Issue 21(2), 2021, pp. 19-40
https://doi.org/10.18757/ejtir.2021.21.2.3956

TU Delft OPEN

EJTIR

ISSN: 1567-7141
http://ejtir.tudelft.nl/

A vulnerability analysis of rail network disruptions during winter weather in the Netherlands

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This paper presents a rail network vulnerability analysis to identify which links within the Dutch rail network are most vulnerable to winter weather. A vulnerability index was developed to measure rail vulnerability during winter weather based on switch-related disruptions, integrating both node and link components into a probabilistic measure of vulnerability. The analysis looked at disruption data for 379 Dutch stations during the years 2007-2017. Links in dense population areas, which operate a high number of switches, are most susceptible to winter disturbances. Particularly, three main railway stations (Utrecht, Amersfoort and Zwolle) are the most critical locations within the network in terms of extreme winter conditions and disruptions. In addition, we developed two scenarios to analyse implications of different railway switch reduction strategies on rail vulnerability. The proposed rail vulnerability index can be a useful tool to define operational strategies to reduce the vulnerability of the Dutch railway network. Decreasing the number of

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switches at station areas appears to be more effective for reducing railway vulnerability than decreasing the number of switches throughout the entire network.

Keywords: *Connectivity, failure probability, railway network vulnerability, switches, winter conditions.*

1. Introduction

Railway networks are sensitive to disruptions resulting from adverse weather conditions due to routing inflexibility; there are few detour possibilities. There are appears to be increasing interest in the literature for measuring the vulnerability of public transport networks (e.g. Cats and Jenelius, 2015; Li *et al*., 2019; Santos *et al*., 2020). However, as Mattsson and Jenelius (2015) state there is no commonly accepted definition of transportation vulnerability as it mostly depends on the context in which it is used. Reggiani *et al*. (2015) described it as the non-operability of a network under fluctuating circumstances and compared vulnerability to network weaknesses and reliability to network performance. Miller *et al*. (2010) argued that vulnerability has a significant correlation with resilience, representing two related yet different approaches to understanding system response. While vulnerability is applied when analysing failure, resilience focuses on recovery and return time following a disturbance. Other widely used concepts related to resilience and vulnerability are criticalities (Jenelius *et al*., 2006; Taylor, 2017; Rodriguez-Nunez and Garcia-Palomares, 2014), seen as the probability and consequences of component failure, and reliability (Reggiani *et al*., 2015; Vromans *et al*., 2006), seen as the operability of the network.

Infrastructure vulnerability is a key element of engineering in terms of supporting operational optimisation, failure prevention, high-level throughput and technological improvements. It is, therefore, crucial to acknowledge vulnerability in order to understand the risks and needs in rail network maintenance, management and operations. Yap *et al*. (2018) recently analysed the link vulnerability in a multimodal light rail/metro network in the southern part of the Netherlands. The authors highlight that including second-order spillback effects (the impact of local disruptions on the entire network) in an analysis can lead to improved vulnerability estimations. They concluded that busy links in the network are vulnerable, due to the combination of the high disruption exposure and high passenger flows.

In this paper, vulnerability is addressed by studying the likelihood of unserviceability within the Dutch rail network under extreme winter weather conditions. We examine rail vulnerability based on the probability of failure due to technical attributes (number of switches), weather conditions and service usage. Switches are the most common reason for infrastructure failure during winter (Kloow, 2011). We used disruption data from the Netherlands for the years 2007-2017 to develop a method that integrates switch failures with elements of demand (e.g. users) and supply (e.g. network attributes). In this paper, we propose a rail vulnerability index related to rail switch malfunctions in the Dutch rail network during winter weather as an operational tool to improve resource planning, maintenance, technological investments and risk management. To that end, we incorporated three dimensions of railway networks: potential users, ridership, and connectivity to construct both node and network vulnerability indexes. To the best of our knowledge, this is the first paper in the literature that takes this multidimensional approach to measure rail vulnerability. This paper contributes to the literature by examining how rail maintenance service providers can monitor and reduce disruptions related to switch malfunctions during winter weather. Enabling service providers to identify vulnerable links in a network and providing relevant information on where and when disruptions are most likely to occur will lead to better resource management. In addition, maintenance plans can be optimised and investments directly applied to the critical areas.

Inspired by risk management theory, we designed our study on the basis of four steps to analyse rail vulnerability as described by Rausand (2011). Firstly, we examine the question '*What can go wrong?*' which is defined as component failure type, i.e. device flaws that can result in service interruption. Secondly, we examine the '*likelihood of occurrence*', which we define as failure probability. Thirdly, we examine the question '*where is it most likely to happen?*' which connects the probabilities to specific locations to develop a geographical vulnerability index by way of a GIS analysis. Fourthly, and finally, we examine the element '*consequences of component failure*', which is interpreted as the network consequences, identifying the most critical route options during extreme winter weather and the impact on users.

The remainder of this paper is structured as follows. The following section contains the literature review. Section 3 presents the case study of the Dutch railway network, while Section 4 describes the methodology we used. Section 5 provides the descriptive statistics and results of this case study. Finally, Section 6 describes our conclusions.

2. Literature review

Attention for the vulnerability of public transport networks appears to be increasing in the literature. Cats (2016) concluded that most research on public transport network vulnerability is focused on topological indicators and how the degradation of physical links affects network connectivity. On the other hand, Taylor (2017) suggested multiple analysis steps which are based on four levels: risk-based (on individual components), topologically based analysis (to identify critical locations), serviceability-based vulnerability (to identify where the transportation system should be impaired by failures) and accessibility-based vulnerability (to understand economic and social consequences). These would cover most of the commonly used strategy development steps 'who, what, why, when, where, how and how much' needed to understand situation and context within vulnerability analysis.

Most transport networks have many workarounds depending on the type of disruption. However, railways are more sensitive to disruptions as a result of routing inflexibility; there are few detour possibilities. Partial and total blockages usually result in trip cancellations, longer travel times and additional operational costs. Among all rail failure causes, weather-related conditions are particularly challenging and diverse. Precipitation and fog affect visibility, while extreme heat can bend the tracks. Excessive snow, ice and frost can cause hours of delay and lead to economic efficiency loss, material damage and poor safety conditions (Rossetti, 2007).

So far, studies on the impact of adverse weather on rail network vulnerability have typically focussed on the effects on infrastructure supply or the impact on demand (users), using various techniques that combine modelling and simulation for different disruption causes. Each approach depends on the characteristics of the data and is developed on the basis of case-specific assumptions. Several studies into weather-related transport vulnerability focused on supply factors, e.g. Hong *et al*. (2015) who estimated vulnerability levels for railways in flood event scenarios using a Monte Carlo simulation and Erath *et al*. (2009) who developed a methodology for integrating vulnerability due to various natural hazards into current infrastructure management systems. Other studies illustrated that not only link factors but also node (stations) factors need to be taken into account. The size and network position of stations (connectivity) have been used as evaluation indicators in some studies. Sun *et al*. (2018) showed that large stations can cause a substantial cascading effect down the network. Dehghani *et al*. (2014) demonstrated that the average link condition in the network, differences in link condition, uncertainties associated with disruption probabilities and the topological position of links all affect network vulnerability. Blume *et al*. (2019) showed that optimization of and flexibility in specific routes of an urban-rail timetable reduced the impact of disruptions and enabled rescheduling and recovery after a disruption. The simulation-based approach to capture the interactions between train operations and passenger behaviour was based on a discrete-event simulation framework and paired with an agent-based model. The goal was to simulate passenger route choices and decisions during undisrupted and disrupted periods.

Regarding disruptions and the impacts on rail operations, Dorbritz (2012) introduced a new methodology that analyses the structural impacts of natural, technical or social hazards events on the network. This approach provides information about the most critical network elements and allows investment prioritization. Dorbritz's (2012) study assesses the structural and operational robustness of railway networks by identifying the critical stations and tracks (nodes and links) and simulating operations without them. His findings provide a visualization of degraded operation sections and identify bottlenecks. These insights are fundamental for proper risk and resource network management.

To measure the impacts of rail vulnerability on rail users, a frequently used method deploys catchment areas (Andersen and Landex, 2008; Gutierrez *et al*., 2011; Hartholt, 2016). Rietveld (2000) showed that different feeder modes have different catchment areas. Other studies have examined passenger flows to analyse the vulnerability of urban rail transit networks (Sun *et al*., 2018). Also, Sun *et al*. (2016) analysed changes in passenger flows during disruptions (detours, delays or passengers abandoning their journey) based on automated fare card data. Combinations can also be used. Gutierrez *et al*. (2011) adopted the distance-decay weighted regression (with bands) and La Paix Puello and Geurs (2016) used a joint revealed preference/stated preference estimation on station access and egress.

In summary, few studies in the literature have incorporated demand factors (passengers) and supply factors (links, stations and connectivity) to study the impact of adverse weather on railway vulnerability.

3. Winter weather disruptions in the Dutch railway system

The Dutch passenger rail network connects all major towns and cities in the country. The network totals approximately 3,700 route kilometres and over 350 frequently used passenger stations. The transport system is operated by several service providers including NS (Dutch Railways – *Nederlandse Spoorwegen*), Syntus, Arriva, Veolia and Connexxion, of which NS accounts for the highest share of operated trains (excluding metro and tram systems). Maintenance, rail capacity distribution and traffic control are the responsibility of ProRail, the train infrastructure manager.

ProRail classifies the causes of unexpected rail disruptions into four categories: weather, technical, third parties and general malfunctions. Examples are heavy snowfall, electricity blackouts or people walking along the tracks. Over the years, the country has met many weather-related challenges, especially unexpected winter conditions. In the past decade, the Dutch railways have suffered from many operational failures, specifically during the winters of 2009/2010 and 2010/2011. In 2012, a program called 'Winter weather on the tracks" (in Dutch: '*Winterweer op het Spoor*') was introduced to mitigate winter disruptions and was implemented by ProRail and Dutch Railways (NS, 2017).

We analysed the Dutch railway network by using the geocoded segments used by Prorail. These represent the tracks and all their components (including catenary and signalling), mainly being rail sections with no bi(multi)furcation. In case the number of components in a section was high, the section is fractioned. The delimitation of these segments follow the start/end of specific rail sections, which represent platforms, buildings, tracks, rail infrastructure and land within the perimeter. The exact location of components are not specified in geocoded segments. In addition, the network is seen geographically in larger areas called contract areas (CA) shown in **Error! Reference source not found.**. Specific companies contracted by ProRail maintain each CA; they are responsible for preserving rail components, guaranteeing the safe and sustainable operability of the network. The busiest parts (highest train frequencies) are located in the Randstad area, the most urbanised part of the country comprising the four largest cities in the Netherlands (Amsterdam, Rotterdam, The Hague and Utrecht) (see **Error! Reference source not found.**).

Figure 1 Distribution of contract areas

Figure 2 Randstad (contract) areas in red.

We used historical data that refer to rail disruption registries in three separate systems: asset management, traffic management and meteorological data. We collected the meteorological data from the website of the KNMI (Royal Netherlands Meteorological Institute, usually abbreviated to the Dutch acronym; KNMI, 2017), and the asset and traffic management data was made available by ProRail. All data refer to time periods between 2007 and 2017. The variables included the cause of disruption, duration, location and weather conditions. The data was prepared, examined, validated and interpreted before the start of the modelling work. The preparation consisted of defining and structuring data in a usable format for the planned analysis making inconsistency checks and studying any missing data. Faulty sets of data were excluded. The inconsistency check was carried out in a prearranged form, focusing firstly on inputs that were outside of the estimated ranges. Outliers were calculated and compared to the highest and lowest values in the dataset. All variables were integrated into a single data set to allow the estimation of statistical models.

After data preparation, we analysed the information quantitatively and qualitatively. The first step was to analyse the overall characteristics of the disruptions in all seasons. Each weather season was identified to have distinct impacts on the rail infrastructure. Lightning, for example, mainly triggers problems in the power supply network and the ICT system, while rain and storms strongly affect drainage systems. High winds can result in lower safety levels and require service interruptions, while floods can diminish the contact of the vehicle with the tracks and increase the chance of derailment.

Table 1 shows the descriptive statistics for the disruption occurrences in the Dutch railway system. The total number of disruptions due to winter weather in the period of 2007 to 2017 was 6,568. The annual number of disruptions during the winter period vary greatly (from 8 to 2,276), in line with the extreme weather conditions observed year by year. While 2007 and 2008 experienced mild winters, there were severe winter storms in both 2010 and 2011 in the Netherlands, leading to a government decision to invest in mitigation strategies to deal with the winter season.

Table 1 Winter weather disruptions

Variable:	Total				
Total number of disruptions	6,568				
Number of geocodes	269				
	Mean	Median	St. deviation	Min	Max
Disruptions per year	247	177	724	8	2276
Length of tracks within CA* (km)	137	117	71	67	280
Disruptions per CA*	242	289	187	10	806
Length of geocode (km)	6.35	6.50	13.04	0.56	74.03
Disruptions per geocode	11	12	34	1	305
Disruptions per winter weather type (per year)					
Snow/hail	-	88	428	0	1260
ice/frost	103	92	274	6	895
Low temperatures	20	19	43	2	121

* CA = Contract Area

The length of the tracks within the contract areas is another key variable. As stated earlier, the Randstad area contains many more train connections and has much higher operational frequencies than the rest of the country. The number of failures during winter weather tends to therefore be higher in those specific contract areas, although it does not provide evidence that the failures occur on the same operating device (switch, crossover, signaling e.g). Another variable worth noting is the length of the geocode (or track section). The length of the geocode depends on the number of components within an area; if a track is long, it is a section with a limited number of functionalities and switches. The closer the track is to a station area, with the necessity of more movement flexibility, the shorter the geocode section is. The shortest geocode contains only 1 km of tracks, while the longest has 305 km of tracks.

The physical characteristics of snow and ice that result in component malfunctioning and network failure were analysed based on different perspectives. The analysed data revealed that humidity and low temperature play a principal role in component malfunction. Around 80% of the disruptions occurred when the average temperature was below 0 (zero) degrees Celsius and the average relative humidity was above 80%.

Figure ***3*** presents the distribution of winter weather occurrences and the related disruptions during the studied time period. The winters of 2009/2010, 2010/2011 and 2012/2013 experienced the highest number of winter weather occurrences, also representing the highest percentage of winter-related disruptions. The brown bars represent the number of extreme winter weather events during the winter season, while the orange shows the number of times these events resulted in a disruption. In addition, the percentage of rail disruptions in relation to the number of winter weather events was included.

Although these were the years with the highest number of rail disruptions, the winter of 2011/2012 presented the highest ratio between the number of winter weather occurrences and the number of disruptions. During this specific year, over 76% of the winter events resulted in a rail disruption.

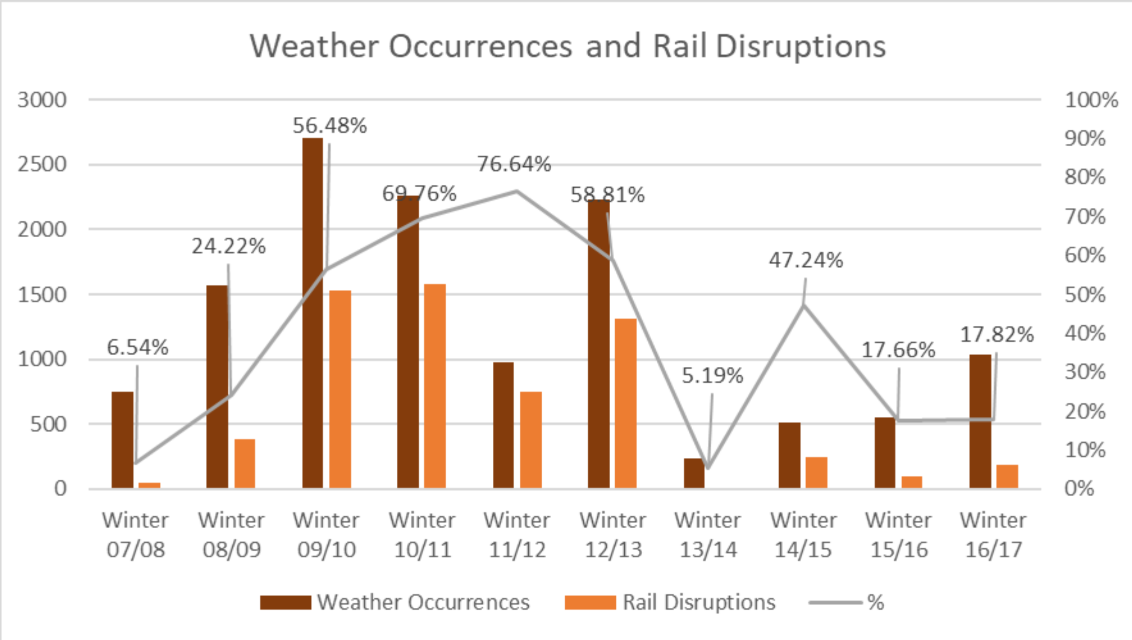


Figure 3 Distribution of winter weather occurrences and winter-related disruptions.

The most affected system types were switches (66%), followed by special track structures (11%) and unknown (13%). The classification 'special track structure' refers to constructions such as bridges, tunnels and flyovers. These sections are sensitive due to slight changes in the rail superstructure (end/beginning of a bridge, tunnel or flyover), which can lead to snow/ice falling off the rail vehicle and onto the tracks. When the unknown causes are excluded, switch failure was responsible for nearly 80% of the disruptions. This answers our first research question, '*what can go wrong?*' As indicated before, snow, frost/freezing rain and low temperatures are strongly related to switch malfunction (66%); during other weather conditions, switches rarely play a major role in network disruptions. Lighting, for example, accounts for 2% of switch malfunctions, whereas high temperatures, rain and wind/storms account for 5%, 9% and 4%, respectively.

Figure ***4*** presents a general visualisation of the winter weather occurrences, rail disruptions and switch-related disruptions in the studied period. Here, we added the amount of disruptions during the winter that are switch related. The percentage of switch-related disruptions over disruptions related to winter weather was also included. The correlation coefficient square (r square) between the number of rail disruptions and the number of switch disruptions during winter weather is 0.986, which indicates that almost all winter-related disruptions are caused by switches. However, the number of switch disruptions has diminished more over the years than the number of winter weather events. This can be partly explained by the strategies implemented in the disruption mitigation program implemented by the Dutch rail operators.

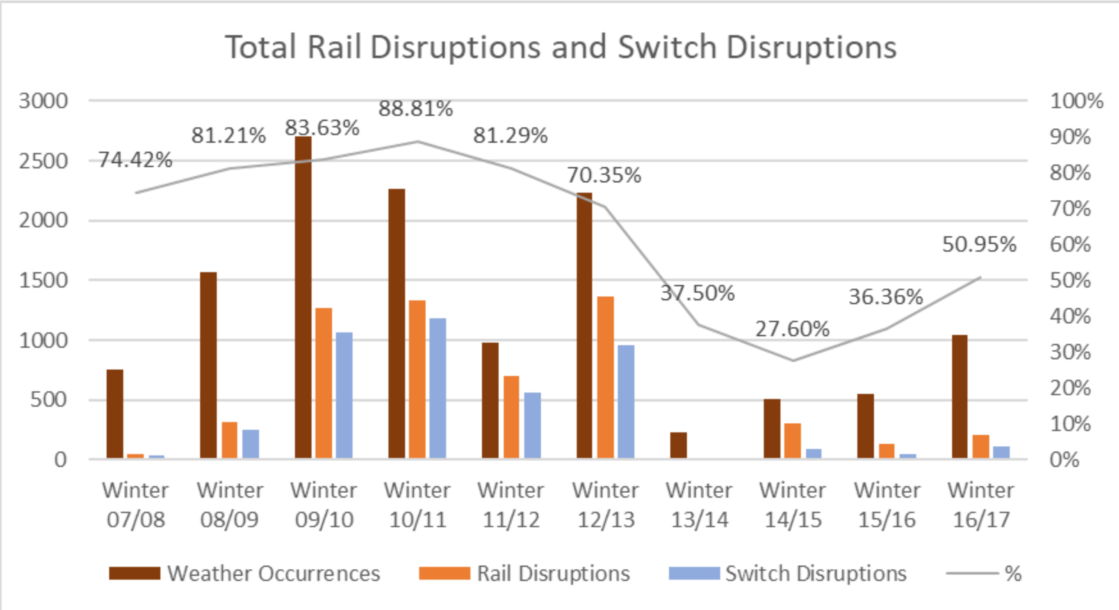


Figure 4 Distribution of rail network and switch disruptions throughout the study period

4. Methodology

We developed a rail network vulnerability index based on switch disruptions to examine link vulnerability during the winter season, by integrating node and link components into a probabilistic measurement of vulnerability. This vulnerability index is based on three components. The first component is a switch failure probability model (link performance). The second component is a station rank index; it shows the relative importance of nodes – railway stations – on network performance (node performance). Thirdly, we designed a route incidence indicator (RI) to integrate node and link performance into one vulnerability index. These three steps are explained hereafter.

4.1 Switch Failure Probability

Switches are used to guide rail vehicles from one track onto another and consist of many elements. These devices are fundamental for the optimisation of any rail network as they confer flexibility to the utilisation of the tracks. It is also important to highlight that switches are crucial within a safety context as poorly operated switches can result in accidents. Changing the position of the switch while a vehicle is running over it leads to derailment. Also, as switches are the connection between tracks, incorrectly set switches can result in multiple trains on the same link, which can cause vehicle collisions. To avoid accidents, it is crucial to preserve the switches' operability through the use of a complex and rigorous maintenance strategy. In addition, technical approaches such as locks to prevent switch reversal can help to diminish the risks.

As we found switches to be the main infrastructure element related to winter disruptions, we selected them as the core of the model developed. Also, as they have such a fundamental role in rail operations, there is sufficient data regarding their physical location.

Although the Dutch railway system has a high density of switches within station areas, this is not required to guarantee serviceability. The strategy in the Netherlands has always been to have many switches in station areas to allow trains to use multiple platforms, bringing flexibility to operations. This also adds more vulnerability to the network during winter weather however. In other countries, trains can often only use one platform, which confers less flexibility but also less vulnerability.

We took a probabilistic approach to answer the second research question: '*What is the likelihood of occurrence?*' and devised a methodology to determine the likelihood of component failure (switch failure) in the Dutch rail network. We selected three disruption characteristics: winter weather, number of switches in the geocode and train frequency. We distinguished three types of winter weather: snow/hail, frost/freezing rain and low temperatures. The next step was to use different functions for testing (exponential, inverse potential and the log-logistic functions). The log-logistic function, with the characteristic s-curve shape, presented the highest correlation with the observed values, followed by the exponential function and the inverse potential function. We used the log-logistic function to calculate the switch failure probability for each geocode in the Dutch network with the defined parameters, which we estimated with the following equation:

$$Log - logistic\ Function{:}\ Pij = \frac{1}{1+Exp(a+b*ln\ (S)\ )} \tag{1}$$

Pij is the probability of disruption on link *ij*, S represents the number of switches in the link and *a* and *b* are the function parameters.

After calculating the switch failure probability for each link, we defined five levels of failure probability for the geocodes, with 1 being the highest probability to suffer from a switch failure (very high vulnerability) and 0 (zero) the lowest probability to suffer from a switch failure (very low vulnerability). Five levels are a common range for risk analyses (very low – 1, low – 2, medium – 3, high – 4, very high – 5); see for example Duvillar *et al*. (2015) for a theoretical analysis of vulnerability. Links with no switch-caused disruption within the data set were considered "not applicable".

We first analysed the levels in relation to each of the three weather types. We performed a t-test (two two-samples, assuming unequal variables), which gave us a mean difference of zero and P(T<=t) of ranges 0.97-0.82 for snow, 0.90-0.97 for frost, and 0.50-0.85 for low temperatures as the best fit. The data show little variation between weather type (snow/hail, frost/freezing rain and low temperatures) and switch failure probability with a correlation (r square) between weather types of 0.95 or higher. Due to the high correlation, we used a single value for the likelihood of disruption based on component characteristics in the analysis. This is important when considering the investments in disruption mitigation strategies. As the vulnerabilities to each winter weather type are similar, we believe the investment in improvements will positively affect all the studied winter weather categories. The average switch failure probability is 0.24 for all of the links in the network (average for all included years), ranging from 0 (link with the lowest switch failure probability) to 0.95 (link with the highest switch failure probability).

Figure **5** presents the average switch failure probability which we call the switch vulnerability index (VI), ranging from very unlikely (0) to very likely (1), for each geocode. The most vulnerable links are located at a convergence of tracks, frequently located at stations.

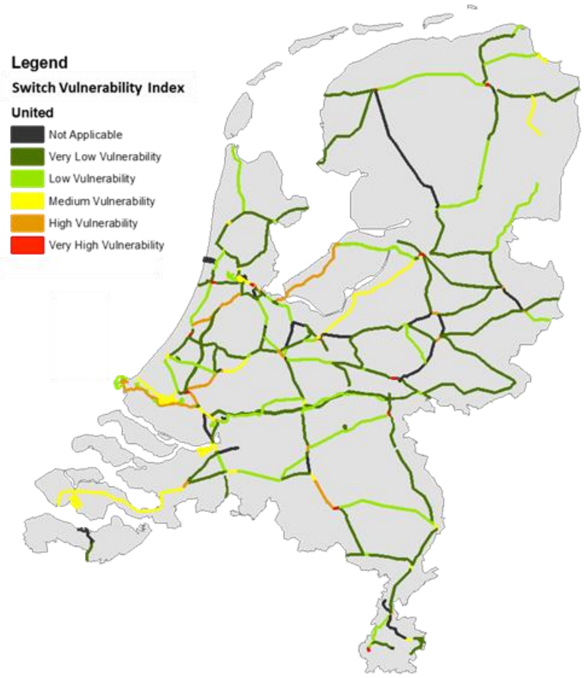


Figure 5 Switch failure probability map

4.2 Development of a station rank index

To establish the connection with supply and demand, it is important to identify the impact disruptions have on stations. This requires an analysis of the network stations to define their relevance in the system. We looked at three indicators: potential train users, actual traveller ridership, and station connectivity. While 'potential users' indicates how a station can grow and how the number of train users may increase, 'ridership' refers to the current demand of the station and 'station connectivity' to how well the station is served within the network. A detailed description of these three indicators follows.

- Population in station catchment areas

To estimate the number of potential users per station, catchment areas were defined based on Rietveld (2000) and Gutierrez *et al* (2001) and population density data from Statistics Netherlands (CBS). Rietveld (2000) states that 100% of cyclists are potential users up to 500m and Gutierrez *et al* (2001) argues that most people are willing to walk 500 ft (the value decreases potentially to the walking distance), the adopted percentage of potential users was 80% in the first band. The second band took account of the large decrease of walking commuters and a small reduction in the number of cyclists. Rietveld (2000) considers a value between 70-80% of cyclists commuting to the station within a band with these characteristics, but pedestrians tend to discard the effort. For the second band, the number of people selected for the catchment area was 50% of the population density. The last band, assuming 20% of the population density, is based on train users with the bicycle and public transport users as access modes.

We differentiated buffer sizes between intercity and local train stations as the number of train users varies by station type. The catchment areas around Intercity stations are known to be larger than for local train stations (Hartholt, 2016). Intercity stations are the largest and best-connected railway stations, facilitating direct train trips between cities in different regions of the Netherlands. Local service stations are stations with so-called sprinter train services. Most Sprinter trips are all-stop services in smaller station areas. *Figure* ***6*** illustrates the defined catchment areas for intercity stations (0m-500m, 500m-2,500m and 2,500m-5,000m) and Figure 7 for sprinter stations (0-500m, 500m-1,800m and 1,800m-3,000m), following Hartholt (2016).

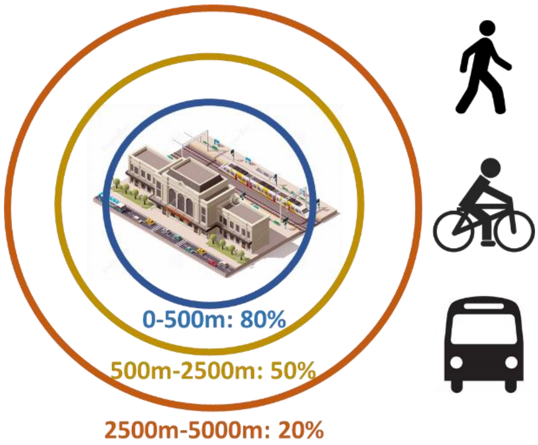


Figure 6 Station catchment buffer areas for intercity stations

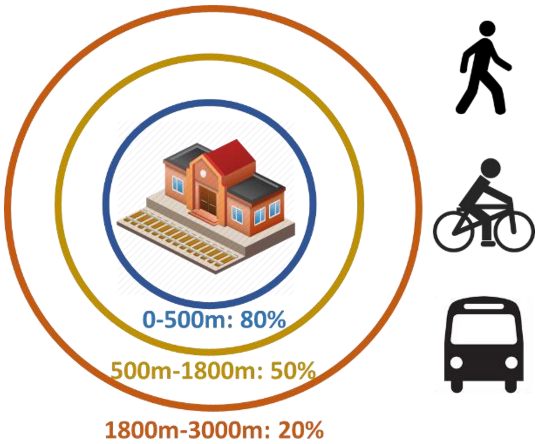


Figure 7 Station catchment buffer areas for local service stations

- Node potential

Figure 8 shows the estimated node potential based on the population density in the catchment buffer areas (as explained above), ridership and station connectivity. The node importance based on the potential number of train users is visualized in Figure 8a. Figure 8b shows the relative importance of stations in terms of traveller ridership (NS, 2017). We defined traveller ridership as the average number of people that entered or exited a station (daily). Next, we used ridership as a weight to rank stations. It is important to identify traveller ridership to understand current demands and to better plan trip distribution, schedules and vehicle sizes. Figure 8c shows the relative importance of stations based on station connectivity. A well-interconnected station generally represents short journey times (in terms of in-vehicle travel time, waiting time and transfer penalty). Station connectivity increases when the number of potentially reachable activities within a specific travel time rises. We included a connectivity index as estimated by Hartholt (2016), based on (1) closeness centrality, i.e. an inverse weighted function of generalised journey time between stations, and (2) efficiency/straightness centrality, i.e. the ratio between the travel distances by train and the shortest distances by road transport from the station in question to all other stations in the network.

Closeness Centrality: Defined as an inverse weighted function of generalized journey time between the station in question and all other stations in the network, calculated with the formula (Equation 2):

$$CCIi = \sum_{j} (\delta Cij * \frac{1}{Cij + 1} * Dj) \tag{2}$$

With $CCIi$ being the Closeness Centrality Index of station I, δCij the probability of taking a trip from i to j, Dj the total number of passengers arriving at station j and Cij the number of transfers needed to get from i to j.

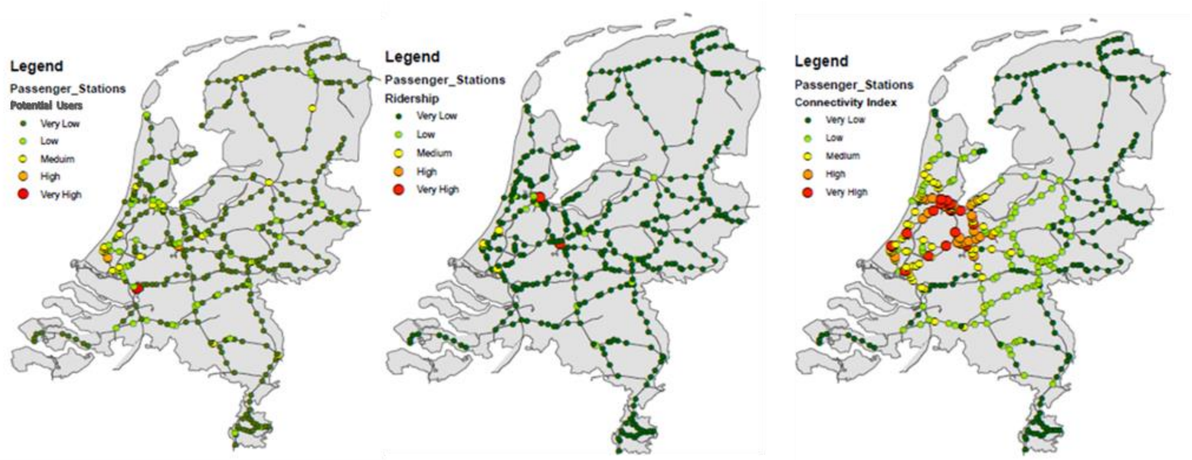
Efficiency or Straightness Centrality: Defined as the ratio between the travel distances by train and the shortest distances by road transport from the station in question to all other stations in the network, calculated with the formula (Equation 3):

$$SCIi = \sum_{j} (\delta Cij * \frac{Lroad(ij)}{Lrail(ij)} * Dj) \tag{3}$$

With $SCIi$ being the Straightness Centrality Index of station I, L$rail(ij)$ the distance from station i to j by train, $Lroad(ij)$ the distance from station i to j over road, δcij the probability of taking a trip from i to j and Dj the total number of passengers arriving at station j.

The connectivity levels are used in this study as weights for the vulnerability index, meaning better-connected stations are more critical when a disruption occurs. Station rank varies from station to station.

Figure 8 shows that the distributions of passenger potential, traveller ridership and station connectivity do not overlap. While traveller ridership and station connectivity appear to be concentrated at busy stations within the Randstad area, potential users presented a different pattern. Higher levels of potential users are located in the southern part of the Randstad area and in other regions of the country (Northeast and East). We defined the node potential per link by calculating the average for the nodes located in that link, in other words, the node impacts are included on link (geocode level) by using the average vulnerability of the nodes that share a link when a station divides a track. The value for the total network is 0.13. For individual links, it ranges from 0 (link with the weakest node potential) to 0.95 (link with the highest node potential). The ranges of values are based on very low (0-0.2), low (0.21-0.4), medium (0.41-0.6), high (0.61-0.8) and very high (0.81-1).



(a) *(b)* *(c)*

Figure 8 Distribution of node potential by potential users, ridership and station connectivity

The potential users, ridership and connectivity were estimated separately and then weighted in importance using a 0-1 unit value based on the weighted sum of OD stations. Finally, station potential can be represented by our weights based on potential users, traveller ridership and station connectivity and link vulnerability by the switch failure likelihood. The next step, as described in section 4.3, is to incorporate routing into the vulnerability index.

4.3 Vulnerability index

We defined a route incidence indicator (RI) based on the routes that are used to reach each station. This indicator is estimated by analysing the number of trips made via each rail geocode. To calculate the RI, we used the closest facility tool on ArcGIS. All stations were connected in routes (origin-destination: OD), adding up to around 140,000 possibilities. The objective is to use the RI as a last weighted index to provide a combined value for rail links and nodes.

The route incidence indicator is a classification of the links based on the possible number of routes that use the link. In other words, the higher the number of OD trips along the specified link, the higher the route incidence indicator. The busiest link has an RI value of 1 (RI=1); links with lower numbers of trains tend to have lower RI values.

Finally, the weighted averages of the calculated indicators were integrated in Equation 4.

$$VI_{l,s} = SFP_l * SP_{s,l} * RI_l \tag{4}$$

Thus, the vulnerability index (*VI*) of link l reaching station S is calculated based on the switch failure probability (*SFP*) per link (*l*) based on weather, infrastructure and train frequency, station potential (*SP*) which is the average of all station potentials (*s*) that are within that link (*l*), and the route incidence indicator (*RI*) of the link (*l*).

Worth noting is that the route incidence indicator does not relate to the betweenness centrality. It describes the business of the link based on the number of OD pairs that use that link, while the betweenness centrality was used as presented by Hartholt (2016). In addition, Train frequency is incorporated in the first step when defining the cross tabulation. To add frequency, clusters were considered based on OD needs. In that sense, the number of Switches per Geocode * Weather Type * Frequency (in clusters) was used to build the cross tabulations to each tested equation (log-logistic, inverted potential and exponential). The switch probability regression model was then established based on the type of winter weather (snow/hail, frost/freezing rain, low temperatures), the number of switches on the link and train frequency (low, medium, high). The log-logistic function was selected for the assessment, as it presented the best fit within the range used compared to the exponential and inverse potential functions.

5. Modelling and results

5.1 Results: Vulnerability index

Figure 9 illustrates the vulnerability index (results of Equation 4) for all geocodes in the Dutch railway network. The index ranges from very high vulnerability (red) to very low vulnerability (dark green). While the pattern of the chance of disruptions in station areas is similar to the pattern for switch failure probability, including the RI in the analysis increased the level of vulnerability around station areas due to their node level importance, notably for the stations Utrecht Centraal and Amersfoort. These are locations that function as hubs in the Dutch railway system. They also represent a very high number of switches in the geocodes because they need them to cope with the high train frequencies. Winter-related disruptions in these two station areas result in significant overall issues in the entire Dutch transportation system.

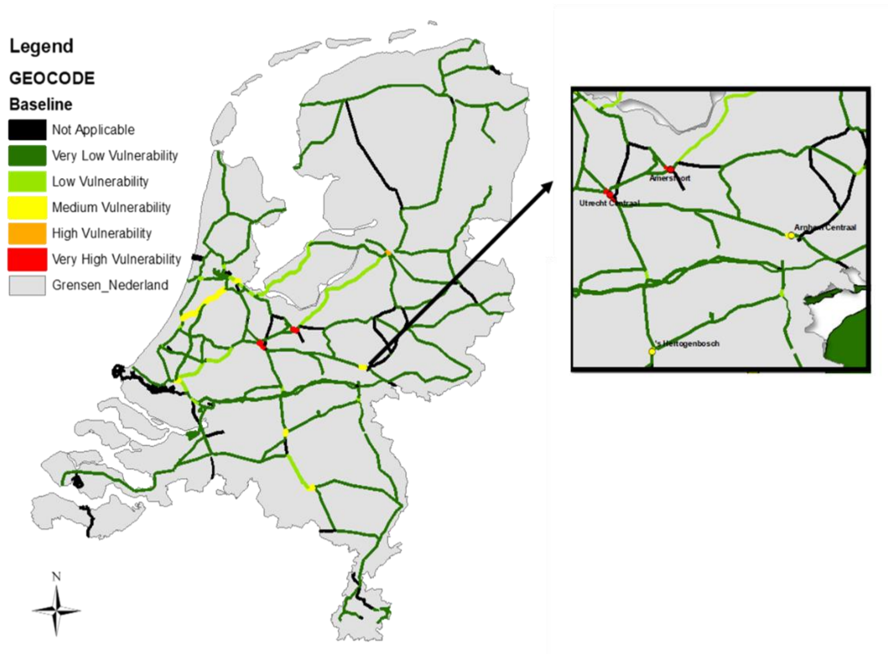


Figure 9 Rail vulnerability index

Figure 10 shows the vulnerability index by station type in the Netherlands (0 - 0.2 (very low), 0.2 - 0.4 (low), 0.4 - 0.6 (medium), 0.6 - 0.8 (high) and 0.8 - 1.0 (very high)). As can be seen, Intercity stations, which have the highest numbers of passengers and the best connectivity levels, tend to be more vulnerable than smaller local stations. This result is consistent with previous research, which found that both the node (e.g. ridership, potential users) and passenger flow (e.g. route index) descriptors are particularly relevant in vulnerability calculations and that large stations significantly reflect the effects of disruptions elsewhere in the network (Sun *et al.*, 2018).

However, when looking at the statistical results, Figure 11 shows that the route index is not linearly correlated with the vulnerability under conditions of snow (r2=0.119) and frost (r2=0.135). Similarly, Figure 12(a), Figure 12(b) and Figure 12(c) show that there is no overall linear correlation between potential users and the vulnerability index and there is no clear relationship between the vulnerability index and low temperature or potential users. These findings indicate that measures to mitigate vulnerability should be specific to weather conditions (focusing for example on reducing humidity within and around the devices) and that one cannot say, for example, that higher passenger numbers cause more vulnerability.

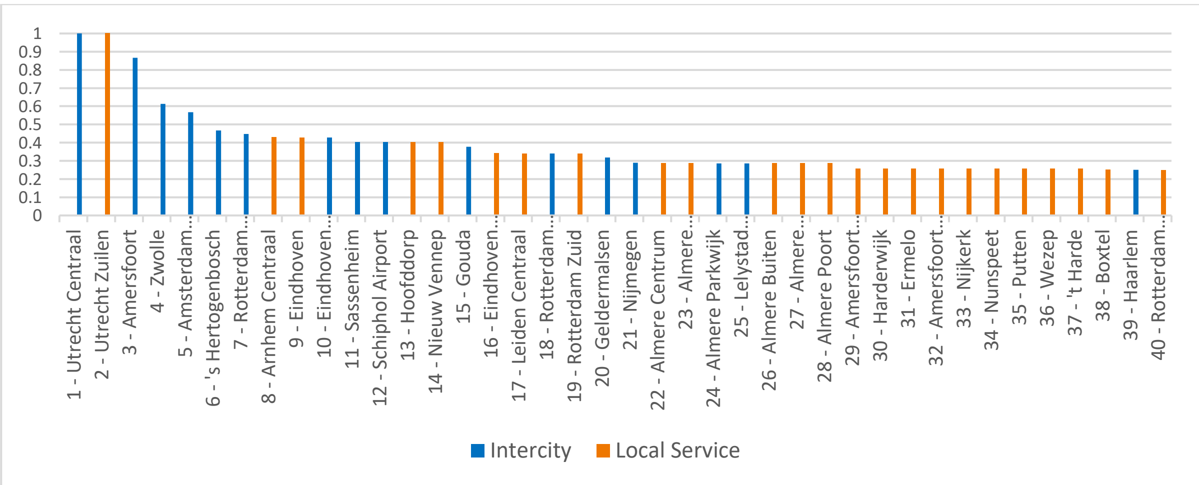


Figure 10 Vulnerability Index by station type (top 40)

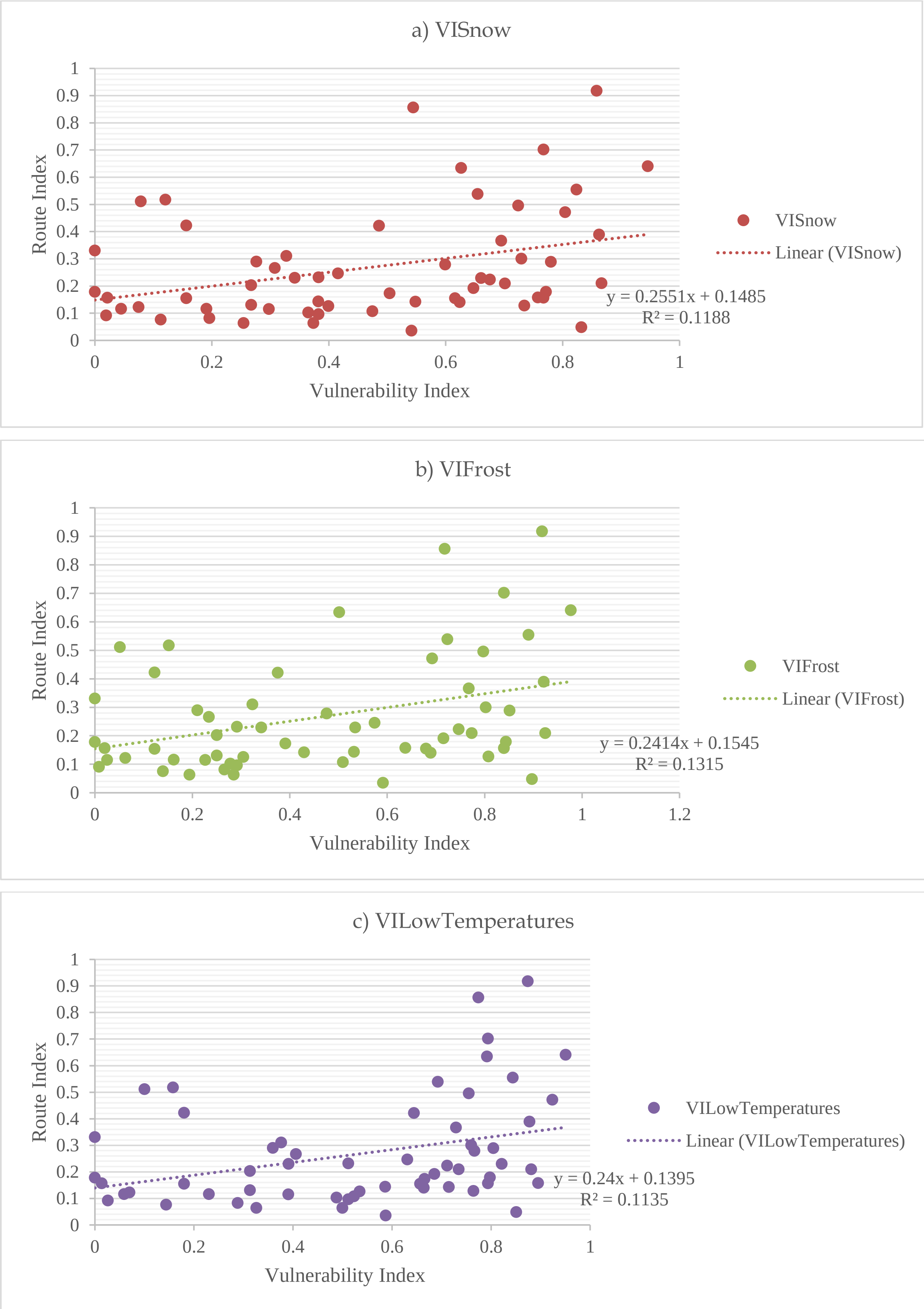
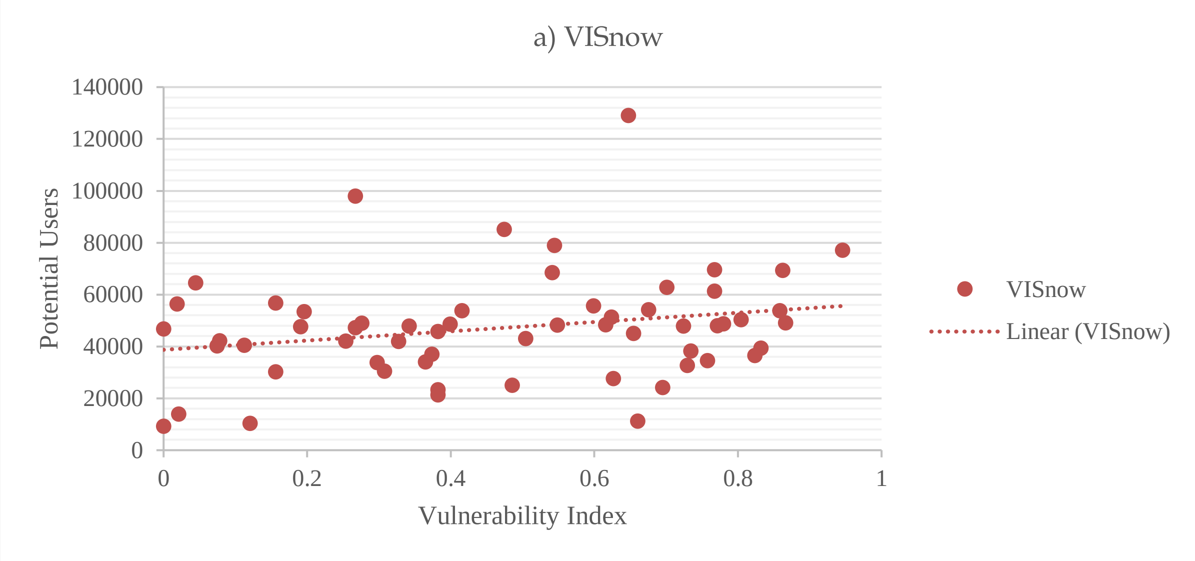
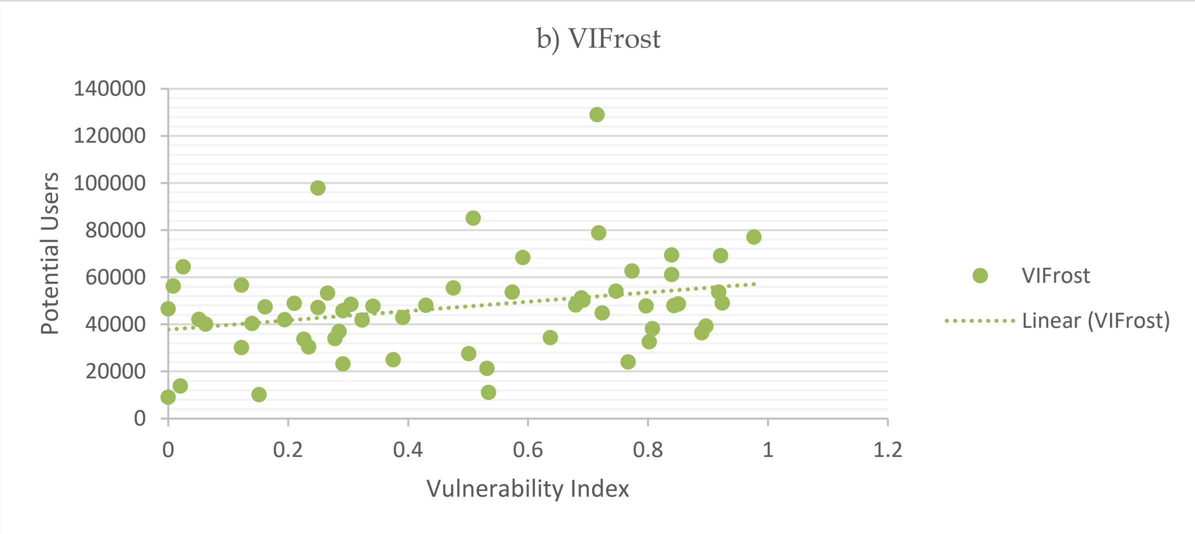
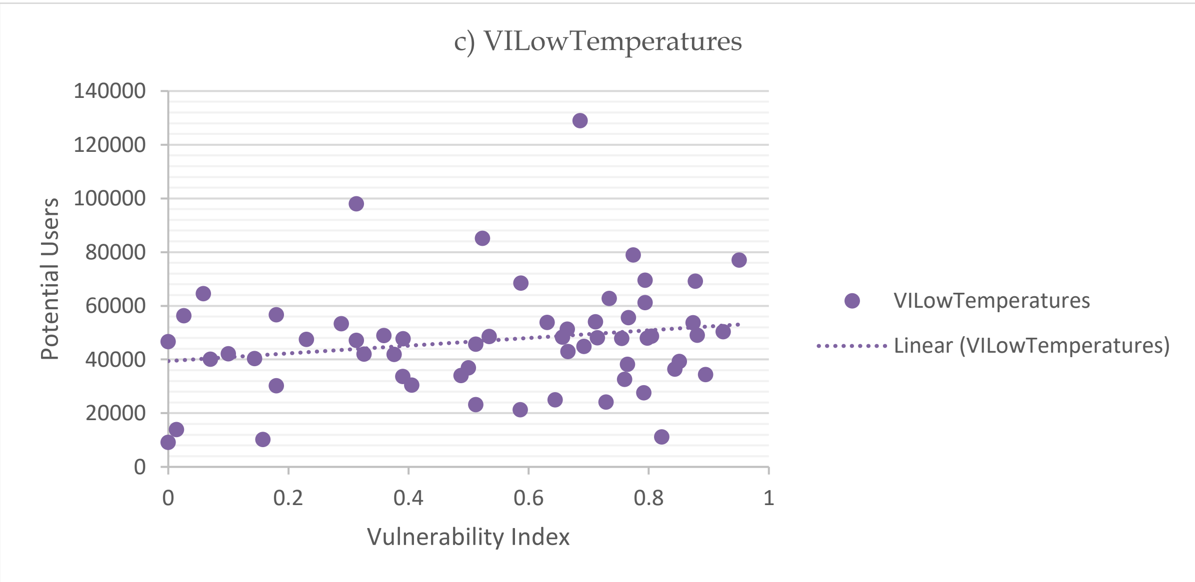


Figure 11 Vulnerability Index by station and route index per weather condition


a) VISnow
140000
120000
100000
80000
60000
40000
20000
0
Potential Users
0
0.2
0.4
0.6
0.8
1
Vulnerability Index
VISnow
Linear (VISnow)


b) VIFrost
140000
120000
100000
80000
60000
40000
20000
0
Potential Users
0
0.2
0.4
0.6
0.8
1
1.2
Vulnerability Index
VIFrost
Linear (VIFrost)


c) VILowTemperatures
140000
120000
100000
80000
60000
40000
20000
0
Potential Users
0
0.2
0.4
0.6
0.8
1
Vulnerability Index
VILowTemperatures
Linear (VILowTemperatures)

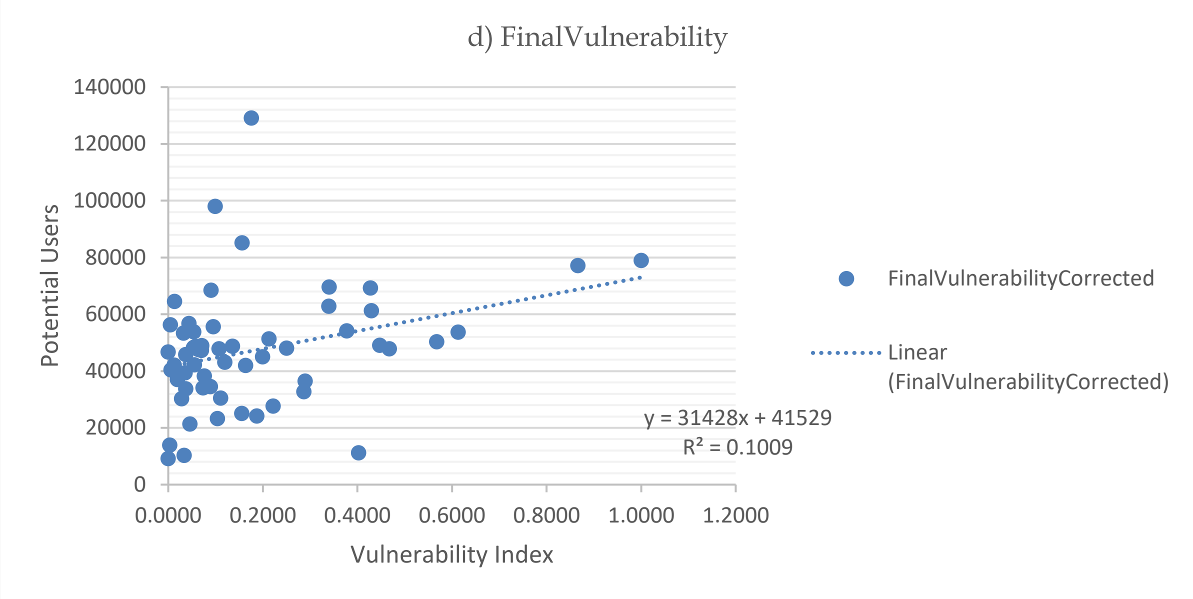


Figure 12 Vulnerability Index by station and potential users per weather condition

Furthermore, the results show that the most critical routes in the Dutch network connect stations within the Randstad area. Rail component failure results in lower train frequencies, cancellations, delays and additional operational costs. This can result in a cascade effect in terms of lower numbers of rail travellers and increased use of other transportation modes, which in turn can cause more road congestion. Additionally, busy regions experience a more significant impact on ridership and users. Connectivity plays a role in this context, as travellers prefer to use stations that have good connection options (Hartholt, 2016).

We conducted a cluster analysis based on the three investigated weather conditions (snow/hail, frost/freezing rain and low temperatures). This led to three groups with high, medium and low vulnerability. Figure 13 shows the average number of potential users for each vulnerability cluster level. Consistent with the previously discussed findings, the clusters show that the highest number of potential users is associated with the highest vulnerability index. For example, at stations with high levels of vulnerability 50,000 users would be affected whereas for stations with low vulnerability, fewer than 40,000 users would be affected.

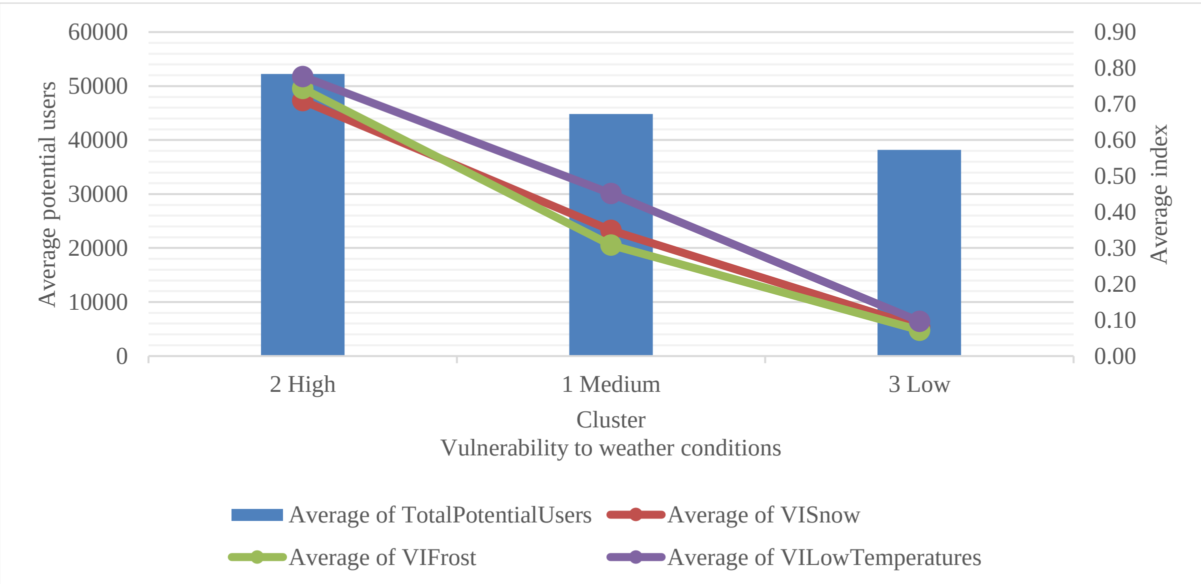


Figure 13 Average potential users by clusters of vulnerability to winter weather conditions

Please note that Figure 12 and Figure 13 are two different visualizations of the Vulnerability Index. Figure 12 shows the points from the calculated VI for the data by station, while Figure 13 shows the clusters. Figure 12 shows a regression equation and its R2, which is very low. It indicates no linear correlation between Potential users and VI. However, Figure 13 shows the aggregated values, where some correlation can be inferred (visually). The variables in the clusters are the three types of vulnerability index (low temperature, frost and snow), implying that these three types of temperature generate three groups of vulnerability indexes.

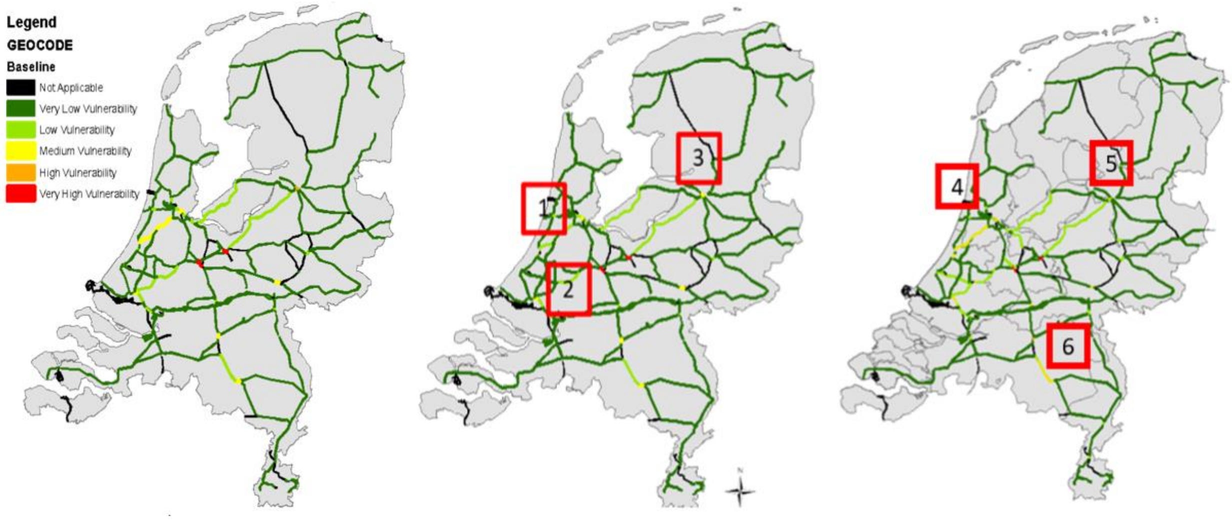
5.2 Development Policy Scenarios

A high density of switches increases flexibility and network performance. Although the Dutch railways plan to increase train frequency over the coming years, the program "Winter weather on (the) track" (*Winterweer op het spoor*) by ProRail focuses on reducing vulnerability in station areas and, depending on location, reduces the number of functional switches by up to 20%. We therefore developed two scenarios to analyse the implications of different railway switch reduction strategies on rail vulnerability.

The first scenario comprises a general reduction by 20% of the number of switches in the entire rail network by eliminating 20% of the switches in each geocode. The second scenario comprises a 20% reduction of the number of switches *in station areas only*. This follows the given that switches mostly occur in station areas and that these are the most vulnerable locations in the network.

The baseline is the situation without changes (the developed vulnerability map in Figure 9). With the developed log-logistic function for each link in the network and the new number of switches, we calculated the switch disruption probability and the vulnerability levels for the scenarios (Figure 14). As can be seen, in the scenarios we have a baseline situation and two developed scenarios: (a) 20% switch reduction over the entire rail network; (b) 20% switch reduction in station areas. The red boxes refer to points in the network discussed in the text – Box 1 refers to the Amsterdam-Sassenheim connection, box 2 to Rotterdam-Gouda, box 3 to Zwolle station, box 4 to the Amsterdam area, box 5 to the Zwolle area and box 6 to Den Bosch- Eindhoven area

As can be seen in Figure 10, Scenario 1 caused an improvement in the vulnerability in comparison with the baseline. The reduction of 7,613 switches to 6,090 (1,523 fixed switches) resulted in an overall 57% reduction in the vulnerability levels in the network. The vulnerability of the connection Amsterdam-Sassenheim (1) changed from medium to low, while the vulnerability of Rotterdam-Gouda (2) changed from low to very low. The station area of Zwolle (3) also displayed a change in classification, from high to medium vulnerability.



(a) Baseline *(b) Scenario 1* *(c) Scenario 2*

Figure 14 Vulnerability Index

For Scenario 2, the impacts of reducing the switches only within station areas resulted in a smaller improvement on overall vulnerabilities. The reduction of 7,613 switches to 6,649 (964 fixed switches) resulted in a 40% reduction in vulnerability levels in the network. In Figure 12, the Amsterdam area (4) is now mostly light green, while the Zwolle region (5) has also switched from yellow to green. Also, between Amersfoort and Maastricht, there is a significant vulnerability reduction in the station areas of Den Bosch and Eindhoven (6). It is interesting that for a similar vulnerability decrease of around 7%, Scenario 2 needs to "disable" a smaller number of switches. As can be seen, most of the vulnerabilities remained in the initial range, which means that the difference is subtle for small changes in the number of switches. In addition, there are noticeable changes in large station areas (e.g., Amsterdam, Rotterdam, Den Bosch), which strengthens the conclusion that a reduction in the number of switches in station areas has a greater impact on rail vulnerability.

It is important to note that the number of users (potential and ridership) plays a fundamental role in the vulnerability index, as they give higher weights to station areas with substantial movement of travellers. This is why the differences in the vulnerability index in the scenarios mostly occur in Amsterdam, Rotterdam, Amersfoort and Zwolle. That the vulnerability of railway network is affected by both accessibility and passenger flows is in line with the findings for urban railway systems (e.g. metro) by Jiang *et al*. (2018).

For example, fixation of switches and reduction of train frequencies, measures taken during extreme winter conditions, can (temporarily) result in lower vulnerability. However, in line with Kloow (2011), technical solutions can, and should, be used to improve the operability of switches during winter weather. A well-planned maintenance and control program with strict supervision in high-risk regions can diminish failure occurrence and support smoother operations.

6. Conclusions

This study presents a vulnerability index to measure rail vulnerability during winter weather based on switch disruptions, integrating both node and link components into a probabilistic measurement of vulnerability. The starting point was an analysis of the disruptions in the Dutch railway system during the years 2007-2017. Although most studies on rail vulnerability cover how to identify main causes and failure likelihood, only a few have integrated demand and supply factors.

Our probabilistic vulnerability model for the Dutch rail network under winter weather conditions showed that most vulnerable links are within station areas. This is partly explained by the need for additional switches to provide platform flexibility, but this increased number of moving devices puts station areas at a higher risk of failures. Links in dense population areas, which operate a high number of switches, are most susceptible to winter disturbances. The centrally located railway stations of Utrecht and Amersfoort are the most critical locations within the Dutch network regarding disruptions caused by extreme winter conditions.

The proposed rail vulnerability index can serve as a valuable tool to define operational strategies to reduce the vulnerability of the Dutch railway network. Our analysis shows that reducing the number of switches in station areas is more effective for lowering rail vulnerability than a general switch reduction strategy. This study extends the results of Yap *et al*. (2018) to the entire Dutch rail network (excluding metro and tram). However, our paper implements a methodology based on failure probabilities due to the number of switches, supply and demand, which explicitly considers the affected factors (i.e. passengers).

6.1 Limitations and Further Research

This study has some limitations which generate avenues for further research. Firstly, the analysis in this paper is based on the system failure records at ProRail which name the device that has failed but not its type. Additional information on the type of devices could improve our understanding of link vulnerability. If available, a classification of switch type (e.g., crossover, three-way) and the age and manufacturer would help to conduct a more detailed vulnerability analysis. Moreover, the switch position and direction could also improve understanding of link vulnerability.

Secondly, the limitation in the number of distributed weather registration stations can introduce a level of bias in the results. The meteorological stations do not cover extensive geocode regions. Also, particularly for this analysis, in which ridership was used to define node potential, it is essential to understand that users are also affected by weather conditions, which we did not take into account. The number of potential users could be affected by the current vulnerability level. This is not considered in the paper when estimating potential users and should be further investigated. Subsequently, ridership tends to vary based on rail performance and the number of service interruptions.

Thirdly, the railway vulnerability index estimated in this paper is based on the assumption that trains use the shortest route during disruptions. Future research could be directed at using scheduled routes during disruptions and scheduled train routes and frequencies during adapted winter time tables. Finally, the propagation of a disruption is usually not a linear consequence. What began as a simple malfunction of a switch is usually aggravated by the criticality of the location, deficient personnel resource management and a slow decision-making process. From a policy perspective, future mitigation strategies need to focus on all levels to diminish the impacts and increase recovery times. Those strategies should consider investing in switch technology and improved rail routing, which are not covered in this study.

Finally, in this paper we did not include alternative routes available for each OD pair and the impact of disruptions on travel times and delays. Future research could be directed at optimising the number of switches taking into account the reduction of vulnerability and the operational response to failure to reduce delays for passengers.

Acknowledgements

We thank ProRail for making the various data available to us. We also acknowledge Arcadis for supporting this work.

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