilience over the train-centred one for obtaining more accurate estimates of the disruption impacts. For the exemplary scenario with 3 disruptions, we observed that the optimal restoration sequence leads to $resCost$ of 29, which is 38% better than the worst case (scenario 1 with $resCost$ of 46.9), showing a great importance of choosing the best sequence. For network-wide resilience assessment of the national railway network, we observe that significant impacts on system performance may be expected for the critical disruption with 5 disruptions already, i.e. maximum drop in performance of 56%.

The presented IRTM approach is applicable to a wide range of railway-specific problems. The model is readily applicable to passenger-centred railway networks that have a single restoration team available, such as metro and urban networks. In addition, it is also applicable larger networks in some special cases, for example, when resolving disruptions requires a highly specialized equipment available in limited quantities, e.g. a crane to move a derailed train. The model can also be used for assessing a wide range of scenario-specific disruptions. For example, it could be applied to evaluate impacts of longer disruptions caused by e.g. floodings, landslides, or catenary wire breakdown, as well as track renewal works, that may last for multiple days/weeks. Also, it can be used for determining the optimal sequence of maintenance closures to minimize impacts on operations over the longer period. Finally, also be used for a more passenger-centred classification of black days, which are currently defined based on train punctuality and the number of failures in the network. This optimization-based approach enables decision makers to decide the sequence in which the disrupted links should be fixed in case of simultaneous multiple disruptions in the railway network, in order to minimize the resulting passenger inconveniences in the railway operation.

Some limitations of the current research are present. First, no exact transition phases are modelled, instead multiple steady-state traffic timetables are used to assess resilience of the system. Therefore, the quantified costs tend to represent an approximation of the exact impacts. Second, the proposed approach assumed a single restoration team, while a railway operator could have more teams available which would allow restoring multiple links simultaneously and thus lead to faster recovery of the system. And, there may be one or more depots for keeping restoration teams. Third, the approach uses an enumeration of all sequences for restoration, and this may lead to excessive computation time of the DMM model. Such approach may be appropriate for a relatively small number of disrupted links in the disruption scenario. However, for bigger networks with more simultaneous disruptions, it may not be suitable. Fourth, this research considered equal demand over the complete disruption, while in reality the demand may change during the day and thus have some impact the overall resilience. Finally, it does not consider explicitly travelling time between two disrupted links. By adding these, it may be expected that a disruption may last longer. However, such travel times would not impact the sequence of the restored links, but mostly the duration of each disrupted state.

Several directions for future work can be recognized. First, the current (scenario-specific) resilience analysis approach can be extended towards simultaneously determining the most critical combination of disruptions and the corresponding resilience of the network. Second, the mathematical model could further incorporate more features of restoration teams including travel times between disrupted links, availability of multiple teams, and their location in the network. Third, for more severe scenarios including many diverse disruptions in large railway networks, more efficient solution algorithms and models shall be investigated. Fourth, it would be beneficial to compare the performance of the model against the real-life behaviour of the system including train scheduling, passenger routing and restoration team scheduling. Finally, one could further learn from practical rules, regulations and constraints and incorporate them into resilience assessment. These would provide added values both towards modelling real-life more accurately, and also highlight possible bottlenecks (e.g. suboptimal dispatching actions) in the current practices. Such future resilience assessment model can be used for evaluating impacts and develop mitigation plans for various types of disruptions ranging from adverse weather, earthquakes, and also malicious attacks. As such, it will represent a solid support tool to decision makers in railway systems.

CRediT authorship contribution statement

Nikola Bešinović: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Raphael Ferrari Nassar:** Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Visualization, Writing – review & editing. **Christopher Szymula:** Data curation, Formal analysis, Investigation, Visualization, Writing – review & editing.

Appendix. Detailed results of all restoration scenarios

This appendix presents a detailed summary of the other five possible scenarios of the restoration process of from the disruption scenario, see Tables 7–11. An overview of these results obtained is in Table 1. A table, is given for each of the scenarios, showing the costs referred to the objective function, the number of passengers transported, the number of disconnected passengers, and the number of affected train lines. These values are added up in a final row with the total costs, this row represents how the network performed under the three hours in which it was affected by the disruptions.

Table 7
Results for scenario 1.

State	Disrupted links	Objective function	Transported passengers	Disconnected passengers	Rerouted trains	Cancelled trains	Short-turned trains	Duration [h]	resCost
1	Echt - Roermond Elst - Arnhem Zuid Lunetten - Vaartsche Rijn	68,894	46,182	11,730	0	0	48	1	20.3
2	Elst - Arnhem Zuid Lunetten - Vaartsche Rijn	69,931	48,247	9,665	0	0	43	1	16.7
3	Lunetten - Vaartsche Rijn	78,583	52,147	5,765	0	0	27	1	10.0
Total		217,408	146,576	27,160	0	0	118	3	46.9

Table 8
Results for scenario 2.

State	Disrupted links	Objective function	Transported passengers	Disconnected passengers	Rerouted trains	Cancelled trains	Short-turned trains	Duration [h]	resCost
1	Echt - Roermond Lunetten - Vaartsche Rijn Elst - Arnhem Zuid	68,894	46,182	11,730	0	0	48	1	20.3
2	Lunetten - Vaartsche Rijn Elst - Arnhem Zuid	69,931	48,247	9,665	0	0	43	1	16.7
3	Elst - Arnhem Zuid	81,121	55,715	2,197	0	0	16	1	3.8
Total		219,946	150,144	23,592	0	0	107	3	40.7

Table 9
Results for scenario 3.

State	Disrupted links	Objective function	Transported passengers	Disconnected passengers	Rerouted trains	Cancelled trains	Short-turned trains	Duration [h]	resCost
1	Elst - Arnhem Zuid Echt - Roermond Lunetten - Vaartsche Rijn	68,894	46,182	11,730	0	0	48	1	20.3
2	Echt - Roermond Lunetten - Vaartsche Rijn	76,539	51,315	6,597	0	0	32	1	11.4
3	Lunetten - Vaartsche Rijn	78,583	52,147	5,765	0	0	27	1	10.0
Total		224,016	149,644	24,092	0	0	107	3	41.6

Table 10
Results for scenario 4.

State	Disrupted links	Objective function	Transported passengers	Disconnected passengers	Rerouted trains	Cancelled trains	Short-turned trains	Duration [h]	resCost
1	Elst - Arnhem Zuid Lunetten - Vaartsche Rijn Echt - Roermond	68,894	46,182	11,730	0	0	48	1	20.3
2	Lunetten - Vaartsche Rijn Echt - Roermond	76,539	51,315	6,597	0	0	32	1	11.4
3	Echt - Roermond	83,068	56,854	1,058	0	0	11	1	1.8
Total		228,501	154,351	19,385	0	0	91	3	33.5

Table 11
Results for restoration scenario 6.

State	Disrupted links	Objective function	Transported passengers	Disconnected passengers	Rerouted trains	Cancelled trains	Short-turned trains	Duration [h]	resCost
1	Lunetten - Vaartsche Rijn Echt - Roermond Elst - Arnhem Zuid	68,894	46,182	11,730	0	0	48	1	20.3
2	Echt - Roermond Elst - Arnhem Zuid	78,901	53,918	3,994	0	0	27	1	6.9
3	Elst - Arnhem Zuid	81,121	55,715	2,197	0	0	16	1	3.8
Total		228,916	155,815	17,921	0	0	91	3	30.9

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