Rail Vulnerability

Impacts of Winter Related Railway Disruption on Network Performance

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Master Thesis
Enschede – The Netherlands

UNIVERSITY OF TWENTE.

ARCADIS

August 2017

Author and Committee

Civil Engineering and Management
Transportation Engineering and Management

Title
Impacts of Winter Related Railway Disruption on Network Performance

Enschede, August 2017

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Abstract

The Netherlands has a solid railway network focused on passenger transportation. With over 3700 route km of rail network and 379 train stations, the rail system is the backbone of intermunicipal trips within the country. Disruptions during winter have caused negative impacts on several levels (including operational costs and passenger experience) and the authorities have noticed the importance of developing an approach to diminish rail vulnerability during the season. Therefore, the network operator (Dutch Railways - NS), the service provider (ProRail) and the Ministry of Infrastructure developed a project focusing on strategies towards winter disruption mitigation: The *Winterweer op het Spoor* – WS. This project has brought positive results based on constant monitoring and continuous propositions for improvements in the system. It has been running since winter 2012/2013 and there is an interest on academic level to improve the understanding of disruption phenomenon caused by winter on the rail network.

Having that in mind, the evaluation of rail vulnerability to winter weather can bring further knowledge on the subject, leading to better and more appropriate mitigation strategies. Therefore, the objective of this research is to analyse and classify the vulnerability of the Dutch rail network based on its infrastructure and the disruption impacts on accessibility.

With statistical analysis of historical data on winter weather disruptions, a vulnerability index was developed for each connection in the Dutch railway network. This index is mainly the combination of a link component based on infrastructure and a node component based on station potential. While the link component was developed using a regression model to estimate the probability of link disruption (based on infrastructure failure), the assessment of node importance (station potential) was carried out using weights for three specific node indicators: potential users, traveller ridership and station connectivity. These findings were necessary to answer the five proposed research questions for this thesis:

1) What are main characteristics of winter-related disruptions in the Dutch rail network?

2) Which railway infrastructure features are more sensitive to unexpected winter weather conditions and why?

3) How can the likelihood of disruptions due to winter weather be estimated based on the encountered critical components?

4) What network performance indicators can be used to understand the impacts of disruptions caused by winter weather and which are the encountered impacts on the Dutch railways in the developed study case?

5) Which actions are currently being developed by NS and ProRail to decrease rail vulnerability (to winter weather) and are these actions focused on the most critical elements and in the most vulnerable regions?

To compose a suitable dataset for the analysis three sources were used: weather data collected by the Royal Netherlands Meteorological Institute (KNMI), asset management disruption data and traffic management disruption data (both collected by the Dutch rail service provider, ProRail).

The goal was to relate the disruption cause, time and location to winter weather aspects such as low temperatures, relative humidity levels or presence of snow and freezing rain.

The definition of the likelihood of disruption due to weather conditions, was based on component criticality. This means the most critical components (with the highest number of failures) were analysed for inclusion in the regression model. During this phase, it was verified that switches are accounted for over 75% of the identified causes of winter weather rail disruptions. Also, following the literature, switches have a key role in the operability of the rail network as they grant flexibility for track usage. In addition, the operation of this component is highly related to the safety of the rail transport system. These results supported the selection of switches as the main infrastructure element for the model. The sample size for the probability regression model was of 4300 switch winter-related disruptions.

The switch probability regression model was established based on type of winter weather (snow/hail, frost/freezing rain, low temperatures), number of switches on the link and train frequency (low, medium, high). A log-logistic function was selected for the assessment, as it presented the best fit within the used range compared to the exponential and inverse potential functions. The product of this first step was the assessment of the probability of disruptions related to switches for each link within the rail network.

As the role of the rail network is to transport passengers, it was defined that the station (node) potential must be included as a weight in the vulnerability index. The next step was then to embrace this variable in the index.

As mentioned, the station importance was estimated based on three indicators: potential users, traveller ridership and station connectivity. The first indicator represents possible users of the rail system by estimating the number of users based on the amount of residents within a station catchment area. The second indicator is the number of passengers that entered or exited each Dutch station (daily average) in 2014. The last one, station connectivity, is an indicator developed by Harthold (2016) which classifies how well the station is placed within the network. This indicator is based on the number of necessary transfers for reachability of the station, meaning the better connected the station, the higher the index value.

To understand the impacts on the network, and the importance of the studied stations, all possible routes within the network where analysed. The criticality of each route was calculated by assessing the node importance level (for the considered origin-destination - OD - pair) and the switch vulnerability sum of the links that compose the route. To define which links are to be considered in a route, a geographic information system (GIS) software for working with maps and geographic information was used. With ArcGis, the impacts of disruptions on accessibility were estimated using the Network Analyst tool. Therefore, the most critical routes (regarding winter weather disruption) were encountered and presented.

Finally, the vulnerability levels per link were estimated by considering the number of routes that use the specified link, the sum of the switch vulnerability levels and the weight of the station importance of each OD pair. These findings enabled the development of a risk map defining which links are most vulnerable within the network.

It was observed that although the infrastructure presented critical locations throughout the network (the northern and southern parts of the country for example), the inclusion of station importance placed most vulnerable links within the Randstad region. This area is more active socially and economically in the Netherlands giving the node importance higher weighs during the assessment. It was also noticed that the most vulnerable links are located within station areas. This can be explained by the necessity of more switches due to the exit, entrance and transfer of passengers, demanding higher flexibility of the tracks. These links are a main concern and although efforts have been made to diminish the inoperability during specific weather circumstances, it is important to develop an improved implementation strategy.

Having this in mind, the answers to the proposed research questions were encountered using the suggested methodology.

Answering the first question, the weather characteristics accountable for rail components malfunction are high relative humidity levels (over 80%) and average temperatures under 0 degrees Celsius. This is important to be considered in the WS used coding system. As the bureau already considers the presence of snow, freezing ice and low temperatures, a suggestion would be to include more specific measurements related to relative humidity.

The second question was answered with the finding that most failures occur due to the malfunctioning of switches (almost 80% of the cases), especially in the Randstad area during December and January. The high number of switches in this region can result in failures due to snow/ice hampering the movement of the component or low temperatures causing malfunction within the communication system.

The likelihood of component failure was assessed by carrying out a probabilistic regression (third research question). The number of switches per link, weather type and train frequency were analysed within three possible functions: exponential, inverse potential and log-logistic. As the log-logistic function presented the best fit, it was selected to represent component failure probability.

The used station importance indicators based on potential users, traveller ridership and station connectivity were used to answer the fourth research question. Most critical routes lie within the Randstad, but in greater proportion of when compared to only considering rail infrastructure (regression model). The number of inhabitants, users and the quality of the rail connections built on the perspective of a stronger and more active economy concentrate station potential in the region. The reduction of trip flexibility results in longer trajectories with more transfers and diminishes the levels of accessibility of the rail users.

The fifth research question focused on understanding the outputs of the winter mitigation program. During the development of the thesis it was verified that the improvement measures have a string focus on the operability of switches. As this device is the most critical regarding winter weather disruptions, it is concluded that the mitigation strategy is in accordance with the estimated vulnerability levels.

To understand the impacts of the implementation of the WS in more detail, scenarios were developed to understand the variations in the vulnerability considering a decrease (scenario 1) and an increase (scenario 2) in the number of switches in the network. After the comparisons with the baseline (calculated vulnerability index), it was concluded that the investments in switch improvement (point heaters) and fixed switches has the capability of diminishing disruption likelihood.

It is however important to note that the fixation of switches during winter has a critical drawback: the strategy has negative impacts on track capacity as it reduces flexibility. As service provider has clear intention of intensifying frequencies in the future, this specific approach should be reconsidered and classified as a short-term solution. Investments in research to better understand the functionality of switches during winter and the disruption characteristics would be of most value.

A list of mitigation strategies was developed and presented in the appendix of this thesis. They are based on best practices of countries that have faced winter disruption issues on their railways. These findings can provide valuable outcomes and solutions for improving the Dutch rail performance during winter season.

Acknowledgements

I treasured working with Arcadis. I have grown a great deal personally and professionally and made many friends that I intend to take for life. I recognize that they all gave me endless support and help and were always accessible and friendly. Thanks to my colleagues at ProRail and NS, which have been so assertive and helpful with all the information regarding the winter weather project. I also thank my Arcadis and UT advisors Erik Lindhout, Maarten Zanen, Andre van Es, dr.ing Lissy La Paix Puello and Prof.dr.ing Karst Geurs, for the patience and hard work on this challenging part of my masters. Special thanks also to Tanya Sancici and Ricke Koopman for giving me the opportunity and tools to develop this study. I would not have accomplished the strategic phases of the research without their commitment and dedication, not forgetting the emotional help during tough times.

I would like to thank my UT friends, Camila, Lia and Juliana, which were always by my side, giving me good laughs and easing the struggles that I was facing. They also added a great deal to my research by being interested on what I was developing and questioning about the topic. This helped me develop a more critical view towards the importance of transportation vulnerability.

I could never forget the tremendous support from my family. My parents, Washington Neves and Catarina Perreira, who are responsible for me being here and achieving this goal by giving me never-ending motivational spirit to carry on when things got hard and believing so much in my potential as they have always done. Thanks dad for teaching me how to persist and thank you mom for being always there when I needed.

Finally, a special thanks to my brothers, Eduardo and Guilherme, for the positive energy and to whom I wish would follow the same challenging steps they have seen me take.

Dedication

I dedicate this thesis to Harrington, for his advice, patience and faith. For believing I could and pushing me forward. Thank you for being such a wonderful companion, friend and supporter.

Preface

Being carried out in Amersfoort (Netherlands), this research was performed within the Public Transport and Rail Engineering Department at Arcadis. The theme was selected after a series of meetings between the student, the company and the University of Twente.

The thesis is the last part of the Masters educational programme, and when successfully accomplished the Master's degree in Civil Engineering and Management at the University of Twente will be completed.

The official supervision has been done by four professionals: two Arcadis engineers and two staff members from the University of Twente. The Arcadis daily advisor during these six months was Maarten Zanen who is head of the Data Analysis and Management team. The general supervision at Arcadis was realized by Erik Lindhout, Lead Engineer of the team. At the University of Twente, the daily supervision was performed by dr.ing Lissy La Paix Puello and the supervision was carried out by Prof.dr.ing Karst Geurs on behalf of the Centre for Transport Studies.

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1. Introduction to the Report

1.1 About the Topic and its Importance in Modern Society

To uphold a competitive, effective and suitable rail transportation system for passengers, it is essential that service providers realize successions of synchronized activities related to planning, maintenance and operation of the railways. Unfortunately, unexpected events still arise and may result in malfunctioning or disruption of the network. These occurrences must be studied for provision of a more resilient arrangement. Extreme weather conditions and/or incidents, for example, can result in the need of track service interruption. This affects the entire system, which needs to recover its operability. By balancing trips on alternative tracks, delaying other connections and cancelling when necessary, the train schedule can be recovered, but this results in negative effects on time-tables, higher resource demand and additional operational costs.

Although trains have proven to be an attractive alternative for avoiding nowadays inner city congestions, rail networks are more sensitive to disruptions than road networks. The impossibility of surpassing obstacles positioned on the tracks makes the sector quite inflexible. Trains cannot easily overcome a disruption and there are less detour possibilities for reaching destinations (stations). Partial and total blockages usually result in extra travel times, worsening the traffic flow and the confidence in the system. To reduce the negative impacts of a disruption, a structured rail network relies on a series of mitigation approaches and strategies to avoid its occurrence and to enhance the speed of recovery in case it is inevitable. These activities are directly related to the reestablishment of normal network conditions.

For elaborating a structured mitigation approach and an optimized recovery plan, the rail operators must recognize its dominant links as well as each related vulnerability level. Predictions should be modelled to estimate the probability of disruption for specific operational conditions. Efforts must be directed for diminishing vulnerability and personnel must be trained to act promptly in case of any track interference.

Estimating vulnerability indexes for rail connections and previewing the impacts of a disruption in the network support the improvement of performance. By investing in new technologies, staff training and better structured management and communication systems, it is possible to improve vulnerability levels, increase overall standards and identify which links need prioritization. Also, the monitoring of the disruption activities can provide important inputs and guide the operator on future investments.

The Dutch Railways (2016), classify the causes of unexpected disruptions in four categories: weather, technical, third parties (people or animal related e.g.) and errors during activities. Heavy snowfalls (hampering the functioning of switches/crossings), electrical blackouts (temporarily disabling signals and computer systems) or people walking along the tracks (causing trains to run slower or stop) are listed as examples. The duration of the interruption depends on location, time of day, intensity and cause. These factors also have influence on the velocity of the recovery, but even the smallest disruption can negatively affect the smoothness of the system. It is therefore essential that rail operators focus on the mitigation of the causes to diminish the propagation of the effects.

This thesis has the objective of identifying the most vulnerable connections of the Dutch railway network in relation to winter weather. Also, the impacts of disruptions will be analysed in order to consider how winter weather susceptibility might reduce performance by listing the most critical routes during winter season. The final output is a risk map which enables a clear visualization of the level of vulnerability of the connections. This document will enable better planning of resources for disruption mitigation and maintenance arrangement. It will also support the operators when directing investments on technological improvements providing a more efficient recovery system.

The report is structured in four main sections. In the first chapter, an introduction on the topic of research is developed to provide some background information and elucidate the importance of the subject. The same section also describes the research context and the problem definition which clarifies why the subject has been selected, which are the research questions and how they are to be answered. The theoretical framework (chapter two) has the objective of covering how the theme is emerged in modern society and at what level is it acknowledged by the industry and academic field. Here, the definitions used in this report are described and analysed. Also in this section, recent technologies and strategies to overcome the problems faced by rail disruption are investigated in more detail. The third chapter explains the Dutch rail study case. In this segment, the taken steps in the assessment of the vulnerability index, the analysis of the data, and the assessment of route criticality are described. The construction of the risk map that considers vulnerability to winter and the accessibility impacts is also clarified. The fourth chapter is an overall discussion on the theme, the encountered limitations of this study and which recommendations arose, followed by the conclusions of this thesis. Lastly, a list of all the used references is presented. They are the basis for the literature review, the selection of goals, data, methodologies, and tools needed for the research.

1.2 About the Research

The Netherlands has a dense railway network which is responsible for the transportation of millions of people. Disruptions in the system can cause major impacts on operation management, costs and passenger experience. A strategy to improve reliability has the capability of reducing the number of occurrences and supports faster network recovery.

Disruptions can be classified as expected or unexpected events, which mean they can be planned or unpredicted. Unexpected disruptions are mainly caused by bad weather conditions, technology failures or people behaviour/actions. These include for example, heavy storms, communication interruption or people invading secured areas.

Analysing the available dataset permitted the confirmation that most disturbances are classified as technological. Technical failures include a wide range of system malfunctions adding up to 33 classification possibilities, including the communication, traffic monitoring and train detection systems. The main issue within the technological failures is the difficulty of accurate classification.

As the problems are usually not mechanical, they are of high complexity regarding the analysis of the main cause and demand a great deal of time to track and understand failure types and systems. Also, due to the complexity, the most registered technical related disruptions were not encountered (approximately 25%) and classified as unknown, bringing an undesired bias level within the analysis and demanding a more structured and extensive analysis on each level.

On the other hand, weather has a 9-level classification of disruption, including lighting, rain, snow/hail, among others. Winter weather disturbances accounted for around 37% of the weather-related disruptions, which places winter within the most critical weather for train operations. Also, winter weather disruptions have proven to be a concern after disastrous operation experience during difficult weather conditions between 2009 and 2012. The number of delays, cancellations and unsatisfied clients proved the rail operators that this specific season needed special attention. For these reasons, the understanding of winter weather disruptions and the vulnerability of the railways to this condition will bring value to the operators and passengers.

Winter disruptions varied a great deal within the data set frame and although winter related issues have gradually diminished over the past decade (which can be explained both by milder winters and extensive mitigation programs) these events still are likely to occur. The service provider invests yearly in operational improvements to mitigate winter related disruptions (*Winterweer op het Spoor Program* - WS). Having that in mind, the objective of this research is to evaluate rail track vulnerability to winter weather based on infrastructure criticality and impacts caused on accessibility. In addition, some of the mitigation strategies developed within the *WS* program will be analysed.

The first step of the thesis was the development of a winter weather vulnerability index based on rail infrastructure. As the data set has mal-functioning per system type, an assessment on the most critical systems was carried out to measure the likelihood of failure. The initial analysis was important to understand which systems are more sensitive to winter weather. The results proved that moving devices, such as switches and turn-outs are responsible for nearly 80% of winter related disruptions. With this information, the most vulnerable links in relation to winter weather, switches and train frequency were identified.

In order to add the impacts on performance, potential users, traveller ridership and station connectivity were analysed in a network perspective. This step enabled the inclusion of node potential in the vulnerability index, bringing the values closer to a realistic level. With these new inputs, a risk map classifying the criticality of each link was developed. The visualization of links that have higher risk levels permits a clearer overview of the behaviour of the system and provides guidance on how to implement disruption mitigation approaches.

Finally, the research questions of this report were:

1) What are main characteristics of winter-related disruptions in the Dutch rail network?

2) Which railway infrastructure features are more sensitive to unexpected winter weather conditions and why?

3) How can the likelihood of disruptions due to winter weather be estimated based on the encountered critical components?

4) What network performance indicators can be used to understand the impacts of disruptions caused by winter weather and which are the encountered impacts on the Dutch railways in the developed study case?

5) Which actions are currently being developed by NS and ProRail to decrease rail vulnerability (to winter weather) and are these actions focused on the most critical elements and in the most vulnerable regions?

For this thesis, data was collected from various sources, such as open published data (Dutch Bureau of statistics – CBS; Royal Netherlands Meteorological Institute - KNMI), previous studies on the Dutch Railways and internal reports provided by Arcadis. The theme is indispensable for improving rail services and is an interesting tool to diminish the risk of trip delays and cancellations during winter seasons. The comprehension of the rail system functionality supported evaluating the main reasons of sensitivity to winter weather and is used as basis for the suggestions of mitigation approaches.

1.2.1 Development

This research was developed in four phases covering the necessary steps to answer the defined research questions. The first was the analysis of weather and rail main characteristics, including descriptive statistics and correlations. The definition of the methodology was carried out in the second phase and supported by encountering a reliable measuring technique to evaluate rail vulnerability. In this stage, the development of a model that estimates disruption probability based on rail infrastructure was performed. The third step deals with the impact analysis on network performance in the interest of including a weight on accessibility levels. For this study, routes were analysed in relation to the encountered component failure probability, and the most critical listed. The last phase was the elaboration of the risk map using a vulnerability index for each rail link. Figure 1 represents the outlines of the development of the thesis.

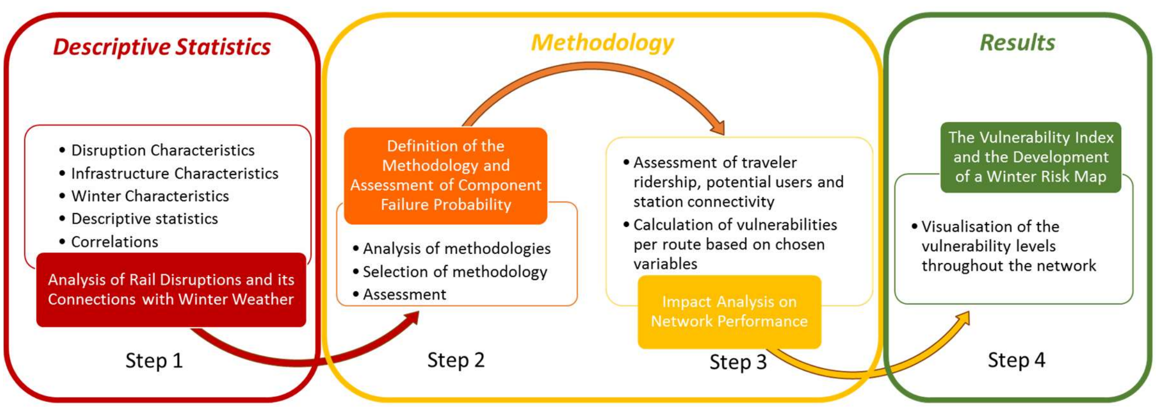


Figure 1 – Research Development

1.2.1.1 Descriptive Statistics

Step 1: Analysis of Rail Disruptions and its Corrections with Winter Weather

The first step was the deepening of the understandings on rail system functionality and its sensitivity to winter weather. During this phase, winter weather data was collected from the Koninklijk Nederlands Meteorologisch Instituut (KNMI), the Dutch website for open source data on weather, and linked to the provided data on rail disruptions. The original data sets were combined and organized in a matter to prioritize the relevant variables for this report. The size and characteristics of the examined network were defined after analysing the type, quantity and quality of received data. Also, the disruptions where classified by operational system failure.

Descriptive statistics provided answers to two of the proposed research questions (question 1 and question 2). These questions are related to the main characteristics of winter-related disruptions and the infrastructure features that are more sensitive to winter weather. It was verified that low temperatures in addition to extremely high relative humidity were present in over 80% of the disruptions. Switches are the most vulnerable rail component to winter weather and the reasons of malfunction and/or failure where discussed with rail specialists within Arcadis and ProRail.

During the statistical analysis, the *Winterweer op het Spoor* program was also studied in more detail. This project, initiated in 2012, is based on several efforts on different levels to diminish the likelihood of winter-related disruptions. The program is supported by the Ministry of Infrastructure and is described in within the study case section.

1.2.1.2 Methodology

Step 2: Definition of the Methodology and Assessment of Component Failure Probability

Based on the theoretical framework, it was possible to develop a vulnerability index which considers three rail winter disruption characteristics: identified weather condition, operational system and link activity. The development of a probabilistic regression model was used and the likelihood of switch disruption estimated answering research question 3. The data went through cross tabulation and a probability curve was developed. Using three regression models (exponential, inverse potential and log-logistic), an estimation was predicted and the one with best fit (log-logistic) selected to represent the likelihood of disruption.

Step 3: Impact Analysis on Network Performance

After a disruption in the network, a series of events occur in a chain. Trains stop, make detours, schedules change and are trips are cancelled. Operators redefine tasks, regroup, pass on new updates on travel information and provide resources for the recovery phase of the disruption. As can be noticed, the impact of the incident can affect many sectors, and it is vital to understand that each node (station) has different importance levels in the functioning of the network.

During this step, indicators for evaluating the importance of the station were de developed answering research question number 4. Based on the scheme presented by Geurs & van Wee (2004), the accessibility was analysed founded on land use, individual and temporal components (potential users, traveller ridership and station connectivity) and used to analyse the impacts of winter disruptions on network performance. The encountered impacts were assessed by analysing the most critical routes in the network, showing that disruptions in the Randstad affect more users and imply in delays and performance reduction.

1.2.1.3 Results

Step 4: The Vulnerability Index and the Development of a Winter Risk Map

The last phase of this research included the development of a risk map which enables a clear visualization of the most critical links in relation to winter weather. To establish the vulnerability of each rail connection, a combined calculation was carried out by multiplying the switch disruption likelihood, a weighted value for the node importance and the number of routes that use the specific link. Each connection was classified within one of the defined vulnerability levels: not applicable, very low, low, medium, high and very high vulnerability. The not applicable range is composed by links that have no switches or did not present any disruptions within the data used for the estimation of the index. This document provides suggestions on which sections need to be carefully monitored and/or improved within the network.

Using the findings in the descriptive statistics section (step 1) on the *Winterweer op het Spoor* program and the final vulnerability values, research question 5 was answered. The actions that are currently developed by NS and ProRail to decrease rail vulnerability (to winter weather) were discussed and the measures focused on switches analysed. The locations of the implementations were studied and cross checked with the encountered most vulnerable regions in the risk map. Also, scenarios were developed to analyse the variations of the vulnerability following the number of switches on a link. The results prove that an increase of switches will cause more disruptions while new investments on technology or management can decrease occurrence.

1.2.2 Encountered Contributions

Overall, the contributions were generated in two different sectors:

Contribution to Theory: The purpose of this research was to develop a combined methodology to determine rail vulnerability including the impacts on network performance. The outcomes provide a new technique for analysing disruptions related to winter weather. These findings can be used also for the analysis of other weather-related transportation disruptions.

Contribution to Practice: The classification of link vulnerability related to winter weather and the creation of the risk map supports overall improvements in resource management. In addition, maintenance plans can be prearranged in a more optimal form and directed investments can be applied in critical areas. The application of new technologies and strategies is a window of opportunity to increase rail reliability and resilience.

Transportation Engineering has for a long time supported researches in this field due to its connection with social and economic improvements. Railways have a significant role in trip distribution and is fundamental for the development of a more sustainable transportation system. Finally, Arcadis has a key role in supporting development towards rail excellence. The company has established several projects on rail development and is in hold of expertise in the area. The accomplishment of this research consequently adds value to the ideologies behind the company and promotes a more engaged transportation system within the Netherlands.

2. Part I: Theoretical Framework

2.1 Introduction to the Theoretical Framework

Sustainable transportation is directly related to social and economic development. Deakin (2001) argues that there is currently a distinct approach towards sustainability of land use and transportation. In this setting, sustainable transportation can be linked to a system that supports mobility while preserving human and ecosystem health, economic progress, and social equity. In relation to passenger transportation. In other words, accessibility has become an important indicator of wellbeing and development.

According to Litman (2016), accessibility can be defined as the ability to reach goods, services and activities in which transportation systems play the main role. Several aspects can affect accessibility, which include mobility, the quality and affordability of transport options, transport system connectivity and land use. Geurs & van Wee (2004) consider four accessibility components from the different definitions and practical measures: transportation, land-use, temporal and individual. Within the transportation process, events might diminish the operability of the system. Vehicle incidents and accidents, badly managed public transport services, low quality infrastructure and poorly developed integration systems can reduce the accessibility of a community, bringing many problems related to social and economic development. Disruptions can be inevitable and/or unpredictable as the vulnerability of the system depends on a diversity of variables. Nevertheless, an estimation of the most critical locations is possible and has turned out to be a valuable tool for planning resources and mitigation strategies.

To provide an efficient planning policy for transportation systems, policy makers, transport operators and authorities need to understand the causes and impacts of disruption to maintain a well-structured and resilient system. Having that in mind, authorities have worked together for increasing transport resilience and consequently diminishing vulnerability. The goal is to improve traffic throughput and avoid service interruptions.

2.2 Transportation Vulnerability

Globalization has brought modern society a new view of relevance to transportation system vulnerability. The need of useful and quick connections between different networks or within networks are necessary for adequate functionality in the case of performance loss or disruptions. Jenelius et al (2006) attributes the increase of studies on this theme not only to globalization and military activities, but also to the shocking terrorist attacks in Kobe (1995) and New York (September 11, 2001) during the last decades.

Disruptions in transportation can be caused by several reasons and are usually classified as unexpected events or intended interventions. Unexpected events, such as poor weather conditions and accidents cannot be completely predicted, but assuming chronological factors, can be modelled based on the leading causes (critical weather conditions, imprudence, infrastructure conditions and overall characteristics). Intended interventions such as maintenance operations are necessary for preserving the system and the impacts of disruption are more easily overcome due to prior strategical planning. The impacts due to unexpected events have great resource mobility paradigms. Many professionals must be involved and the actions need to be prompt to diminish the negative effects related to the disturbance. The improvement of vulnerability levels can provide less chances of occurrence and faster recoveries. Understanding the limitations of the network, knowing the vulnerability rates, studying probability scenarios and estimating network impacts will enable operators to perform improved services.

The definitions on vulnerability and related measures pleat over various comparable insights. As stated by Mattsson & Jenelius (2015), there is no commonly accepted definition for vulnerability. The used meaning mostly depends on the context it is inserted in. The author defines vulnerability as being the susceptibility to incidents that can result in reductions of network serviceability. Reggiani et al (2015) describes it as being the non-operability of the network under fluctuating circumstances and goes a little further linking vulnerability to network weaknesses and reliability to network performance. Another definition on vulnerability stated by Mattsson & Jenelius (2015) is it as society's risk of transportation disruptions and degradations, conceptualizing risk as the set of possible combinations between cause, probability and consequence.

Vulnerability has developed over many meanings in the engineering sector. According to Miller et al (2010), the term has intensive correlation to resilience which represent two related yet different approaches to understanding the response of a system. While vulnerability is applied as a core concept when analysing failure, resilience focuses on recovery and return time following a disturbance. Other resilience and vulnerability related definitions widely mentioned are *criticality* (Jenelius et al, 2006; Taylor, 2012; Rodriguez-Nunez & Garcia-Palomares, 2014), which can be defined as the probability and consequences of component failure; and *reliability* (Reggiani 2015, Vromans 2006), as the operability of the network, which in Europe is usually evaluated by measuring average delays and observed punctuality.

Still following Mattsson & Jenelius (2015), the literature on transport system vulnerability has two distinct traditions with limited interaction: the topological vulnerability analysis of transport networks and the system-based vulnerability analysis of transport networks. The first is characterized by presenting the transport network through nodes and links, which can be classified as undirected (no order between the connected nodes), directed (start and end node of each link), unweighted (same link lengths), weighted (different link lengths). The second, focuses on the representation of the structure of the real transport system. In this case, the network is frequently weighted regarding actual link lengths, travel times, costs or generalised costs. Here travel demand is often modelled.

Rail transportation also relies on a series of strategies to diminish disruption occurrence. The system is more inflexible than road networks resulting in larger difficulties for rearrangement. As even the slightest disturbance can end up in knock-off effects (overlapping train schedules) it is fundamental that operations are planned to an optimized recovery process and cancellations used when necessary to diminish delays on subsequent vehicles. This is only possible when the service provider understands the system, the operation and its limitations, reason why the estimation of vulnerable locations is fundamental for disruption mitigation and traffic improvement.

2.3 Railway Vulnerability

The risk of transportation disruptions and degradations on this specific system presents an even more worrying situation in the case of railways. As mentioned, the inflexibility of the rail systems results in the need of a more structured approach towards a disruption mitigation plan. This is mostly due to the appalling impacts that can arise during a rail interruption.

The negative impacts tend to be higher on rails because of the systems main characteristics: distinguished accessibility of the tracks, complexity of vehicles and remote surrounding infrastructure. These aspects result in the necessity of a compound recovery plan, which involves several entities, distinguished investments and qualified work force.

Even the smallest disruption on a railway can have a disastrous result. The necessity of maintaining tight schedules with small dwelling times and the dependency of vehicle synchronization balance on a thin line. Many times, its wiser to cancel a trip to avoid knock off effects than to risk worsening of the situation by increasing travelling speeds to make up for the lost time.

Improvements in network vulnerability sustain a better arranged recovery strategy. To plan implementations for vulnerability mitigation, the operator must understand the type, frequency, cause and impacts of the disruptions and set targets regarding sections, infrastructure and component characteristics.

Delgado & Aktas (2016) suggest an approach focusing on awareness of safety, sustainability, and timeliness towards a more resilient rail system. They analyse the existing infrastructure of the Northeast Corridor of the U.S. highlighting current problems and future potential hotspots. The developed strategies are based on the overall improvement of the system resilience and the recommended changes are based on the implementation of existing technologies or making structural upgrades to specific tracks and bridges. The strategies include the necessity of capital investment in its infrastructure, well-structured and monitored track and wheel maintenance, implementation of a advanced system to optimize track occupation and increase the signalling system's overall reliability, improvement of the heat resistance on movable bridges, upgrading of the electrical infrastructure reliability (focused on the catenary system) by investing in projects to develop flexibility towards temperature oscillation, enhance and expedite maintenance and repair routines to ensure maximum railcar availability.

As described before, the causes of unexpected disruptions can be classified in relation to weather, technology, third parties or errors during operations. They have different intensities, impacts and recovery strategies and depend on a series of approaches to be mitigated. The academic sector has publications on all three classified disruption types. Study cases on rail, weather, technology and society have been carried out in several cities and regions around the world. William Brazil et al (2017), for example, has analysed weather related train delays on the metropolitan rail in Dublin, while failure analysis and diagnostics for railway trackside equipment has been studied by Marquez at al (2007). Some examples of people related rail disruptions are: "Suicides on Commuter Rail in California: Possible Patterns" by Botha et al (2010) and "Analysis of railway fatalities in central India" by Wasnik (2010) which also focus on the social part of the incident.

2.3.1 Winter Weather Effects on Rail Transport

In this thesis, the focus is weather related disruptions, the methods to evaluate the system and strategies to overcome the related negative impacts. As rail operators deal with a diversity of weather-related conditions, some are particularly challenging for rail transportation, it is important to focus on their main causes and characteristics. Many problems are yearly caused by build-ups of rain, ice and snow. While precipitation and fog affect visibility and extreme heat can bend tracks, heavy winds might lead to blow-over of railcars. Snow, frost and hail can result in long delays or even complete shutdowns (Rossetti, 2007).

According to Marteaux (2016), the costs of bad weather conditions are high and are likely to increase with climate change in the coming decades. Although overall temperatures are trending to increase resulting in warmer winters, the intensification of storms and precipitation are the main concern. This fact may aggravate the frequency and intensity of disruptions to rail operations, which can result in more damage to infrastructure and components, more train delays and cancellations. Climate change adaptation projects should be developed focusing on suitable economic and financial methods, previewing and avoiding major network disruptions.

As excessive snow, ice and frost are one of the major issues on northern European rail networks (International Union of Railways, 2016) it is currently a subject of great interest. Delays caused by snow and ice can lead to loss of economic efficiency, possible damage of tracks and decrease of safety (Rossetti, 2007). Although there are many rail devices that might cause a disruption, rail switches and crossings are specially monitored due to their high sensitivity to winter weather. The moving parts of these devices can be damaged or present malfunctioning in case snow and ice piles up within them. Problems due to switch malfunctioning are the most common reason for infrastructure disturbances during the winter period (Kloow, 2011).

Rail operators have extensive knowledge on weather related risks and have started to develop mitigation plans for disruptions caused by climate change, but a greater investment and support is required to maintain an effective rail system (Marteaux, 2016). Predicting the impacts of winter-related weather on transport infrastructure is yet an inexact science and the research community has the expertise to support the rail industry in developing effective, flexible and affordable strategies for overcoming this challenge.

2.3.2 The Impacts of Disruption on Network Performance

Vulnerability and disruptions have a negative effect on the railway network performance. As the inflexibility of defining new routes results in inoperability, trains tend to suffer knock-off effects causing delays and cancellations. Differently from other types of network systems, which usually have many possibilities for balancing connections in case of disturbances, rail networks are generally more sensitive due to its dependence on the infrastructure. Having that in mind, service interruptions have a great influence on customer satisfaction. The users of rail tend to be very selective and a reliable network makes a big difference on the distribution of modal share.

As rail networks present limited options to redirect trains, disruptions may immediately incite delays and cancellations on subsequent trains. A steady risk assessment supports the diminishment of impacts after disruption and a well-structured and trained staff that makes fast and appropriate decisions, enables quicker recovery.

The development of a full risk assessment is necessary to identify threats, vulnerabilities and evaluate the impact on rail network assets, infrastructures and systems. Giannopoulos et al (2012) argues that the probability of the occurrence is a critical element and differentiates risk assessment from a typical impact methodology. The authors state that a linear approach is relatively common: Identification and classification of threats, identification of vulnerabilities and evaluation of impact. They stress that methodologies that aim at assessing risks at a higher level involve additional refinement. In other words, the level of detail and methodology will mostly depend on the scope and the chosen target group, as the information must meet the requirements of the professional that will use it (for example a rail operator, decision planner or policy maker).

According to Rausand (2011) the objective of risk analysis is to find answers for three fundamental questions: What can go wrong? What is the likelihood of that happening? What are the consequences? Systematic use of data is essential to identify these hazards and estimate risks to individuals, property and the environment. The methods of assessing rail vulnerability standards depend on the objective of the user of the information. Probability levels can orient and guide the service providers on type and location of needed improvement investments.

2.4 Assessment of Vulnerability Levels

To support the development of a less vulnerable transport system, operators need to direct efforts in locating the most susceptible connections and their impacts on the transportation network. The selection of a research methodology is a complex step in the research process as the subject has a wide range of developed studies using different and combined techniques. The first stage towards defining the used methodology for rail risk assessment is the selection of measurement approach. In accordance to Hughes & Healy (2014) the selection of a methodology can be assessed through qualitative or quantitative frameworks.

Qualitative measurement approaches are carried out by setting relevant principles and defining measurement categories while a quantitative context undertakes more detailed analysis and modelling defining correspondent indexes. The developed scheme enables a more precise selection of the methodology approach based on features related to characteristics in which data requirements, computational supplies, ease of implementation and flexibility are included. It is also possible to carry out a combined approach. This strategy is interesting because it uses quantitative analysis when the inputs are available and reliable and a qualitative framework when the data is incomplete or requires a flexible methodology.

A complete approach can be structured in three steps: the assessment of vulnerability levels within the network to a specified condition, the analysis of disruption impacts in the network and the selection of proper mitigations strategies. These phases are described in the next sections.

2.4.1 Measuring Rail Vulnerability

There are several methods being used for estimating rail vulnerability. Researchers have developed different techniques that combine modelling and simulation for several related disruption causes. Each approach depends on the quantity and quality of available data and is developed based on which characteristics the study is constructed on.

For estimating rail vulnerability in relation to flood events, Hong et al (2015) used the link vulnerability computation method. This indicator is based on the perspective that if a railway link is in a high weather incident frequency area with low instances of disruption, then its vulnerability should be low. Similarly, if a link is in a low frequency event area but has been disrupted frequently in the past, then its vulnerability should be high. Using two basic assumptions: (1) all segments along a railway link have the same failure probability; (2) different areas in a province have similar geographical and climatic conditions. The authors estimate failure probability based on the link length, the number of disruption events in the province (over time), and the total length of railway links in the province.

Hong et al (2015) used method is interesting when the research focuses on weather related disruptions. On the other hand, rail infrastructure has great variations of components within each section. If the study case has information on infrastructure characteristics, the probability of malfunctioning/failure and related consequences can provide a more accurate approach. Erath et al (2009) for example, carried out a study on vulnerability of network components. The vulnerability was calculated by analysing the probability of it experiencing failure due to a given hazard event multiplied by the sum of the direct or indirect natural hazard consequences.

Knoop et al (2012) used a combined approach for road disturbance, where the selected indicators were included to find the most vulnerable road links. It was assumed that the complete dynamic simulation of all possible blockings had an accurate result on the vulnerabilities. Supposing all indicators worked equally well, simulations on each variable were carried out. Knoop et al (2012) agrees that the method shows the proximity of each indicator to the result of the full dynamic simulation. It is important to highlight that the authors did not consider spill over effects, which can be critical for correct vulnerability evaluation.

To build a model that considers a wide range of variables a more generic method must be implemented. A probabilistic approach enables the inclusion of different variable categories in a simple yet sophisticated matter. Probabilistic models have been developed throughout many fields for understanding phenomenon behaviour, and with transport it hasn't been different. Viti & Zuylen (2010) developed a model for the prediction of traffic at control signs while Sigbjörnsson & Snæbjörnsson (1998) developed a model for the probabilistic estimation of wind related accidents of road vehicles. Probabilistic modelling has supported the development of the artificial intelligence field and has significant importance when providing tools for the analysis of historical data. This technique was and is being applied in a variety of transport engineering related fields and is powerful since it focuses on the number of events, removing some of the biasness of when other characteristics are not included.

2.4.2 Analysing Disruption Impacts on Performance

The impacts of disruption can be estimated in different forms. Vilko & Hallikas (2011) for example carried out an interview process using expert panel discussions to determine the impacts and risk probability, while Harris (2006) suggests a modelling approach for a specific case of trains delay probability. Hong et al (2015) applied a model to compute system-level vulnerability of the Chinese Rail System using a time-independent vulnerability metric which integrates the interruption durations.

Cats & Jenelius (2014) developed a model for supply and demand interactions to evaluate the impacts of disruptions in a more refined manner. Most studies until then considered basically the network topology and the authors argue that the granular nature of services requires a more sophisticated approach. The measures of centrality (often used to identify potentially important links) from the perspectives of both operators and passengers are elucidated. Yu & Lin (2008) discuss about three possible performance indicators for a transit system: cost efficiency, service effectiveness, and cost effectiveness. Cost efficiency is defined as the ratio of outputs to inputs, service effectiveness as the ratio of consumption to outputs, and cost effectiveness as the ratio of consumption to inputs. To follow what is suggested by Yu & Lin (2008), it is necessary that data on expenses are available. The impacts on cycle time, throughput and delay propagation are also suggested as indicators of network performance (Goverde & Odijk, 2002).

The impacts caused in a network can also be analysed considering accessibility components as described by Geurs & van Wee (2004). The selection of the network performance indicators depends on the availability of data and proposed objectives. Potential users, ridership levels and station connectivity can provide interesting outputs on the accessibility levels of rail passengers and provide weights on the importance of the operational stations. Potential users represent the built environment in the surroundings of a station (defining the number of residents, jobs or services) and is related to the land use accessibility component. On the other hand, traveller ridership can be directly related with the individual component, as this variable is linked to the number of train users, the demands and needs. Station connectivity is how well integrated is a specific station in relation to the network (Hartholt, 2016). It is fundamental to select a feasible methodology and tools that can provide the outcomes as expected and with the desired reliability. These specific indicators are described in detail in the following sections.

2.4.2.1 Potential Users

This variable is directly related to the accessibility land use component as it depends on the type of built environment in the surrounding area. Commercial areas tend to attract people based on the number of available services, while residential areas support the use of public transport. The closer the station to a residence, for example, the higher the probability of the usage of the rail system by those inhabitants.

As discussed by Geurs & van Wee (2004), the distance decay function represents the probability of one making or not a trip based on the distance to the station. In other works, the probability of travelling diminishes as the distance increases. Using the same reasoning, users tend to use stations near their home, while distant stations are less attractive. In that sense, a decay estimation can be developed for assessing the number of potential users.

A series of methods can be found within the literature to determine potential station users. Andersen & Landex (2008), for example, highlight that catchment areas are often used. They agree that different GIS-based methods can be carried out depending on the chosen level of detail. They discuss mainly two techniques, the circular buffer which considers a radius around the station area and estimates all the occurrences based on the research goals (residents, jobs or services e.g) and the service area method which considers the street layout that gives access to the station. While the circular buffer technique is simple with admissible outcomes, the service area method can produce more accurate results. Combinations can also be used. Gutierrez et al (2011) adopts the distance-decay weighted regression (with bands) and La Paix Puello & Geurs (2015) use a joint RP/SP estimation on station access and egress. For ridership estimations, Hartholt (2016) makes it clear that certain included variables will have more effect on passenger demand on one location compared with another. The author, developed a demand estimation model based on aggregated and disaggregated demand (Equation 1).

$$Yi = \beta 0 + \sum \beta k * \beta ik + \varepsilon i \qquad eq.(1)$$

Where *Yi* is the total number of predicted passengers, *β0* the constant or intercept, *βk* the estimated parameter for variable *k*, *βik* variable value *i* for variable *k* and *εi* the error term for variable *i*. The analysis focused on different station types and the result proved that there are variances in the catchment areas based on station characteristics.

Givoni & Rietveld (2014) studied multimodal accessibility to the Dutch railway stations by carrying out a discrete choice analysis in the Amsterdam region and developed a (dis)utility function from travelling by rail (Figure 2). They conclude that the optimal choice given the disutility from using different modes is between using bicycle and public transport to access the railway stations.

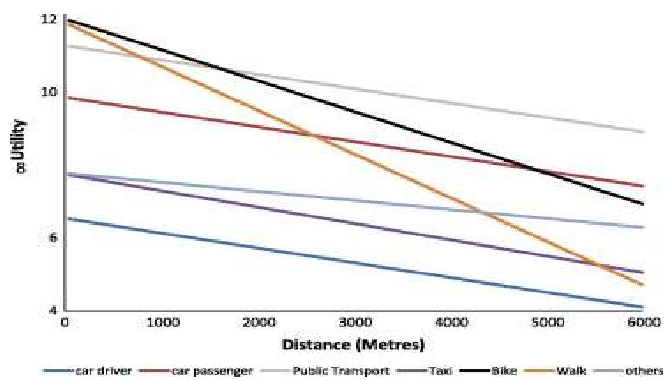


Figure 2 – The utility for using different access modes with respect to distance from the station (Givoni & Rietveld, 2014)

Each type of access mode will display a different catchment area. Some authors agree that for walking commuters for example, the radius should be kept under 800m (Guerra et al, 2011; Landex et al, 2006; Andersen & Landex, 2008), while bicycle access should not go over 5km (Rietveld, 2000). Larger distances should be carefully analysed. It is consensus that in this case, most users will access the station by motorized vehicles. It is important to note that buffers change according to the region or country of analysis. In the Netherlands, people living in a buffer 500–1000m from a railway station tend to use rail services 20% less than people living less than 500m from stations (Gutierrez et al, 2001), while 80% of cyclists will access the station in a 500-1000m buffer (Rietveld, 2000). In addition, Gutierrez et al (2001) states that most people are willing to walk 500 ft, 40% would walk 1000 ft, but only 10% would walk a half mile while around 50% of cyclists would use the station if within 5000m (Rietveld, 2000). Givoni & Rietveld (2007) state that the Netherlands has a high usage of bicycle, a dense railway network and good multimodal connections, which provide a relatively easy access to the stations. The mean distance of inhabitants to the nearest railway station is around 4.5 km, whereas only 8.4% of the population live over 10.0 km from one.

Guerra et al (2011) understands that different catchment areas have little influence on a model's predictive power for the purposes of estimating station-level transit ridership and that the simplest and most readily available data should be used when estimating direct demand models.

For developing visual outcomes of network performance, Landex (2008) suggests using a GIS (Geographic information system) approach. The author assesses the performance by developing maps of the network capacity. Landex (2008) states that with this tool it is possible to evaluate other details of the capacity consumption by selecting the observed line section. The interdisciplinary field of GIS for transportation (GIS-T) has developed to focus on analysis and planning (Miller, 1999) as many benefits can arise from the association between spatial analysis, GIS and transportation. The upload of routes, ridership and land-use to a GIS software enables visualization of disruption impacts and supports performance analysis.

2.4.2.2 Traveller Ridership

Traveller ridership can be based on daily average of train users entering and exiting a determined station. This measurement can be performed by analysing the sold tickets or using electronic systems that count the number of passengers that arrive or depart from a station area. Busy stations will have a higher traveller ridership while ide stations will have lower levels of passenger movement.

It is important to identify traveller ridership to understand overall demands and better plan trip distribution, schedules and vehicle sizes. This variable is also fundamental when analysing which stations are in need of physical expansion or additional services such as ticket booths and information centres. Traveller ridership is an important indicator to estimate the impact of rail disruptions on users. In other words, the busier the station, the higher the number of affected and unsatisfied clients. Also, the number of trains that serve a busier station is higher, which also increases the chance of knock-off effects caused by delayed trains.

The use of ridership as an additional variable to analyse rail vulnerability, meaning that stations which have high demands will be classified as more relevant for the system, providing more accurate output of the impacts of disruption on network performance.

2.4.2.3 Station Connectivity

Hartholt (2016) explains that attractiveness can be determined by how well interconnected the station is in relation to the network. A well interconnected station presents low generalized journey time (in terms of in=vehicle travel time, waiting time and transfer penalty). In other words, station connectivity increases when the number of potential reachable activities rise. His research included a connectivity index based on two network accessibility definitions:

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

$$CCIi = \sum \delta Cij * \frac{1}{Cij + 1} * Dj \qquad eq(2)$$

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 station in the network. Being calculated with the formula (Equation 3):

$$SCIi = \sum \delta Cij * \frac{Lroad(ij)}{Lrail(ij)} * Dj \qquad eq(3)$$

With $SCIi$ being the Straightness Centrality Index of station *i*, $Lrail(ij)$ 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.

According to the author, generically major Intercity stations score better compared to local train stations, although in the Randstad area both returned better scores than stations from other parts of the country. The explanation is that the Randstad area has direct (intercity train) connections with most other major cities in the Netherlands and the fact that this area is home to most economic activities. In that sense, even a small sprinter train station in the Randstad has the potential to reach more places within a certain (generalized) journey time compared to an Intercity station in the far North or south.

The usage of additional indicators is important to bring the calculated values closer to a realistic factor. In this report, these indicators will support the finding of the importance of the nodes in relation to the network, supporting the correct implementation of maintenance strategies and guidelines, new technological investments and providing more competitivity of rail within the transport system.

2.5 Possible Management Guidelines

As discussed, operators have developed recuperation strategies based on their specific geographical areas and resources. Many have experience handling floods, strong winds, heat strikes, storms and excessive snow. It is important that each provider understands its own capacities and limitations and invests on operational improvement based also on historical data.

According to Rossetti (2007), improvements in meteorological studies have resulted in modern weather sensing technologies and better forecasting abilities. Also, rail smart systems are being developed contently for moderating weather-related impacts. Positive train control (PTC) technology, electronically controlled brakes, intelligent grade crossings, automatic equipment identification, and automated scheduling systems for enhancing weather information are given as examples. The availability of data on the most vulnerable sections of the network in addition to the impacts that they cause are an important tool for developing the mitigation strategy.

The TransRail Report (2006) discusses disruption issues in networks that have a long history of problems related to winter climate. Some strategies for diminishing damages on infrastructure involve focusing on critical sections and rail components, proper drainage systems, appropriate planning of resources for cleaning, adequate maintenance, monitoring and implementation of new technologies/equipment. Some of the given solutions are investing in mechanically protect exposed components, increased inspections, using heating systems and coatings that diminish the adhesion of snow/ice.

Jaroszweski et al (2004) studied winter conditions on the Swedish rails. The authors state that the received meteorological information is important, but that the preparation of maintenance personnel, machines and equipment are fundamental and need to be at appropriate levels. They also highlight the issues caused by the lack of preventative maintenance during winter 2001-2002 and discuss the three recommendations that followed the Channel Tunnel event: (i) increasing train reliability, (ii) establishment and regular updating of evacuation and response plans and (iii) improved communication and management of the situation. The South-eastern Pennsylvania Transportation Authority (SEPTA) has also developed notable mitigations strategies towards winter impacts on rail based on the improvement of equipment, personnel and communication. The developed adaptation strategy followed by SEPTA is presented in the appendix (Item 01).

These actions should be followed by the implementation of an accurate weather forecast system, including the instalment of forecast measurement instruments in critical areas. The receive information should be analysed and triggers set to guide personnel on specific winter events. Previewing the disruptions and planning the recovery strategy will minimize the effects of extreme winter weather. But, it is important to recognize that the resources, limitations and difficulties are specific to each rail network and must be analysed in detail for proper strategy development.

3. Part II: Case Study

3.1 The Dutch Railway Network

The Dutch passenger rail network connects all major towns and cities within the country. The network totals approximately 3.700 route km, and over 350 frequently used passenger stations (Figure 3). The transport system is operated by several service providers including NS, Syntus, Arriva, Veolia and Connexxion, whereas NS is the company with the highest share of operability of the network (not including metro or tram systems). The maintenance, rail capacity distribution and traffic control is responsibility of ProRail, a government task organisation that covers most extensions of the national railway network. This company is supported by rail corporations for assuring the serviceability of the rail infrastructure. A map identifying the major train stations is presented in the appendix section (Item 06).

Figure 3 – The Dutch Railway Network

The Dutch railways is considered a stable and well managed system. It is mainly focused on passenger rail services and connects all Dutch key cities. Freight is around 7% of total train trips and most routes run east-west, connecting the Port of Rotterdam with Germany (van Es, 2016). In the Netherlands, cargo trains frequently share the tracks with passenger trains.

Most of the network is electrified at 1.5 kV DC and train speeds are usually around 130 km/h, although the averages drop to 80km/h when analysing deceleration, acceleration and stops at stations. The trains are classified as Intercity or Sprinter connections. While the first is a faster amenity between major stations, the second is an all stop service, meaning the train serves every station along the route. The Netherlands has the highest passenger train frequency in Europe. In smaller stations, the frequency is usually between two and four trains per hour, whereas in large ones (such as Utrecht and Rotterdam) these numbers can increase to around forty trains per hour.

The Dutch rail tracks are divided in geocodes. These segments vary in length and represent the tracks and all its components (including catenary and signalling). They also consist of station areas and rail yards. The areas are delimited with no apparent pattern, but focusing on the start or end of a specific rail section. A station area, for example, represents the platforms, buildings, tracks, rail infrastructure and land in the perimeter of a station. In total 508 geocodes were analysed. A representation of the distribution of geocodes in the Northern Randstad region of the country can be visualized in Figure 4. Each region is maintained by a certain company which responds directly to ProRail. These corporations are responsible for preserving the rail components, guaranteeing the operability of the network in safe and sustainable conditions.

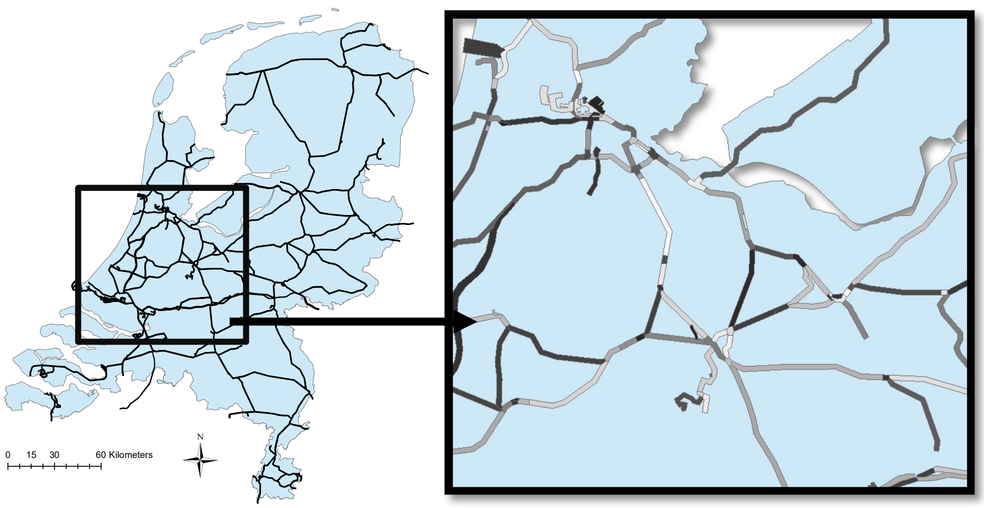


Figure 4 – The Dutch Railway Network and Geocodes.

The contract regions where used in this report as a geographic representation to identify where winter related disruptions occur the most. Although they have changed over the years, it was possible to locate the disruptions in relation to the geocodes which makes the analysis accurate. On the other hand, it was not possible to analyse qualitatively the data in relation to the contracted companies. The contract areas (traces) and the Randstad are presented in Figure 5.

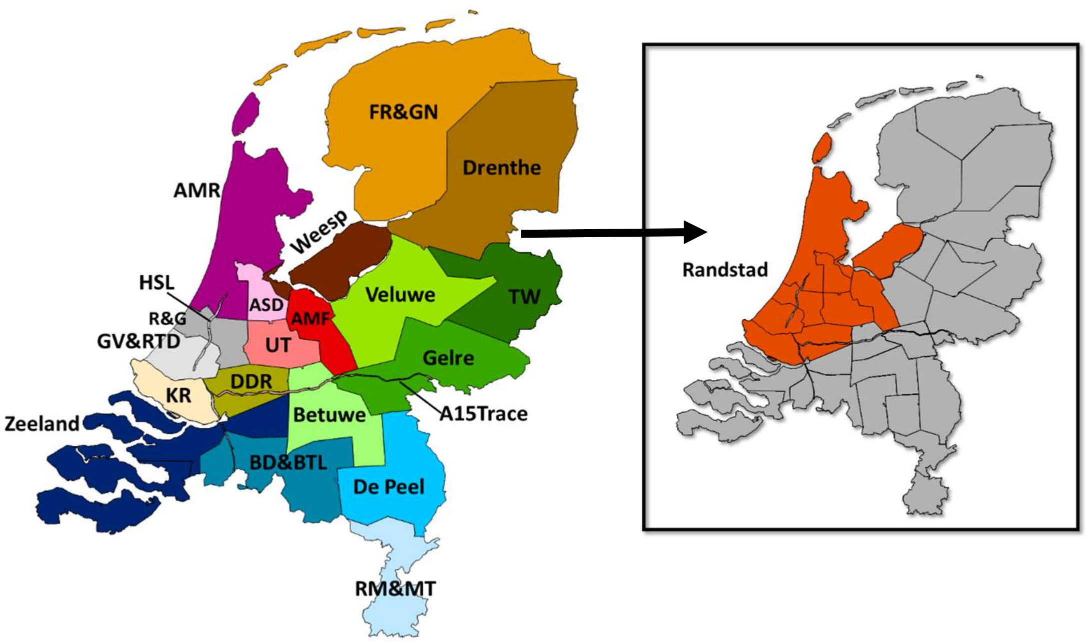


*Figure 5 –Distribution of Contract Regions**

** A15Trace – West/east corridor; ASD – Amsterdam and Duivendrecht; AMR - Alkmaar, Haarlem and Heerhugowaard; DDR – Dordrecht; GV&RTD – Den Haag and Rotterdam; HSL – North/south corridor; FR&GN – Friesland and Groningen; KR – Europoort; R&G – Rijn en Gouwe; RM&MT – Roermond and Maastricht; TW – Twente; UT – Utrecht.*

The regions differ in size and in number of track km. For that reason, the disruptions were also analysed taking these variables into consideration.

Although it was verified that most disturbances in the Dutch network are classified as technical failure (46%). Many of these disruptions are unknown and need an improved data collection approach for an accurate analysis. Also, technical failures are more complex to analyse requiring a more structured and protracted process. Disruptions caused by weather conditions are a little over 5% of the total causes, but have a long recovery period of around six hour's average. These disruptions have a more complete data set as they are usually linked to component malfunction.

Winter disruptions are responsible for approximately 37% of weather related disruptions when adding up snow to ice, frost and impacts due to extremely low temperatures. According to Meyers (2013), a study sponsored by the 7th Framework Program of the European Commission identified specific levels of stress on the European countries attributed to climate change. After evaluating patterns, the Commission came to the conclusion that northern Europe will be subject to heavier levels of precipitation of rain, snow and fog. Activities that might impact even more the rail network. Delays caused by snow and ice can lead to loss of economic efficiency, possible damage of tracks and decrease of safety.

Weather can physically effect one of two rail structures: the rail infrastructure or the rail rolling stock. While the infrastructure is represented by the railway itself, including substructure, bridges, tunnels, tracks, switches, crossings, signalling system and so on, the rolling stock refers to any vehicles that move on a railway. In that sense, the disruptions can be classified as infrastructure related and rolling stock related, which will be explained in more detail in the following sections.

3.1.1 Rail Infrastructure

To avoid disruptions due to excessive snow and ice on the rail infrastructure), the rail operators have a series of activities to prepare, monitor and control the network. This system is represented by tracks (including sleepers, ballast and substructure), turn-outs (switches and crossings), signalling, special structures (such as tunnels and bridges), and the catenary system

The railway infrastructure components differ in sensitivity to weather conditions. During winter weather, meteorological situations can be of various types. Snow, hail, frost, wind gusts and low temperature can damage or hamper the operability of the rail system. Excessive amounts of snow, ice and frost can also set many problems on network performance. While snow and ice pilling can cause derailment or the stopping of the train, a frozen catenary might damage the overhead wire, restricting the train from receiving electrical energy. Ice between the movable parts of a switch can disable route flexibility. On the other hand, irregular and rapid variations in temperature result in thermal expansion/lessening, which have the cumulative effect of degrading track surface and might result in the rupture of rail welding.

As explained in the literature, switches are critical devices during winter periods. Also, switches permit network flexibility as they are mechanical installations that enable vehicles to be guided from one section of track to another. Having a network with many switches allows the trains to enter and leave distinct parts of the system, increasing overall serviceability.

The device is linked between two track sections and consists of six main components: frog, guard rail, operating rod, points, front and rear. The tongue is the movable part of the switch and can be changed (from left to right or right to left) to direct a train. The wheels are guided to the desired switch end and the device is returned to the initial position or maintained fixed for the following operations.

The movements of the tongue follow the train schedule and are monitored and operated by the company operational centre. Although most switches are virtually operated, some are still manually changed. Usually these devices are in remote areas with a low circulation of vehicles.

3.1.2 Rolling Stock

According to the International Union of Railways (2016), the rolling stock mostly presents malfunctioning of three systems when regarding extreme winter weather conditions: bogies, couplers and pantograph. Snow and ice pilling increases mechanical loads on the bogies and result in coupler malfunction. Extreme events might even block the movements of the bogie or present coupling fail when connecting wagons. In relation to the pantograph, which is usually the most recurrent issue in winter weather and rolling stock, the presence of ice on the catenary can result in the cracking of the carbon strip. The International Union of Railways (2016) also lists problems with snow and ice on sliding doors and communication/technological failures caused by moisture in the electric or electronic system.

Many can be the approaches towards a more resilient infrastructure system during winter. Some examples are the change of daily schedules (to prevent major knock-off effects from minor delays due to extra maintenance on tracks), increase of cleaning maintenance programs, instalment of snow/ice coverage systems or barriers or investments in new technologies that diminish probability of component failure (such as point heaters on switches or defrosting coverages on the catenary). The chosen strategy must include all sensitive rail areas and components, based on the reality and limitations of each system, focusing on the improvement of rail parts and optimized maintenance so the failures can be previewed and prevented.

Although the rail operators have extensive knowledge on weather related risks and have developed mitigation plans for disruptions caused by climate, a greater investment and support is required to maintain an effective rail system (Marteaux, 2016). Predicting the effects of winter-related weather on transport infrastructure is yet an inexact science and the research community has the expertise to support the rail industry in developing effective, flexible and affordable strategies for overcoming the challenge.

The *"Winterweer op het Spoor Program"* initiated in 2012 has already established positive results on the mitigation of winter related disruptions, but the service operators still perceive room for improvement. The involved parties have focused on the implementation of new strategies, technologies and maintenance plans every year and keep a close monitoring approach.

3.2 The Winter Disruption Mitigation Program

The *Winterweer op het Spoor* (WS) is a complete scheme of analysis, investments, implementation, monitoring and feedback activities for winter disruption mitigation. The project is a cooperation between ProRail, NS and the Ministry of Infrastructure and the Environment with the objective of improving network performance during winter in the Netherlands.

The initiative came into discussion after three consecutive winter seasons with many service interruptions (winters 2009-2010, 2010-2011 and 2011-2012). Snow, ice, frost, freezing rain and low temperatures caused many equipment failures and exposed the fragility of the Dutch rail network. The winters were harsh and proved that the network was not prepared for extreme weather conditions. Within the 2011-2012 winter period, initial initiatives to reduce train frequency during track disruption turned out to successfully prevent the extensive knock-off effects experienced during the previous winters. These measures were still not standardized but where important to realize the need of specific planning for the season.

Initiated in 2012, the WS strategies have been developed on seven levels: scheduling (winter timetable), infrastructure, material, management, personnel, travel information and customer care. The main goals are to continuously improve infrastructure resilience, optimize recovery time and the capacity of treatment and adjustment. The key goal is to maintain the functionality of the network and satisfaction of the travellers. Each level of improvement has its own targets, analysis and follow up, whereas the operational teams get together to investigate, discuss and propose new investments, solutions and good practices. The strategies and results are debated within the organizations and a summarized open report is published. Currently four reports are available: winters 2012-2013, 2013-2014, 2014-2015 and 2015-2016. Some of the actions related to the two first levels, winter timetable and infrastructure, are presented in more detail in the following sections.

3.2.1 Developed Winter Timetable

The winter timetable, developed to run when specific weather conditions are previewed, was the first and one of the most important approaches towards less impacts on performance during track disruption. As explained, if snow or freezing rain is predicted, trains might be suspended (half hour services instead of quarterly services for example) changing the daily schedule. With this approach, local disruptions are less likely to impact traffic in a larger scale. Also, the measures enable faster reorganization of the trains in case of delays due to the possibility of bypassing traffic. In addition, staff and equipment can easily be planned to reach the location going through technical problems.

In order to accurately preview winter weather, meteorological information is exchanged between weather agencies and the Operational Control Centre Rail (OCCR) of ProRail. There, discussions about the impacts and risks that the broadcasted conditions are carried out. The winter weather condition is classified based on a standard coding system which is the basis for the actions that must be taken. These arrangements can involve train frequency reduction, new layouts for maintenance teams and additional personnel for passenger support. Afterwards, ProRail and NS decide whether the modified timetable will be used or not.

The codes are based on three specific weather type conditions and are represented by colours (purple the most critical situation and green the least). The coding system is shown in Figure 6.

A) Snow/hail

The weather agency will issue a warning if snowfall is expected within the next 36 hours, or if possible within the next 8 days. The operator will also be warned if there is a change and / or deviation from the most recent weather forecast in the intensity, location, size or course.

B) Low temperatures

The weather bureau states that at temperatures below 0 ° C there is frost. Four levels of frost possibilities are used: Light frost: -5 ° C to 0 ° C; Moderate frost: -10 ° C to -5.1 ° C; Strict frost: -15 ° C to -10.1 ° C; Very severe frost: -15.1 ° C or lower. In combination with low humidity, there is a term "dry frost", which is considered not to cause smoothness. The weather agency delivers a warning if freezing precipitation and / or frost (in combination with high humidity) it is expected within the next 36 hours or if possible within the next 8 days.

C) Freezing rain/frost

The weather agency will issue a warning if ice falls under the category of winter precipitation, including undercooled/frozen rain/precipitation that falls on the ground or on objects or rain/precipitation that falls on frozen ground. The alert will be set if freezing rain/frost is expected within the next 36 hours, or if it is possible to occur within the next 8 days.

Critical Snowfall

- 50 to 100% chance of 1.5cm (or more) of snow
- 10 to 50% chance of 1.5cm (or more) of snow
- 10 to 100% chance of 0.5cm (or more) of snow
- 0 to 10% chance of 0.5cm of (or more) of snow

(a) Code alert for critical snowfall

Critical Temperatures

- Temperatures under -15 Celcius
- Temperatures between -10 and -15 Celcius
- Temperatures between -5 and -10 Celcius
- All other situations

(b) Code alert for low temperatures

Critical Frost or Freezing Rain

- 80 to 100% chance of 0.5mm/hr (or more) of frost/freezing rain
- 30 to 80% chance of 0.5mm/hr (or more) of frost/freezing rain
- 5 to 100% chance of 0.3mm/hr (or more) of frost/ freezing rain
- 0 to 5% chance of 0.3mm/hr (or more) of frost/freezing rain

(c) Code alert for freezing rain/frost

Figure 6 – Code alert for critical snowfall(a), low temperatures (b) and freezing rain/frost(c).

Based on the coding, maintenance teams are allocated to ensure that the tracks remain as ice and snow free as possible and that malfunctioning of components is quickly solved. As snow/ice increases the likelihood of switch malfunctions, the project has implemented several heating points throughout the years. Also, the controlled timetable (with less trains) allows the inoperability of a selection of the switches of the network. Having this in mind, the planning team chooses the most critical and strategical switches to keep unchangeable during the winter event based on previous experiences.

The code alert was analysed in a general perspective to understand which weather characteristics could trigger the usage of the reduced time-table. Information on if the reduced time-table was in use or not when a specific disruption occurred was not made available. The analysis of the coding is important to verify if the most relevant weather characteristics are currently considered in the coding methodology. As the weather conditions for each disruption is available in the weather bureau website, it is possible to check if any important characteristics are not considered or if the used code alert can remove any variable.

3.2.2 Infrastructure Investments: Implementation of Point Heaters

As explained, movable parts in the rail system are sensitive to winter weather. It is not uncommon that snow and ice obstruct the device. A solution to diminish the amount of build-up snow between movable parts is the installation of rail switch point heaters in critical areas. This equipment, which can be electric of gas operated, is coupled to the switch and used when snow or frost are previewed. The goal is to melt any blocks of ice that can hamper the movement of the tongue, certifying that rail switches operate satisfactorily during adverse winter conditions.

Although this system performs relatively well when talking about snow, hail, frost and ice, low temperatures are still a main issue due to its impacts on the switch communication system. Some simple approaches can diminish the mal contact within the motor and avoid the misunderstanding of the positioning of the device. As high humidity and low temperatures are the most critical weather conditions, avoiding maintenance during rain or using coverages while opening the switch motor could diminish inner humidity levels and reduce the probability of malfunctioning.

The installation of point heaters has been done gradually during the *Winterweer op het Spoor* project. A data set containing the locations of the installations was analysed and is discussed within the thesis.

3.2.3 Infrastructure Planning: Inoperability of Critical Switches

Currently the Netherlands counts with around 8330 switches throughout the rail network. As the device is the most critical during winter weather, an important mitigation approach is to not operate the most vulnerable ones when the forecast previews severe weather conditions. This approach is planned every year based on the performance of the past winter and works in combination with the reduced train schedule. As there will be less operating switches, the network will be less flexible and the trains will demand more dwelling times. Data regarding the fixed switches for the winter year of 2016/2017 was made available and is analysed throughout the report.

3.3 Development of the Thesis

As mentioned, the development of the research was carried out in four phases. These steps are consistent with the descriptive statistic, methodology and results phase, which were fundamental to provide answers to the proposed research questions.

The first step, the analysis of rail disruptions and the connections with winter weather, brings the first understandings about the data and its characteristics. The statistical analysis compromises the reasoning behind aspects related to the disruptions, such as impacts on traffic management, recovery times and most affected systems. Some of the implemented mitigation approaches are discussed in this section. This phase is also where the variables for the vulnerability index are studied for inclusion. Based on the studied literature and the first findings, it was then possible to select a methodology to estimate disruption likelihood in relation to weather and rail infrastructure, which was the second step.

The second and third steps, included in the methodology development, include the findings on disruption probability based on switches and the assessment of node potential. The impact analysis, is carried out by relating station potential to each route within the Dutch network. In this case, three important aspects of stations where considered: potential users, traveller ridership and station connectivity. For estimation of potential users, catchment areas were analysed for each studied station. The traveller ridership was obtained from previous rail studies and the station connectivity collected from earlier researches. With these values, the importance of the origin and destination stations of the routes were included as additional weights in the vulnerability index.

The last step, the development of the risk map, is the building of the visualisation of the vulnerability levels throughout the network. The risk map is therefore the product of this thesis and considered the result of all the analyses. These values, as can be derived, are based on railway characteristics (infrastructure and disruption types), train frequency and station potential that were obtained using the developed methodology.

It is important to highlight that the data considered in the vulnerability index was the collected measures from after the implementation of the winter disruption mitigation project (*Winterweer op het Spoor*), meaning the considered data was from winter 2012/2013 up to winter 2016/2017. This decision was made due to the different realities before and after the beginning of the program. The inclusion of data prior to the program would bring a level of bias to the index, as currently there are several strategies, technologies and improvements within the network. Nevertheless, this data was important to understand the criticality of the network in relation to weather conditions, the progress of the program, the general rail component functioning and the reasoning for the chosen measures in the implementation plan. Although details of the applied measures are not publicly available, it is possible to generally evaluate them and suggest new approaches based on the open reports.

3.3.1 Descriptive Statistics

Step 1: Analysis of Rail Disruptions and its Correlations with Winter Weather

The first step within the methodology was the deepening of the understandings on rail system functionality and its sensitivity to winter weather. In that sense, weather data was collected through the KNMI website from December 2007 to April 2017. The objective was to link the disruptions to the available weather indicators and run a correlation analysis.

In total, 38 weather stations had collected measurements throughout the studied years. Some of the weather stations had recently been implemented, so data was not entirely available throughout the study period. The used variables were wind speed, air pressure, average temperatures, relative humidity and the presence of snow and ice formation.

The data collected from the KNMI was processed and the characteristics of the last winter seasons analysed. Some assumptions were taken for structuring the weather data:

I. A winter weather occurrence means the presence of a specific winter type (snow/frost/low temperatures) during a day within the specified period. As they are registered separately, it may occur that one or more weather types happen in a specific day. If it snows and registers low temperature e.g., two winter weather occurrences will be accounted for.
II. Some weather stations (KNMI) did not have registrations for specific disruption periods. The solution was to use the weather characteristics from a neighbour weather station for the disruption located within the weather station area.
III. As the contract regions differ in area, shape and size from the areas of the weather stations, the weather occurrences were linked to the geocodes of each region for a clearer analysis.
IV. The registered cause of disruption in the used data (snow/hail, frost/freezing rain and low temperatures) were only considered for comparison within the study. In other words, the cause of disruption registered by the technician was considered when it concurred with the data collected by KNMI. In case the weather condition differed, the used one was the one from the weather station.
V. If the cause of disruption was classified as winter weather but the historical weather data from KNMI didn't have any occurrence registrations during that day, the disruption was considered an outlier.

The rail disruption data refers to SAP (asset management) and Mon (traffic management) collected between 2007 and 2017. It is important to understand that these two systems function separately. As an example, it is not mandatory that a disruption on the asset (track) affects the traffic of trains. If it is a secondary system which is not fundamental for safety or transit, the disruption might not be noticed by the traffic management at all. Also, it might occur that the malfunctioning of a device is handled quickly enough not to affect the train schedule. On the other hand, if the winter condition is impacting the vehicle (ice on the bogie e.g.) it will not be registered within the SAP data as it does not affect the asset. Having these definitions in mind, the produced dataset is based on SAP and uses Mon inputs when the disruption has impacts on traffic. The variables include the cause of disruption, duration, location and traffic impacts of nearly every occurrence.

At the end, the data set is composed by variables on three levels, SAP data, Mon data and weather data. SAP and Mon data, was made available by the service provider ProRail. These variables were merged and additional information on weather characteristics included based on the KNMI source (Figure 7). Two major data sheets where initially produced, one based on all disruption types for general statistical analysis and one containing only switch related disruptions. The first data set was developed and used for the characterization of the disruption types and the necessary findings on the most sensitive infrastructure components to winter weather. These results were used to guide which methodology and variables would be used within the research. Findings related to the *Winterweer op het Spoor* program are presented in a separated section for a directed discussion.

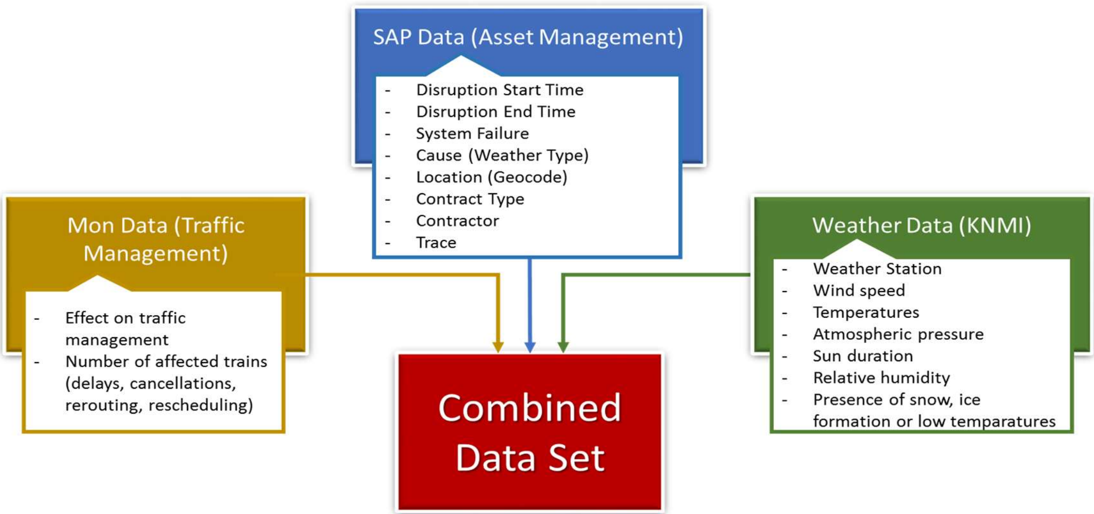


Figure 7 – Data merging process.

3.3.1.1 Data Analysis

The data analysis was carried out in five stages: data preparation (selection, organization, inconsistency check, missing data investigation) and editing (categorization and estimations), examination, validation, interpretation and identification of patterns (descriptive statistics analysis), and results and synthesis. The description of the variables and the first results are presented in the following sections.

A) Data Preparation and Editing

Data preparation can be described as the process of collecting, merging, aggregating, cleansing, and consolidating data into one file. This process is indispensable for preparing and providing the data in a usable format for the planned analysis. The activities related to understanding and managing the variables are the essence of the data preparation, which was developed in four steps: selection, organization, inconsistency check and missing data analysis.

The selection of the variables was based on the goals of the thesis. As the focus is understanding patterns related to winter weather disruption, the infrastructure characteristics and the impacts on the network, the selected variables were essentially related to time, duration, location, infrastructure system type and weather condition. The organization of the data involved the structuring of the variables in a form with the objective of creating an intuitive workflow. This strategy permitted a simplified overview of the variables and supported an objective and solid initial descriptive analysis.

The inconsistency check was carried out in a prearranged form, focusing firstly on inputs that were out of the estimated ranges. Outliers were calculated and compared to the highest and lowest values in the dataset. In case possible, the input was replaced with a more accurate value. An example was the defined location of the disruption. For Mon data, the location is identified by a different system, which disables the linkage with geocodes. In this case, it was possible to detect the correct geocode using the Mon location system (Primair Proces Leidings Gebied – PPLG, translation: Primary Processing Area) in addition to the listed contractor as an additional input. The (PPLG) is a primary area, which is determined by the projection of a demarcated set of operating powers on a centrally operated part of the rail infrastructure.

Unfortunately, it was necessary to proceed manually using ArcGIS, which demanded an excessive amount of time. Inconsistency checks were also performed with the disruption inputs in relation to weather type and cause of disruption. An example is a disruption that was considered to be winter related during a warm summer month with elevated temperatures. These occurrences were removed from the dataset.

According to Pigott (2001), missing data needs to be carefully evaluated in order to select how to treat the problem. The author states that it is important to firstly define the objectives of the research. Depending on the goal it might be interesting to estimate and include missing values in some cases or only consider complete datasets in others. As it is necessary to have a complete set for an estimation model, it was determined that the variables included in the regression model needed to be integrated. For the descriptive analysis, it was decided to maintain the other disruption information that was considered reliable. The duration of disruptions, for example, was the variable with most cases of missing data. This can be explained by many reasons. Firstly, due of the process because the responsible for filling in the event did not complete the activity as in many cases the disruption time overlaps work hours. Secondly it may occur because of a misinterpretation of the cause, which can be initially identified as one specific issue and when in the field, the technician finds a different reason, bringing problems in relation of specifying a correct initial or end time. A third reason could even be the misunderstanding of the importance of the collection of the data. If the technicians are not expected to fill in the form completely, are not informed about the relevance of registering the duration of a disruption and don't understand the goals behind analysing the data, they will probably not give it much importance and only register if they have an easy and straightforward measure.

Although some variable inputs were missing, the disruption events that were considered important for understanding overall data characteristics were maintained. When possible, the missing cases were filled with a plausible value. As KNMI only provides data variables related to the presence of snow or ice formation e.g., it was necessary to include a variable based on the occurrence of low temperatures. This variable was estimated using averages per day that were under zero degrees Celsius.

B) Data Validation

When a data set is satisfactorily complete (with minor errors) to be substantial for its purpose and context, it is considered to be reliable (Morgan & Waring, 2004). For that purpose, data must go through a validation analysis. The validation process defines if the data represents what is planned to be assessed. For this study, data fields were analysed in sequence to understand if the values are well presented and clear. A cross-reference validation method was performed, combining the variables in sets and analysing the disruptions separately to figure out if the data sets were consistent. Locations, times, periods, type of system and weather characteristics were set based on underlying assumptions. Does the type of winter weather explain the registered event? Does that specific location dispose of the system that was classified as having a malfunction? Was the period of day of the disruption consistent with the registered weather features? And so on.

C) Data Examination

The characterization of the data is important to find the total variability in the data set. Also, within the data examination, correlations between variables were analysed. These values can be accessed in the appendix section (Items 02, 03 and 04).

During the data examination, it was noticed that the occurrence of snow or frost in a specified area is positively related to the presence of high humidity with a correlation of approximately 0,200. Temperatures below zero and relative humidity above 80% triggered precipitation in the form of snow and freezing rain. This information is important for the rail weather bureau when analysing the needed planning approach. It might be wise to include an alert for high humidity in addition to low temperatures for example.

Generically the weather data has higher correlation variables than the disruptions. The wind speed has positive correlation of 0,511 with the average temperature and negative correlation of 0,270 with ice formation, while disruption duration and number of disruptions barely correlate with the presence of snow, frost or low temperatures. This means the wind has a strong influence on the temperature and stronger winds imply in lower temperatures. Also, intense winds slightly diminish the formation of ice. In relation to the disruption data, the correlations are all fluctuating around zero, meaning the correlation is too weak to make any assumptions.

D) Data Interpretation and Identification of Patterns - Descriptive Statistics

Winter Related Disruption Data

After the preparation, editing, validation and examination of the data set, it was possible to analyse the information quantitatively and qualitatively. The first step was to analyse the overall characteristics of the disruptions in all seasons. It is important to highlight that each weather season has distinct impacts on the rail infrastructure. Lightning, for example, has mainly triggered problems in the power supply and the ICT (Information and Communication Technology) systems, while rain and storms strongly affect drainage systems. Snow, frost/freezing rain and low temperatures are strongly related to switch malfunctions (over 75%), while during other weather conditions switches barely enters the rank of most affected components (lighting – 2%, elevated temperatures – 5%, rain – 9% and storms – 4%).

The distribution of occurrences related to snow, ice formation and low temperatures (KNMI) during the studied years is represented in Figure 8. As can be visualized, the numbers of winter weather occurrences present an unstable variation, meaning the winter weathers of 2009/2010, 2010/2011 and 2012/2013 seemed to be harsher than the others. Unfortunately, the intensity of snow and ice formation were not accessible for a more accurate analysis and were listed as one of the limitations of this report.

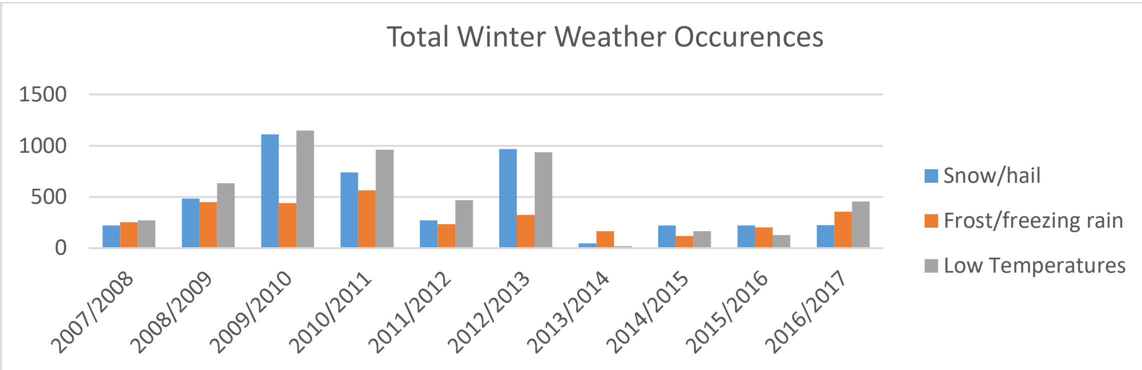
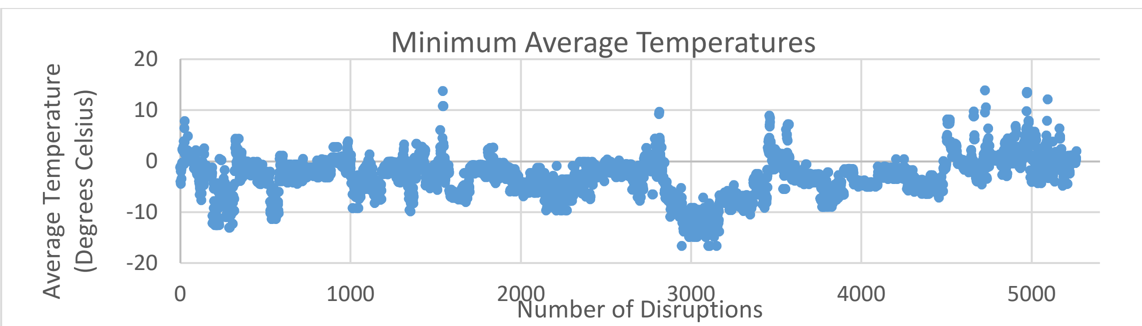
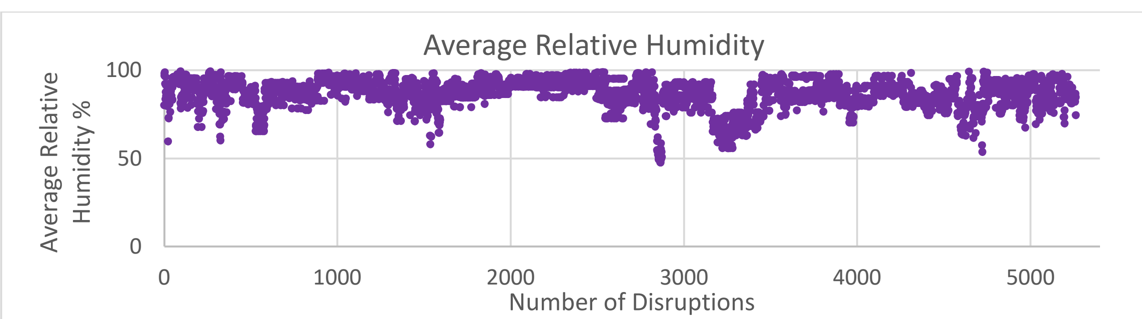


Figure 8 – Distribution of Winter Weather Events.

The physical characteristics of snow and ice that result in component malfunctioning and failure were analysed based on different perspectives. What can be noticed within the analysed data is that humidity and low temperature play the most important roles regarding winter weather and component malfunction. This can be observed within the registered values which were linked to the rail disruptions (Figure 9a and 9b). These elements are critical to a number of rail components, such as the catenary and movable devices (turn-overs).



(a) Distribution of Average Temperatures.



(b) Distribution of Relative Humidity Averages.

Figure 9 – Distribution of Weather Measurements during Winter Weather Related Disruptions.

Around 80% of the disruptions occurred while average temperatures were below 0 degrees Celsius and average relative humidity was above 80%. Additionally, the majority (over 80%) of disruptions happen when the wind speed was over 2 meters/second and the atmospheric pressure over 980 hPa. The supplementary weather-related measurements are within the appendix section (Item 05).

Under harsh winter years, when the number of occurrences of snow, ice formation and low temperatures were higher, rail component malfunction tended to occur more often. The winters of 2009/2010, 2010/2011 and 2012/2013 where the ones within the studied period that presented the highest number of winter weather occurrences, also representing the highest percentage of winter related disruptions (between 2300 and 2700 registered failures). Although these were the years with the highest number of rail disruptions, winter 2011/2012 presented the highest ratio between the number of occurrences and the number of disruptions. During this specific year, over 76% of the winter events resulted in a rail disruption, the worst outcome in the studied range (Figure 10).

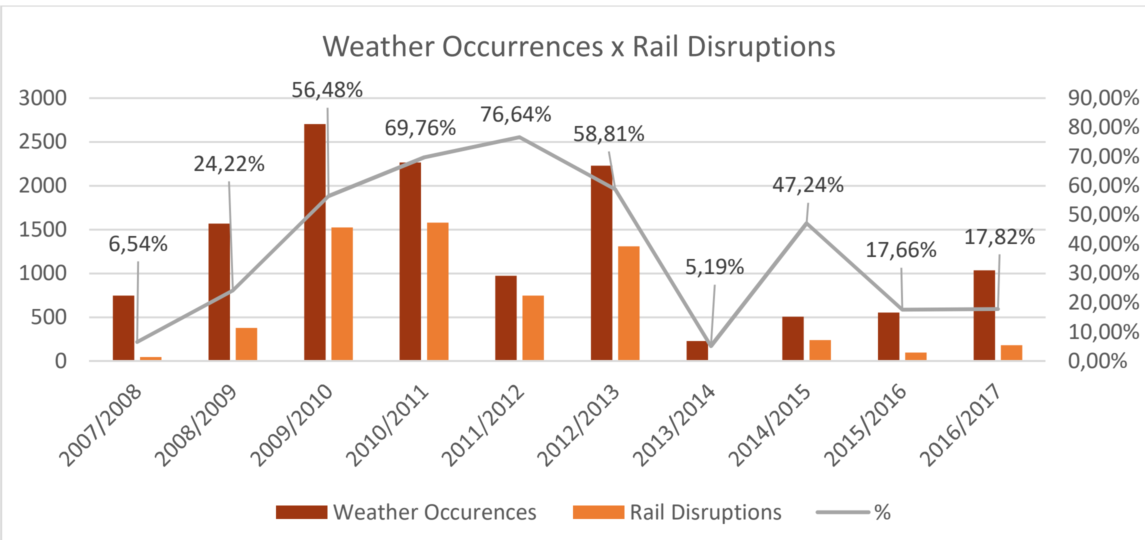


Figure 10 – Distribution of Weather Occurrences during Winter Weather Related Disruptions.

As informed, the systems negatively affected by winter conditions and that suffered disruption were classified in 14 major operational areas. The most affected system is switches (66%), followed by special track structure (11%). The classification "special track structure" represents special constructions such as bridges, tunnels and flyovers. Curiously 13% of the disruptions were not linked to a specific system and classified as *Unknown* (Figure 11).

Winter 2013/2014 presented quite untypical outputs with very few weather occurrences and disruptions. With only 16 registered disruptions, none were classified as "unknown", switches represented 38%, special track structure 32% and power supply system 25%.

During the 10 year range, most of the unknown system disruptions (55%) were linked to low temperatures. This can be an indicator that this specific weather condition results in more challenging analysis. As snow and frost cause mechanical issues (blocked switch, slippery tracks, frozen catenary e.g.) they are more likely to be quickly detected and solved, while low temperatures are problematic to perceive. When not considering the unknown failures, switches raises to nearly 80% of the disruption causes, placing the device as the most critical in the rail system during winter weather.

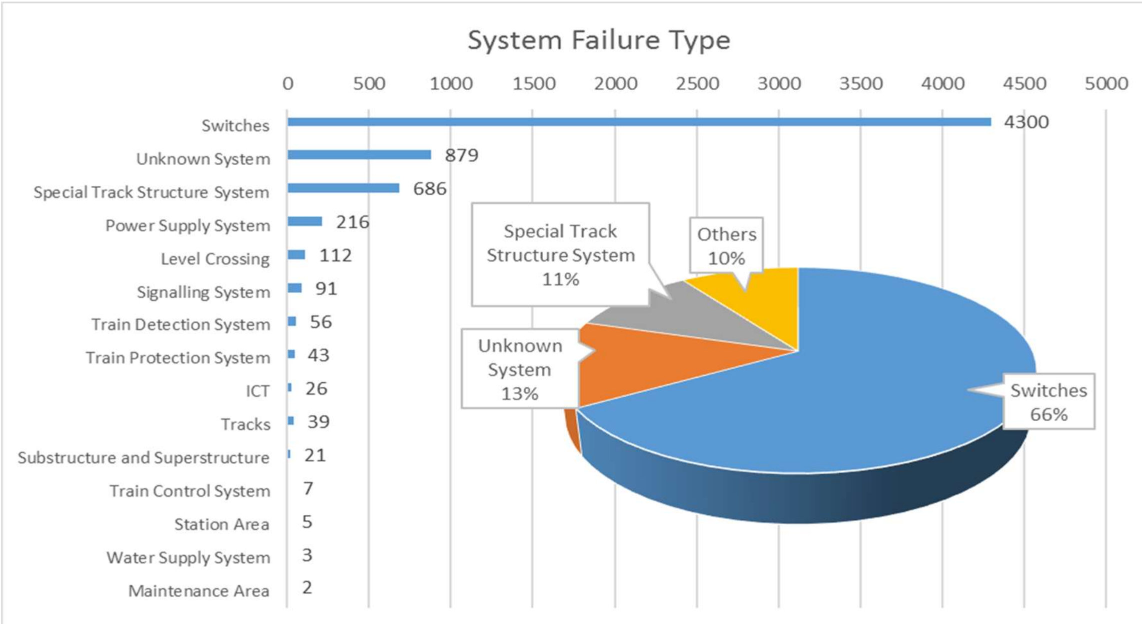


Figure 11 – Number of Failures and Classification of Types.

Switch disruptions varied greatly throughout the studied winter years. Following the pattern of harsh winters, the years with the highest number of switch disruptions were 2009/2010, 2010/2011, 2011/2012 and 2012/2013 (Figure 12), while the most critical months were December and January representing approximately 80% of the cases (Figure 13).

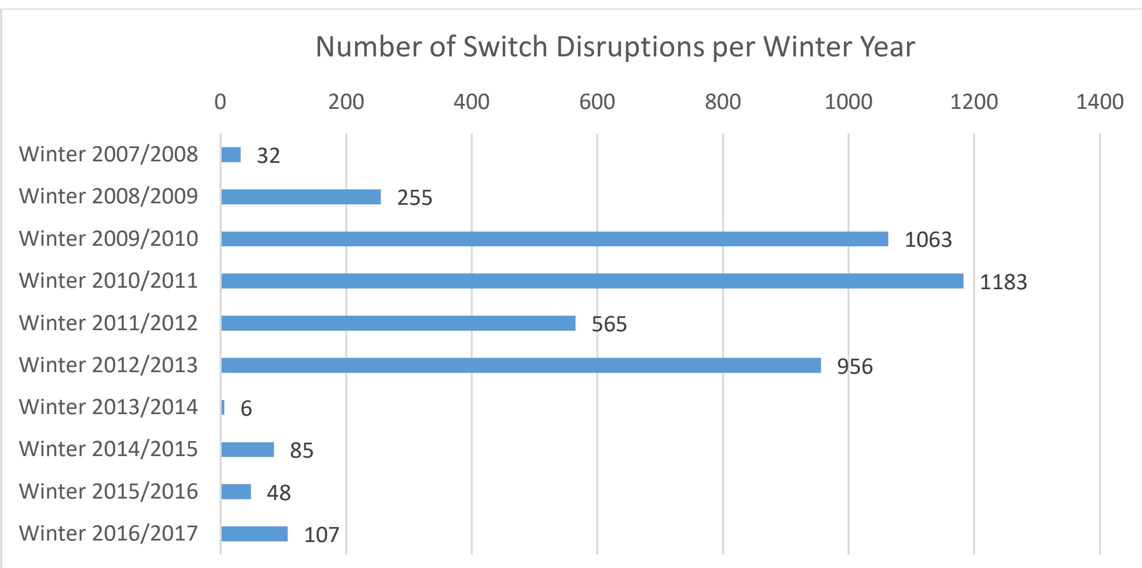


Figure 12 – Distribution of Number of Switch Disruptions.

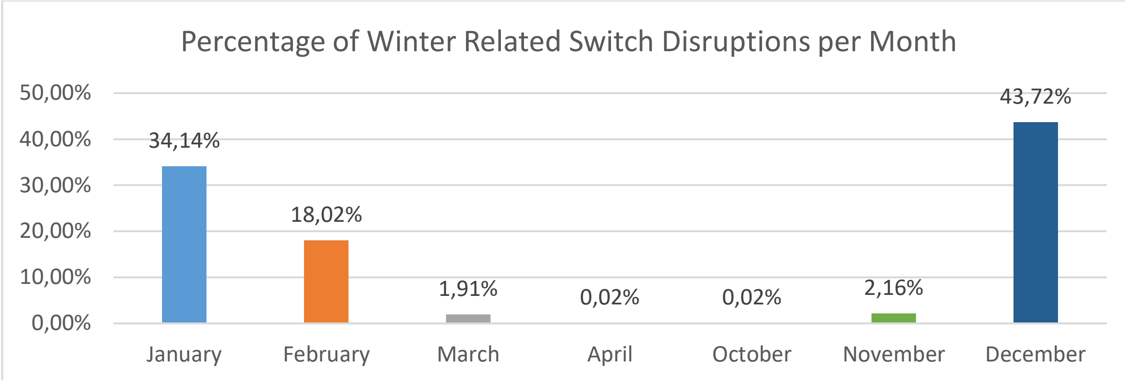


Figure 13 – Distribution of Number of Switch Disruptions.

Within the winter type per switch disruption, low temperature is the most common adding to around 45% (followed by snow with 33% and frost/freezing rain with 22%). An example of malfunction related to low temperature in switches is contact problems within the switch motor. Within the switch motor there is a simple connection device that sends a signal of the switch position to the central administration. If humidity builds up within the motor to a point where the wires have an interference (the connection is impaired), the central administration won't receive the signal and will believe that the switch didn't change the position (even though it might have). In this specific case, there is another overlap of possible system failure type: winter related or technological related, which needs to be discussed with the technicians for a clear understanding. The distribution of switch disruptions over the studied years per weather type is presented in Figure 14.

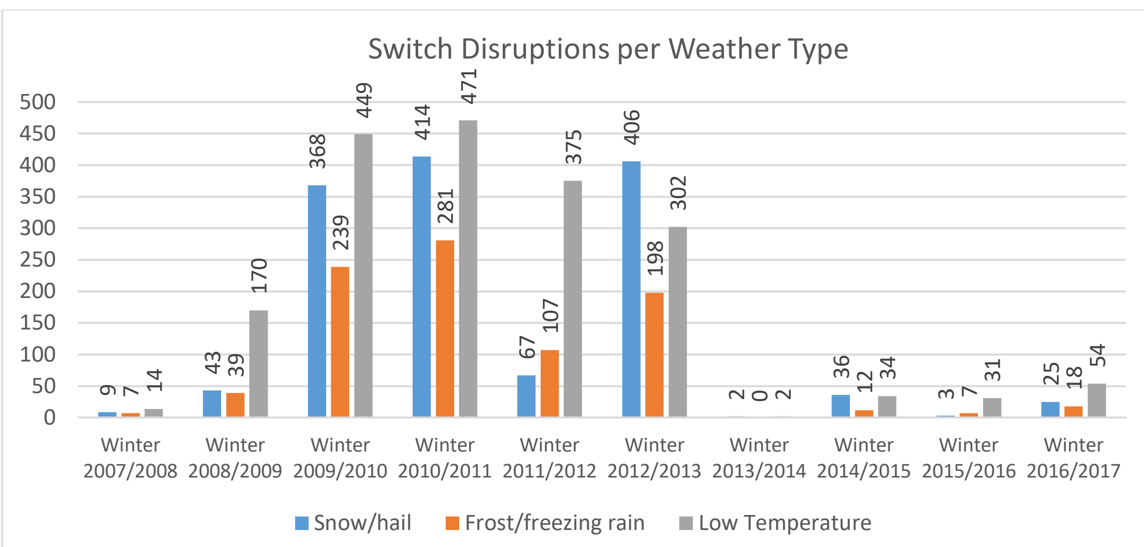


Figure 14 – Distribution of Switch Disruptions per Weather Type.

It can be verified that the number of switch disruptions has diminished over the years in a greater proportion than the reduction of winter weather events. This can be partially explained by the strategies implemented in the disruption mitigation program. A general visualization of the weather occurrences, the rail disruptions and the switch disruptions is presented in Figure 15. The ratio refers to the percentage of disruptions that are switch related. The correlation coefficient between the number of rail disruptions and the number of switch disruptions is of 0,986.

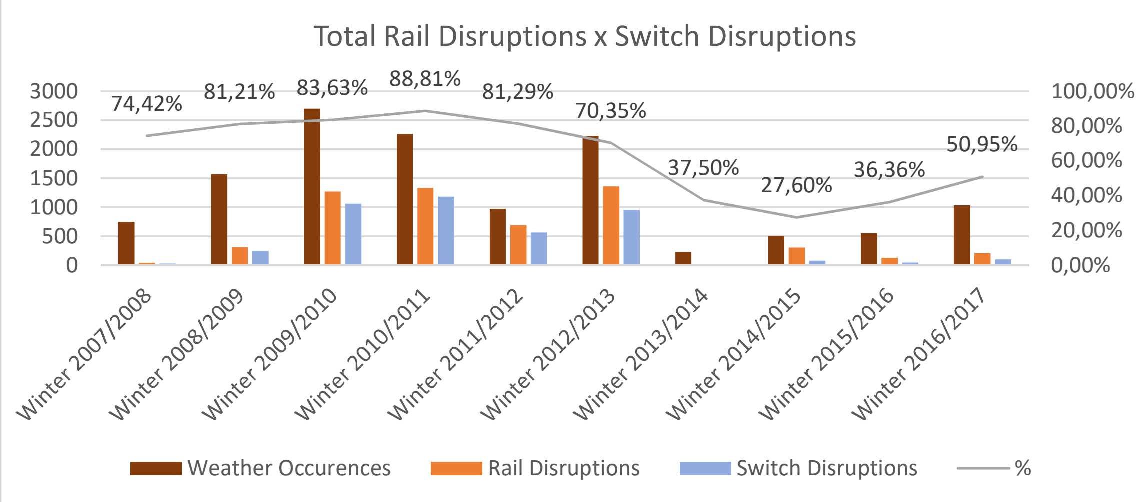


Figure 15 – Distribution of Rail and Switch Disruptions throughout the study period.

The locations that suffered the most switch disruptions during the studied period were the traces AMR, UT and ASD (Figure 16). As the regions differ in size and route km, a calculation was performed to have the rank of traces with most disruptions per route km. The number of switches in each region was then divided by the number of route km, which gives a better understanding of critical switch disruption areas. Figure 17 present the number of switch disruptions per route km. The most critical in this case were Drenthe, FR&GN and Veluwe. Table 1 presents the overall characteristics of the disruptions per Trace. It can be noticed that the numbers vary greatly throughout the different regions during the winter years, being AMR, UT and ASD the ones with the highest number of disruptions, but also the regions with the highest standard deviations. This can be explained by the gradual investment in mitigation approaches in these regions, which dropped the number of disruptions during winter weather conditions.

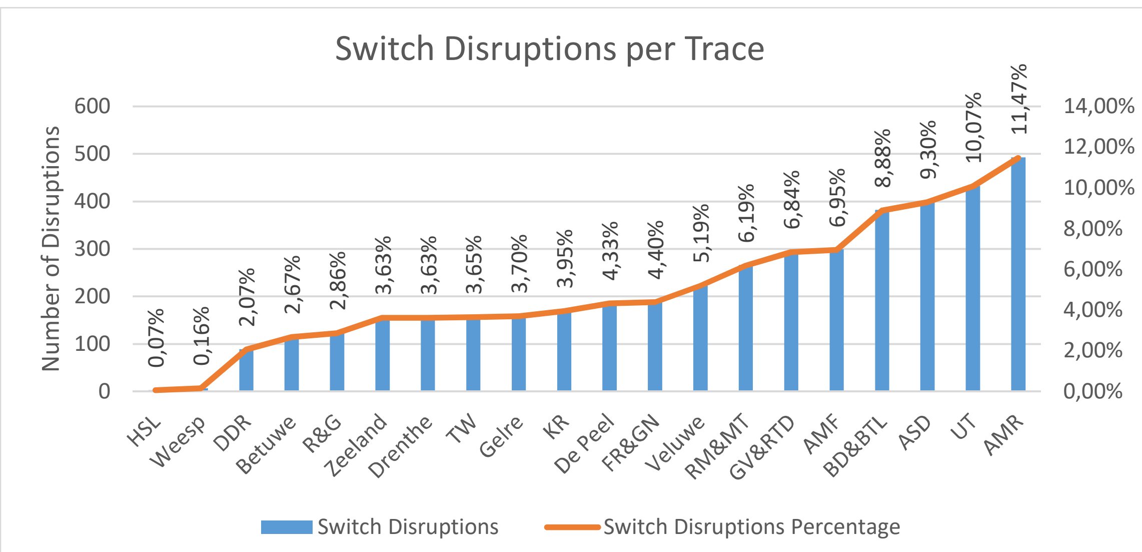


Figure 16 – Distribution of Switch Disruptions per Trace.

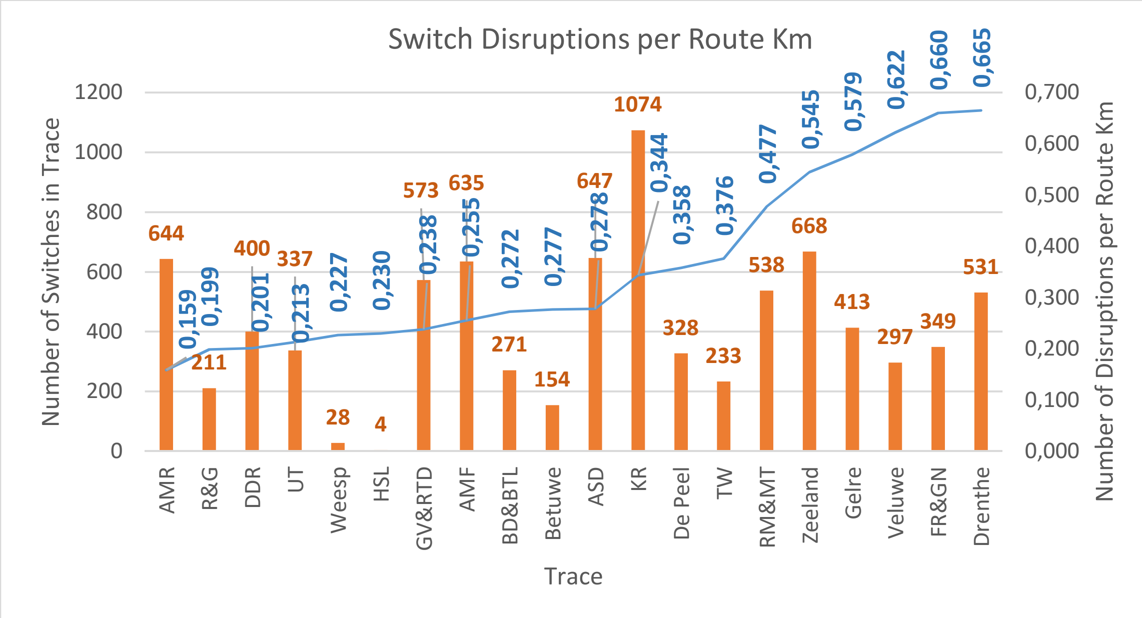


Figure 17 – Distribution of Switch Disruptions per Trace per route km.

Table 1 – Disruption Data Characteristics per Trace per Year.

Trace	Total Disruptions (Number)	Disruptions /route Km	Average	Standard Deviation	Min	Max
HSL	3	0,230	0,3	0,640	0	2
Weesp	7	0,227	0,7	1,552	0	5
DDR	89	0,201	8,9	7,217	0	21
Betuwe	115	0,277	11,5	11,218	0	36
R&G	123	0,199	12,3	14,846	0	43
Zeeland	156	0,545	15,6	16,487	0	49
Drenthe	156	0,665	15,6	21,143	0	65
TW	157	0,376	15,7	16,840	0	55
Gelre	159	0,579	15,9	20,216	0	70
KR	170	0,344	17	18,654	0	56
De Peel	186	0,358	18,6	18,730	0	53
FR&GN	189	0,660	18,9	26,530	1	89
Veluwe	223	0,622	22,3	21,835	0	68
RM&MT	266	0,477	26,6	31,429	0	94
GV&RTD	294	0,238	29,4	41,917	0	144
AMF	299	0,255	29,9	33,886	0	87
BD&BTL	382	0,272	38,2	41,138	1	105
ASD	400	0,278	40	50,322	0	137
UT	433	0,213	43,3	53,536	0	140
AMR	493	0,159	49,3	59,128	0	149

In Figure 18, it can be noticed that the recovery times related to the switch disruptions vary greatly within the selected data set. Most range within one hour to two hours (30%), whereas very little (1%) are solved under 15 minutes. It is important to highlight that disruptions under 15 minutes usually don't have great impacts the train traffic as the dwelling times are typically over of a quarter of an hour. Disruptions over 15 minutes and below five hours add up to 76% of the occurrences. The ones over five hours are demanding, but the operation centre gradually overcomes these conditions. It can be said that the first couple of hours are the most critical.

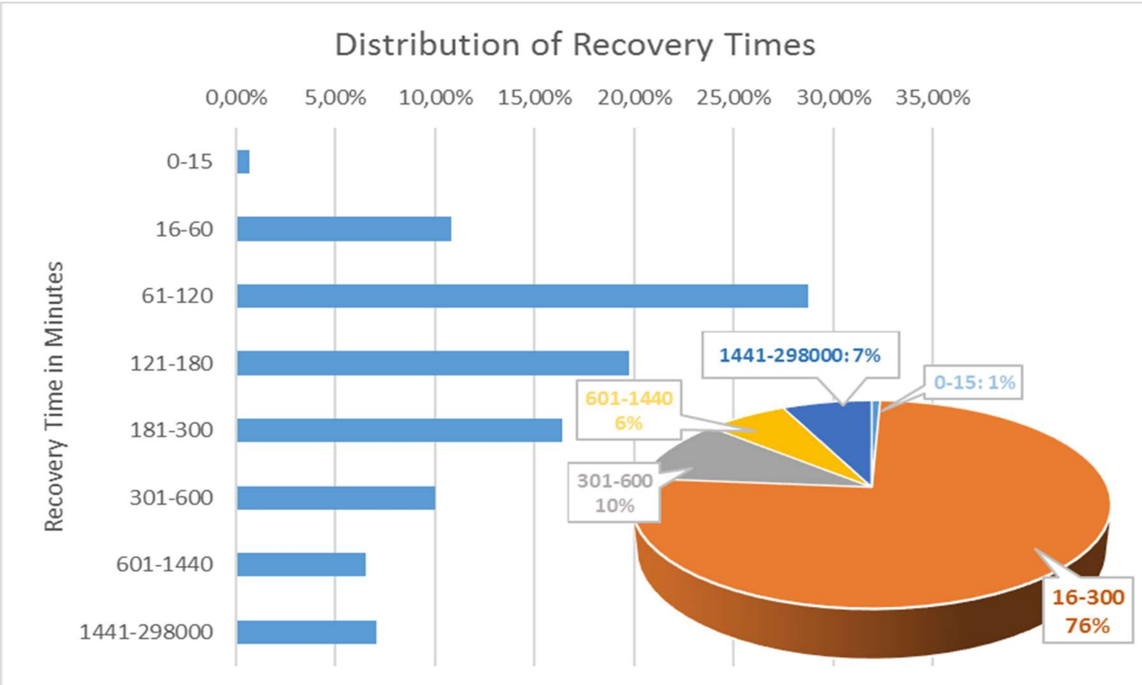


Figure 18 – Switch Disruption Recovery Times.

Long recovery times for switches suggest a fixed switch operationally speaking, whereas the device is maintained in position and is used without operation during the restoration. That means the segment will not be flexible and the device is unmovable during that period. This explains also why the impacts on traffic when the disruption is over 5 hours is not higher than the disruptions within this time frame (Figure 19).

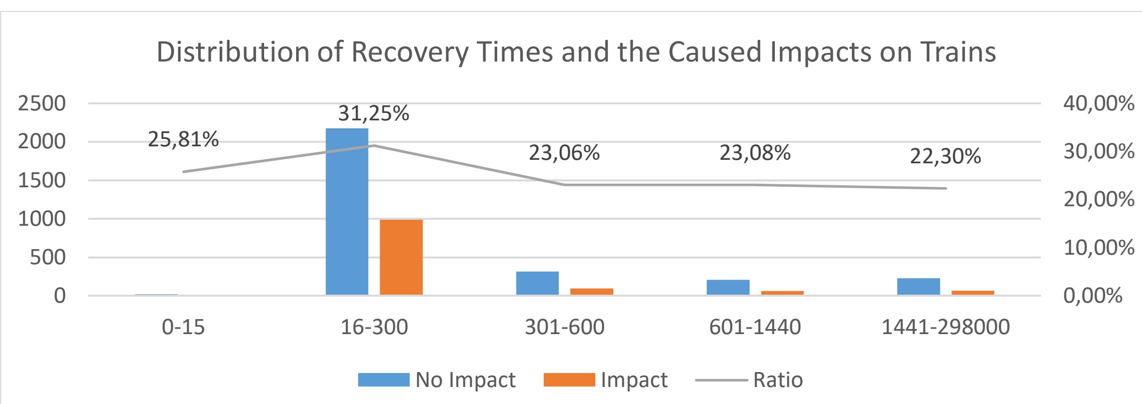


Figure 19 – Distribution of Recovery Times related to Impacts on Trains.

Still analysing Figure 19, it can be argued that disruptions that are over 15 minutes and under five hours tend to have greater impacts on the network. This can be partially explained due to the initial reorganization strategies that are taken in the first moments which need the next couple of hours to have positive results. The range of time that most impacts traffic is within 15 minutes and three hours (31,25%). This is partially explained by the fact that after five hours of disruption the operator has managed to cancel or redirect most vehicles within the problematic area.

As explained in the literature review, the rail switch is used to guide rail vehicles from one track to another and is constitutes of many elements. These devices are fundamental for the optimization of the rail network as they flexibilise the usage of the tracks. It is also important to highlight that switches are fundamental for the safety of the railway. Many can be the types of accidents or incidents caused by poorly operated switches. The manoeuvre of the device while a vehicle is over it is an elevated risk for derailment, for example. Also, as switches are the connection between tracks, incorrect set points can result in multiple trains on the same link, which can cause vehicle collision. To avoid accidents, it is extremely important to preserve the switches operable with a complex and severe maintenance strategy. In addition, technical approaches such as locks to prevent switch reversing diminish these risks.

Being the most sensitive component to malfunction in winter weather, having a fundamental role in rail operations and being the device with most complete data set (regarding physical location and applied improvement strategies), switches were selected to be the main infrastructure element, and therefore the vulnerability index is based on the number of switches on a rail link.

Winter Disruption Mitigation Program Data

As explained previously, the winter weather disruption mitigation program focuses on several levels of implementation. Currently there are approaches towards a reduction of train frequency when severe weather is previewed (winter timetable), infrastructure investment improvements (point heaters for example), infrastructure management for switch fixation and many others. As data on point heaters and fixed switches was made available, it was possible to analyse these implementations in a little more detail.

The installation of point heaters has been done gradually during the project. Between 2016 and 2017 for example, around 500 new point heaters were installed in the Dutch network (Figure 20). The trace with the highest number of new devices was GV&RTD (Den Haag and Rotterdam regions), followed by AMR (North of Amsterdam) and AMF (Amersfoort).

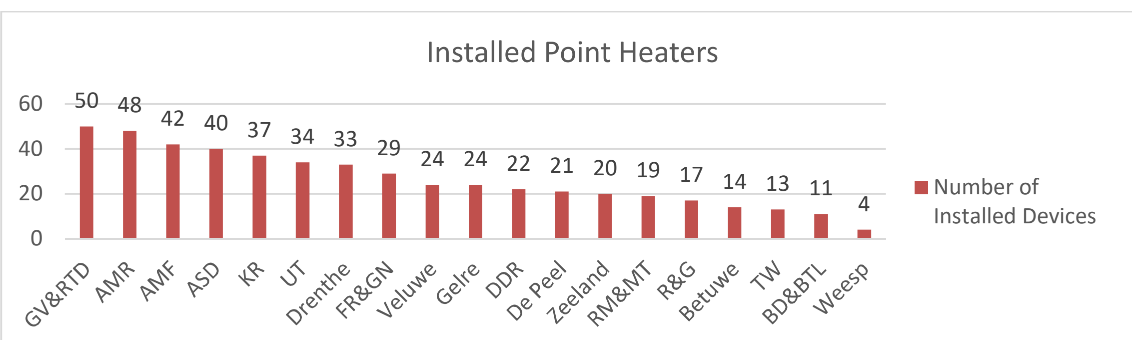


Figure 20 – Number of Installed Point Heaters per Trace.

It is interesting to notice that the regions with the highest investments in point heaters are not necessarily the ones with the highest number of switch related disruptions during winter (Figure 21). This can be explained by the type of failure that the switches presented. As there is no additional data on the exact type of malfunction (snow and ice build-up or communication system, e.g.) the switch has presented, it is not possible to conclude on the reasoning behind the selected installation location. However, the six regions with the highest investments (GV&RTD, AMR, AMF, ASD, KR and UT) are also within the most critical in relation to the number of switch disruptions, which can indicate that the planning of new technologies is focusing on the most critical traces.

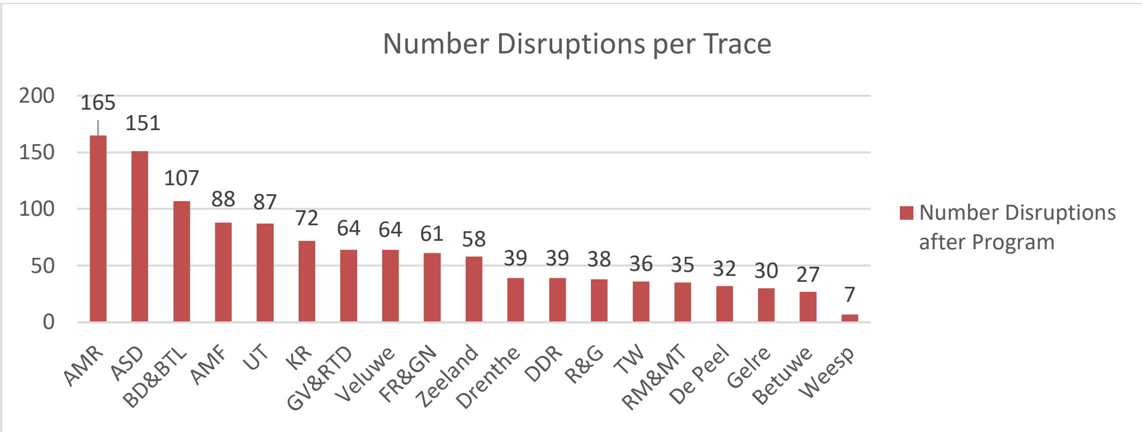


Figure 21 – Number of Switch Disruptions per Trace.

In relation to the management of switches, the fixation of critical switches has been an important approach towards disruption mitigation. As explained, if the switch is fixed during severe winter weather, the possibility of malfunction on these devices is solved, but requires the usage of the reduced timetable as the flexibility of the network is affected. The main goal of this strategy is to diminish the chance of knock-off effects within the rail traffic.

As the switch fixation planning for 2016/2017 was made available, additional insights could be analysed. During this specific winter year, 1972 switches were fixed when severe winter weather was forecasted. The winter timetable only was applied a couple of days, as following the previous years the amount of snow and ice was mild. The number of fixed switches per trace during winter 2016/2017 can be visualized in Figure 22.

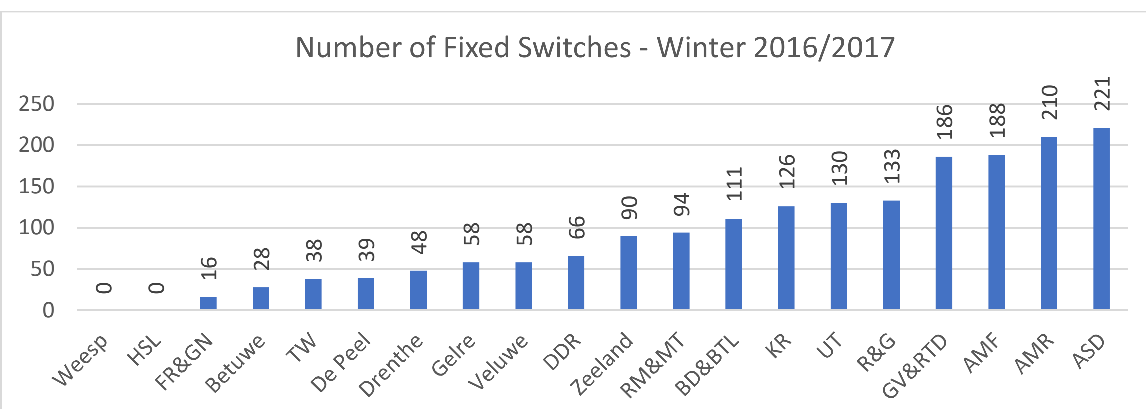


Figure 22 – Number of Fixed Switch per Trace during Winter Year 2016/2017.

Analysing the number of disruptions during the past years, it is noticed that the chosen regions for fixed switches follow the most critical in relation to the number of disruptions. These locations are mostly in the Randstad area, where the train frequencies and traveller ridership levels are higher.

Although it is difficult to evaluate the implementation of disruption mitigation measures due to mild winter weather during the last years, additional analysis can be performed based on the number of winter occurrences and the number of switch related disruptions. As can be seen in Figure 23 and 24, the number of switch malfunctioning during winter weather has dropped around 60%, but as the winters have been milder the comparison and assessment turns in to a more complex analysis.

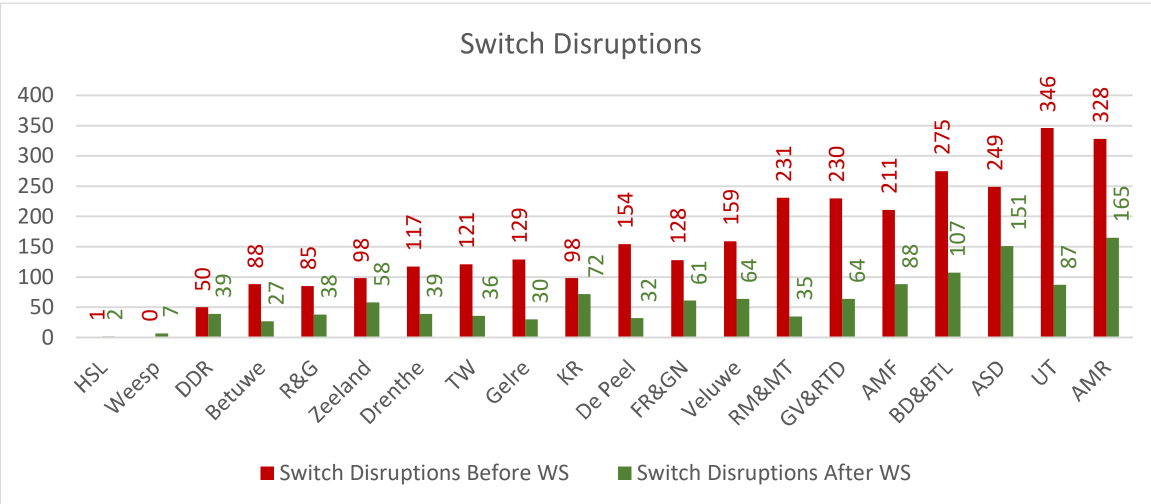


Figure 23 – Number of Switch Disruptions per Trace before and after WS Program.

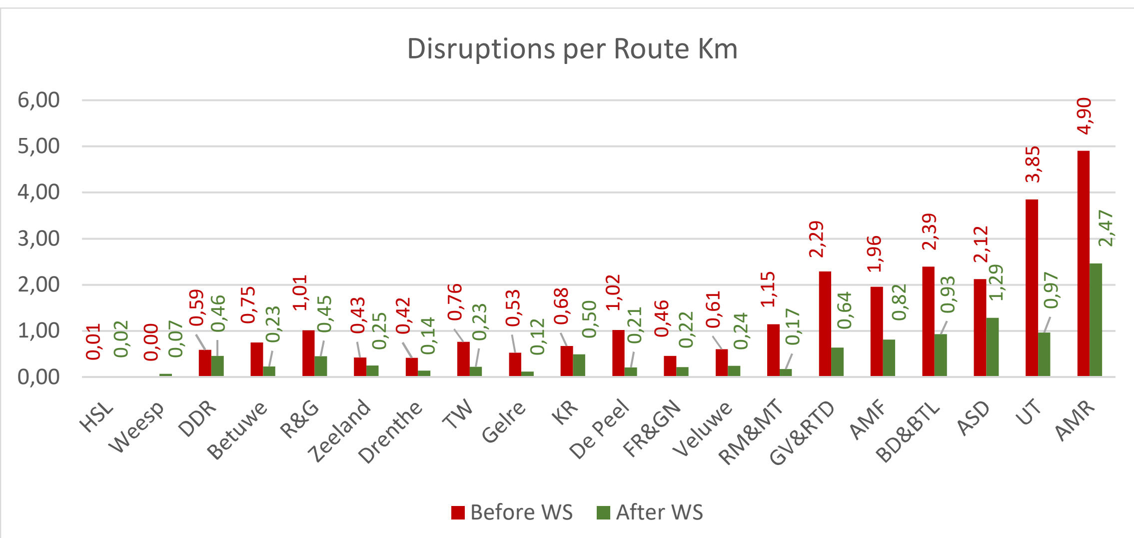


Figure 24 –Switch Disruptions per Route Km before and after WS Program.

In relation to the number of switch disruptions, it can be said that they have generically diminished, while analysing the train impacts that resulted from a switch disruption present a different scenario. Figure 25 presents the number of affected trains (delays, cancelations, rescheduling and rerouting) during the disruptions. It is possible to notice that the impacts on train traffic have diminished in some traces and increased in others when we the before situation is compared to the after implementation. As the number of disruptions diminished in all regions, it would be expected that the impacts on traffic would follow. HSL, Weesp, DDR, Zeeland, FR&GN, BD&BTL and ASD have all presented an increase of affected trains.

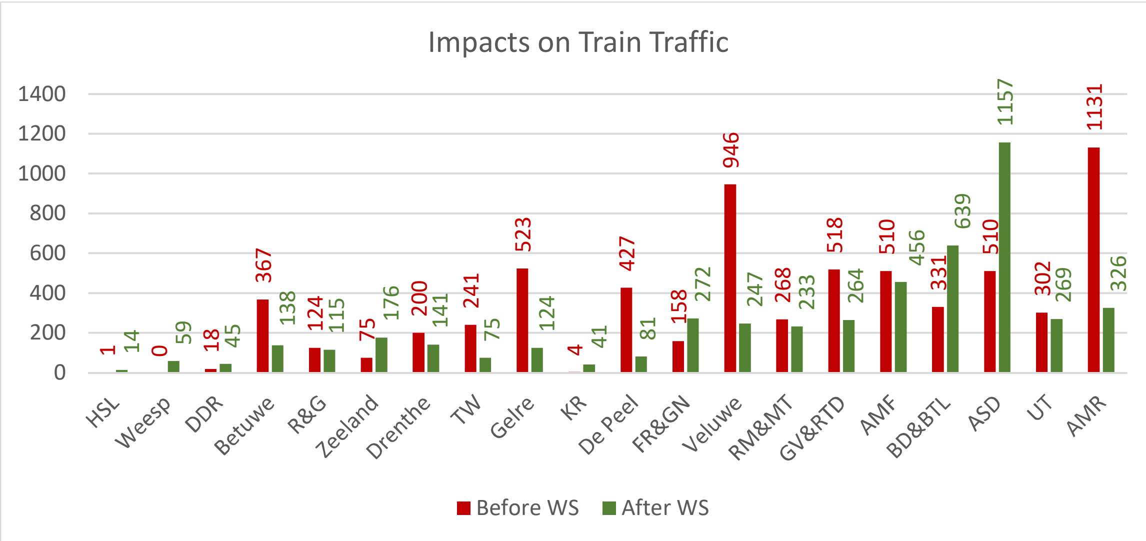


Figure 25 – Impacts on Trains before and after WS Program.

If the reduction of the number of weather occurrences is compared to the reductions in switch disruptions and train traffic impacts (Figure 26), it can be derived that although the performance of the switches has overall improved (61,20% reduction compared to 44,76% of less winter occurrences), train impacts have worsened over the past years. This does not necessarily mean that the train management had an inferior performance (the number of affected trains can be higher but the delay times shorter, for example), but this fact should trigger a deeper analysis on the impacts of disruption on train traffic in order to improve overall standards.

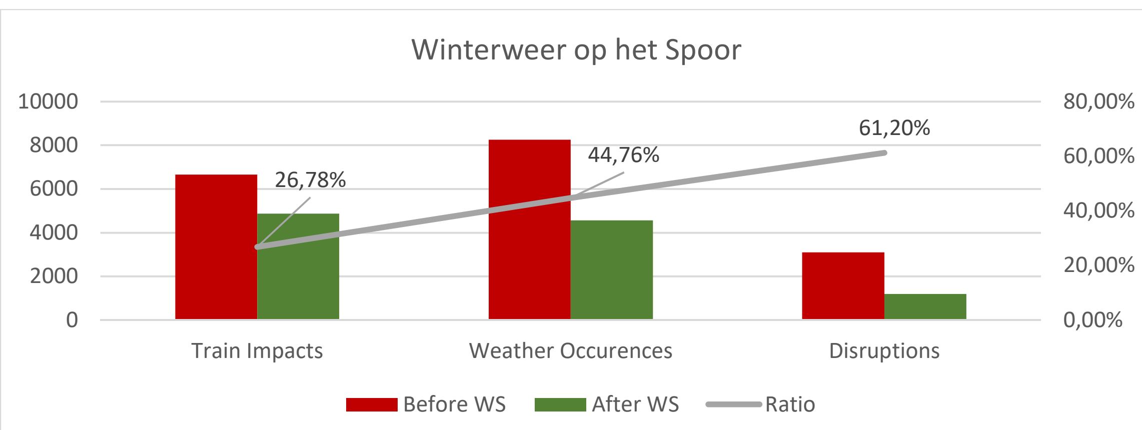
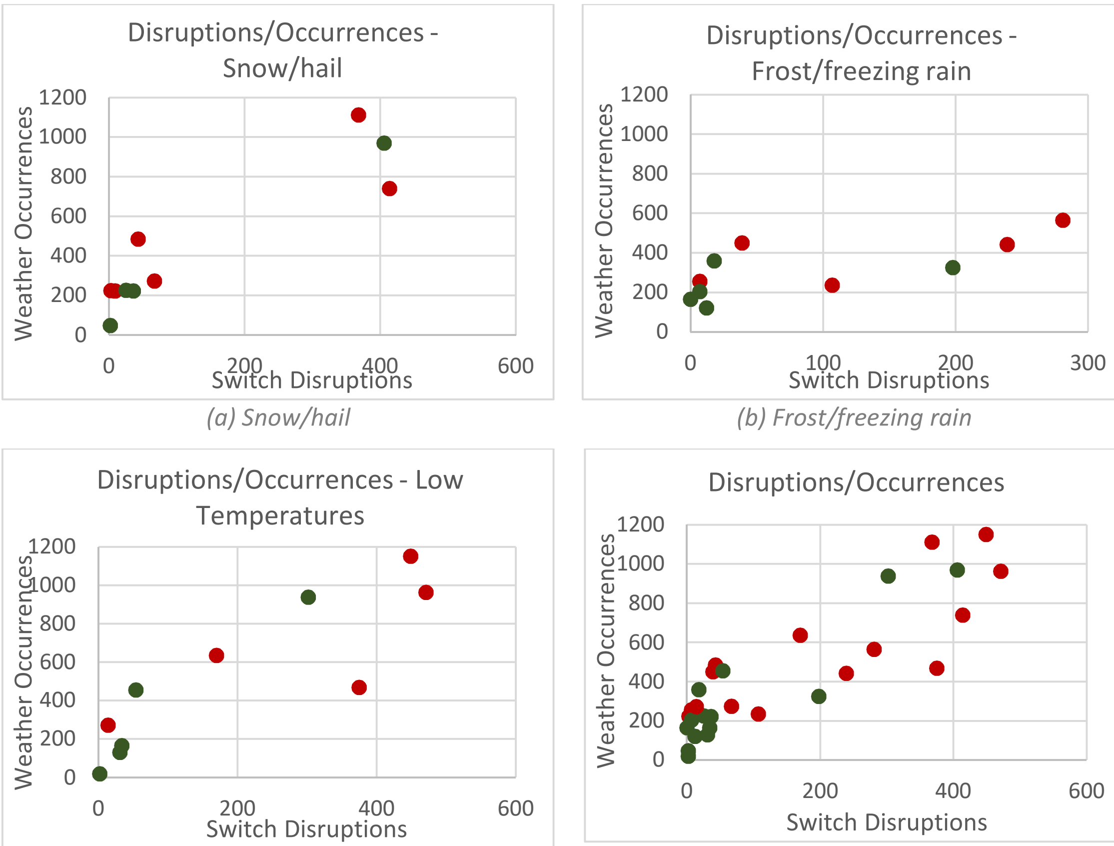


Figure 26 – Progress before/after WS in relation to Train Impacts, Weather Occurrences and Switch Disruptions.

When plotting the graphs on number of switch disruptions x number of weather winter occurrences it can be noticed that the patterns present a linear growth. When the number of winter occurrences increased, so did the number of switch disruptions (Figure 27). The before condition is represented in red while the after is green. The values of winters before the *Winterweer* program tend to concentrate in the upper right quadrant (heavy winters with high number of disruptions), while the values after the WS implementation group within the lower left quadrant (mild winters with few disruption cases).



(a) Snow/hail *(b) Frost/freezing rain*

(c) Low Temperatures *(d) Combination*

Figure 27 – Distribution of disruptions and winter occurrences per winter year.

Finally, it can be derived that the strategy of focusing the mitigation plan on switches seems appropriate due to the level of criticality of the complement, but also that there needs to be investments in the form of data collection. The implemented approaches need to be monitored and evaluated and compared with the intensity of the winter event. Data from open weather bureau is currently not sufficient for a clear evaluation. The amount of snow/hail, frost/freezing rain and ice formation is an important indicator of the efficiency of the measurement.

To evaluate both measures that focus on the mitigation of switch disruptions (fixed switches and point heaters), three scenarios were developed to be compared to the worst winter year performance within the dataset, winter year 2010/2011. This specific winter had a little over 1300 disruptions, being 88,81% switch related.

E) Results and Synthesis

The descriptive statistical analysis brings many insights on the disruption characteristics and the improvements that the mitigation program have brought to the system. Findings on the most sensitive rail equipment and the most critical locations regarding winter related disruptions are fundamental for analysing the mitigation approaches and defining a suitable vulnerability index.

The weather conditions that trigger rail disruptions during weather are mainly low average temperatures (below zero degrees Celsius) and high relative humidity levels (above 80%). These measurements need effective monitoring for a clear and reliable forecast. The winter weather disruption mitigation program has a structured approach towards previewing the occurrence of snow, frost/ freezing rain and low temperatures. However, it is not possible to conclude in what level of detail relative humidity is analysed. As this condition has a strong relation with the disruption of rail elements, it is interesting to suggest a keener approach on including relative humidity levels in the coding system. Also, the locations of the measurements need to be analysed and evaluated. As mentioned, the occurrence of snow in a certain region doesn't guarantee that the whole extent of the tracks is under these conditions. Studies on the number of measuring points and the accuracy of the information are important tools for better classifying and understanding the phenomenon.

Switches are by far the most critical rail device when analysing winter related disruptions. Being nearly 80% of all winter weather disruption causes (not including the systems that where classified as unknown), switches can be affected by winter weather in a mechanical (snow or ice blocking the movable parts) or technological form (defects within the communication system for example). These devices are fundamental not only for the flexibility of the network, but also play a vital role in the safety of passengers. Regarding switch related disruptions, the months of December and January were responsible for approximately 80% of total occurrences. These months are also the ones with the lowest temperatures and highest humidity levels within the data set. In addition, the most impacting winter weather type is low temperatures, accounting for approximately 45% of all switch disruptions. This specific weather condition has set out many challenges to the service provider, as the malfunctions that arise cannot be easily understood and solved with a simple cleaning or scraping tactic.

The recovery times of switch related disruptions oscillate throughout a wide range, although it is important to realize that the most critical conditions are between 15 minutes and three hours of disruption. This is explained due to two main reasons, firstly because the dwelling times between trains on tracks is of a quarter of an hour, secondly because during the first few hours most the actions taken to solve the disruption have been complete. During the first hours, the necessary cancellations and delays have already occurred, so the tendency is that the network starts recovering from the problem.

When analysing the disruptions in relation to the regions (traces), the ones with the most switch disruptions are near or within the Amsterdam-Utrecht area. These regions also have high train frequencies and traveller ridership. Therefore, it can be initially derived that the *Winterweer op het Spoor* approach has made proper decisions as the program directed investments in these areas.

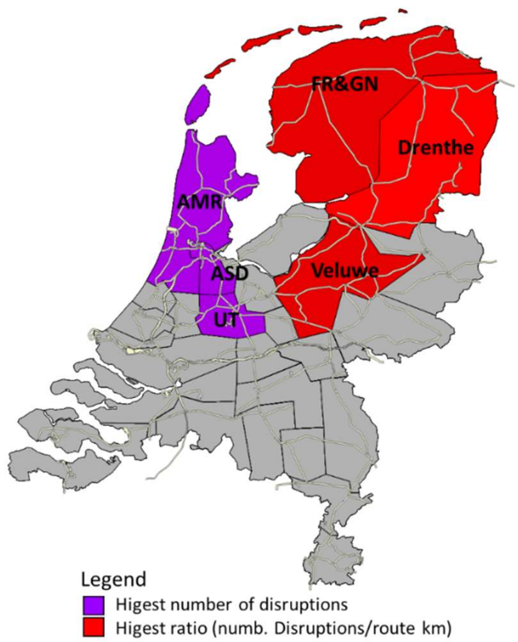


Figure 28 – Most critical regions.

On the other hand, the regions with the highest number of switch disruptions per route km are spread-out in the northern region. The heavy maintenance and focus on the Randstad region due to its importance in number of trips and connectivity can be one of the explanations. Figure 28 shows the most critical registered disruption areas (highest number of disruptions in purple and highest ratio of disruptions per route km in red).

More details on the node importance is discussed in the network performance section (chapter 3.3.3), whereas the potential of the stations is estimated based on potential users, traveller ridership and station connectivity. These results are included in the final vulnerability index.

Regarding the analysed data on the winter weather mitigation program, it can be stated the program has chosen prudently when focusing on the improvement of switches. As this is the most critical device within the system during winter, the improvements on infrastructure (point heaters) and management (fixed switches) seem appropriate to support the mitigation of failure. It is important to highlight, however, that fixed switches should be seen only as a short-term approach due to the implications on reduced train frequency that results from this strategy. In addition, the locations of implementation are in accordance to the most critical regions, meaning the selected traces can truly benefit from the employed technology and/or management technique.

Overall there has been an improvement in switch performance (switch disruptions have been reduced in a higher proportion that the reduction of number of winter weather occurrences), but the impacts on traffic seem to have worsened. It would be important to analyse if there was an increase in train frequencies throughout these years in order to justify the poor performance.

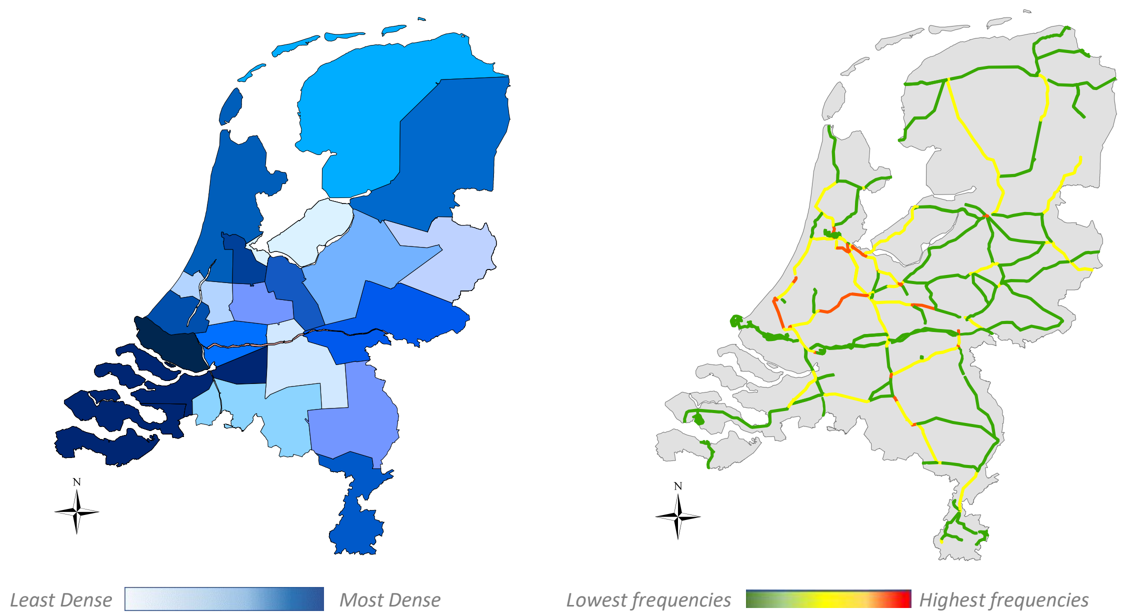
3.3.2 Methodology

Step 2: Definition of the Methodology and Assessment of Component Failure Probability

Although a wide range of variables were used and studied in the descriptive analysis, some are more relevant for this thesis and selected to be part of the vulnerability index. The literature lists many possibilities on developing an indicator for analysing vulnerability. While Hong et al (2015) focuses on the number of disruptions versus the number of weather events, for example, Erath et al (2009) calculated the vulnerability levels by analysing the probability of failure multiplied by the sum of hazard consequences.

As for this study three main variables are selected (winter weather type, number of switches in the link, train frequency). The first variable, winter weather type had three possible classifications: snow/hail, frost/freezing rain and low temperatures. The number of switches followed the amount of components on each studied link which varied from none (zero) to 219. The last variable, train frequency, was divided in three possibilities: low frequencies (up to 15 trains per hour), medium frequency (between 16 and 25 trains per hour) and high frequencies (more than 26 trains per hour). It is important to highlight that the frequencies consider the corridor and not the track itself (route analysis).

It was defined that a probabilistic approach focusing on critical rail components would be an appropriate vulnerability evaluation method. Using a probabilistic technique better represents the defined goal of the thesis, as the objective is to dispose of a value that represents the likelihood of component failure in each link. Also, the quality of inputs on switch disruptions, the importance of the component in rail operations and the fact that this device is responsible for the majority of winter related disruptions can essentially characterize the vulnerability of the Dutch railways. Figures 29a and 29b represent the regions with the highest number of switches and the busiest links (train frequencies) respectively.



(a) – Switch Density per Trace *(b) – Train Frequency per Link*

Figure 29 – Variables considered in the Component Failure Probability Assessment.

As mentioned, the data considered in the development of the component failure probability was the collected measures from after the implementation of the winter disruption mitigation project (*Winterweer op het Spoor*). To develop the model, the first step was the development of the impedance functions.

The selection of the most suitable impedance function can strongly influence the results of the analysis (Geurs & van Eck, 2001).

For this case, besides the observed values, three functions were estimated to encounter the most adequate solution (Equations 6, 7 and 8):

$$Exponential\ Function: Pij = e^{S*a} \qquad eq. (6)$$

$$Inverse\ Potential\ Funciton: Pij = \frac{1}{S^a} \qquad eq. (7)$$

$$Log - logistic\ Function: Pij = \frac{1}{1 + Exp(a + b * \ln(S))} \qquad eq. (8)$$

With P*ij* being the probability of disruption on link *ij*, *S* being the number of switches in the link and a and b the function parameters.

Using the obtained values from the historical data, the observed curve was drawn. For the assessment of the curves for the chosen impedance functions, the data went through cross tabulation and the parameter values encountered using the IBM Statistics software. The developed impedance functions (exponential, inverse potential and log-logistic) were modelled and compared among each other and the observed set.

Nine comparison graphs where developed. Each graph represents switch failure probability in relation to a specific weather type and a specific train frequency. There is a curve for each function (exponential, inverse potential and log-logistic) and a blue curve which represents the observed values (Obs). They are represented in Figures 30 up to 38. The calculation the Student's t-distribution test was used to determine if the sets are significantly different from each other, whereas the log-logistic function presented the closest values. These values can be assessed in item 08 of the appendix section.

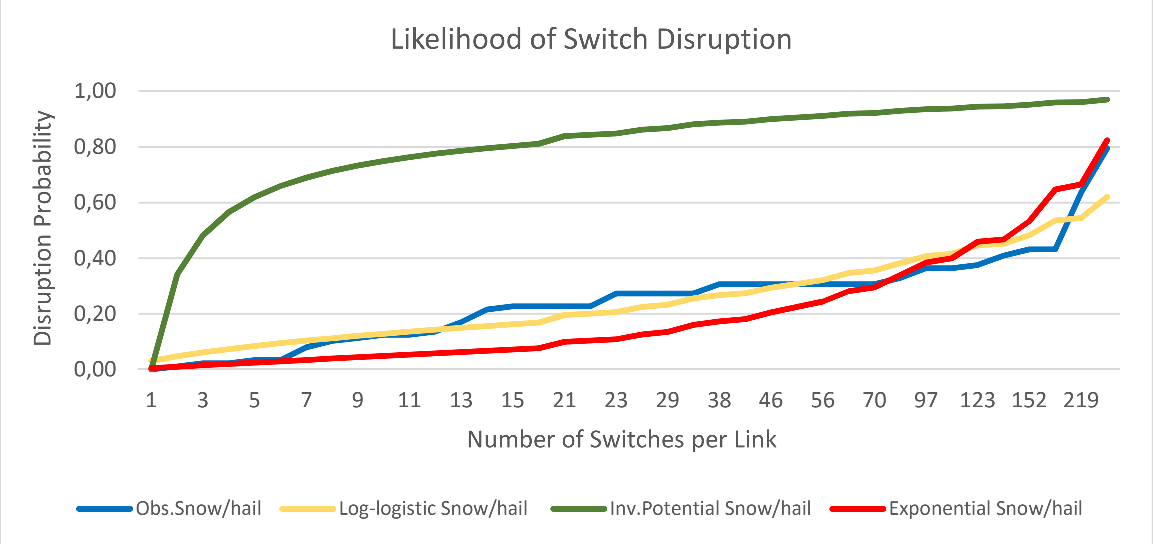


Figure 30 – Developed Functions Considering Links with Low Train Frequencies for Snow/hail

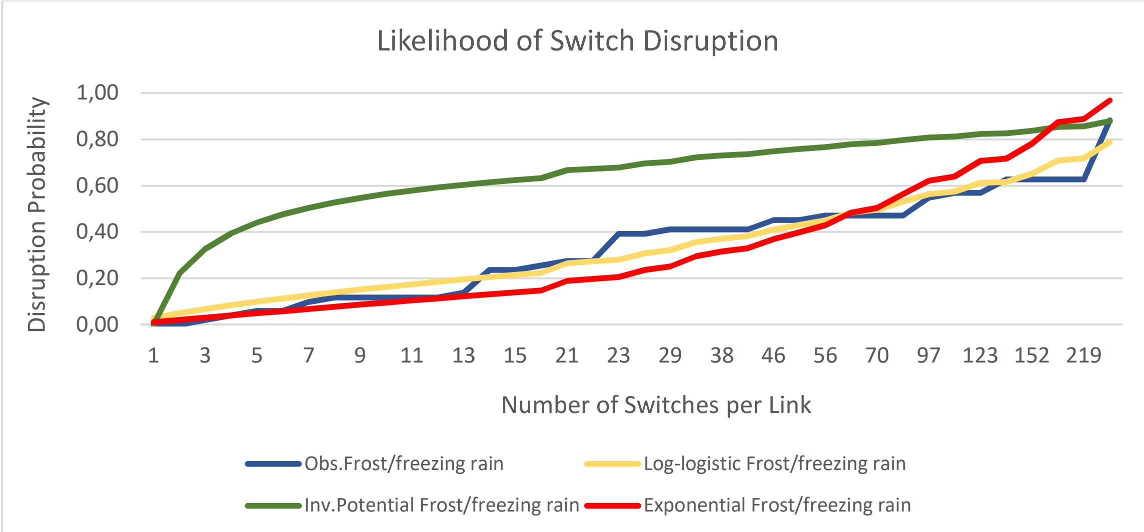


Figure 31 – Developed Functions Considering Links with Low Train Frequencies for Frost/freezing rain

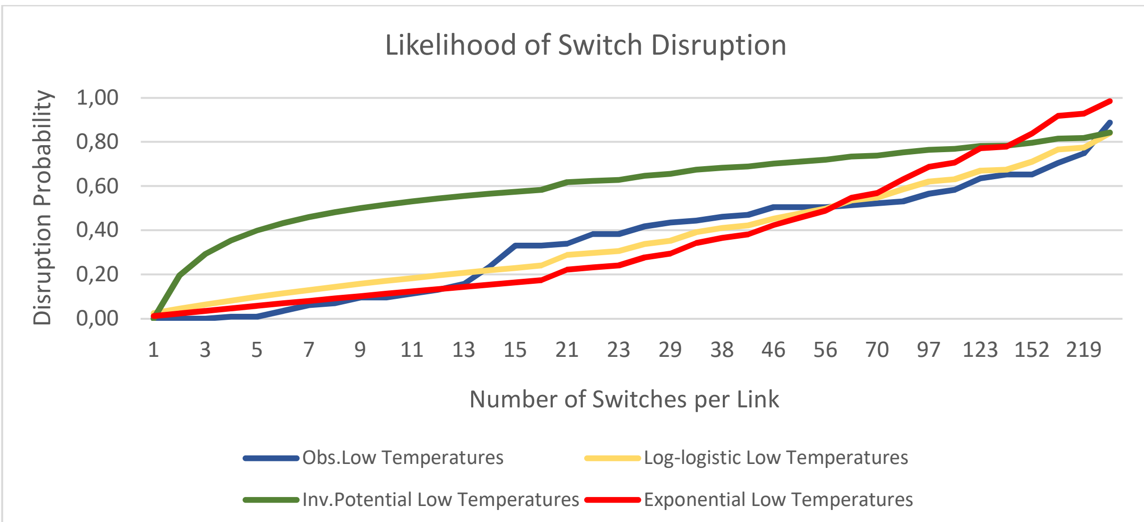


Figure 32 – Developed Functions Considering Links with Low Train Frequencies for Low Temperatures

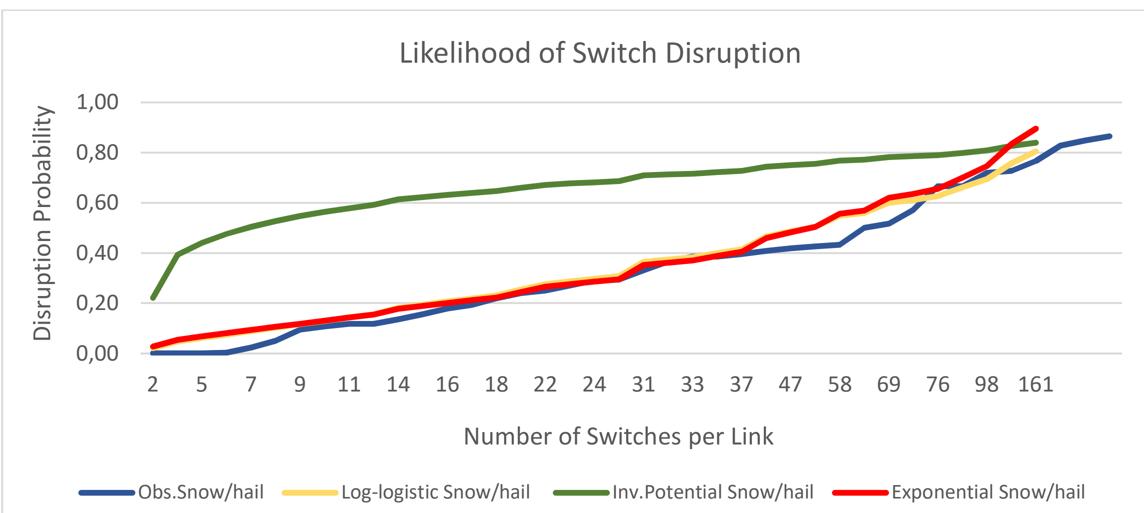


Figure 33 – Developed Functions Considering Links with Medium Train Frequencies for Snow/hail

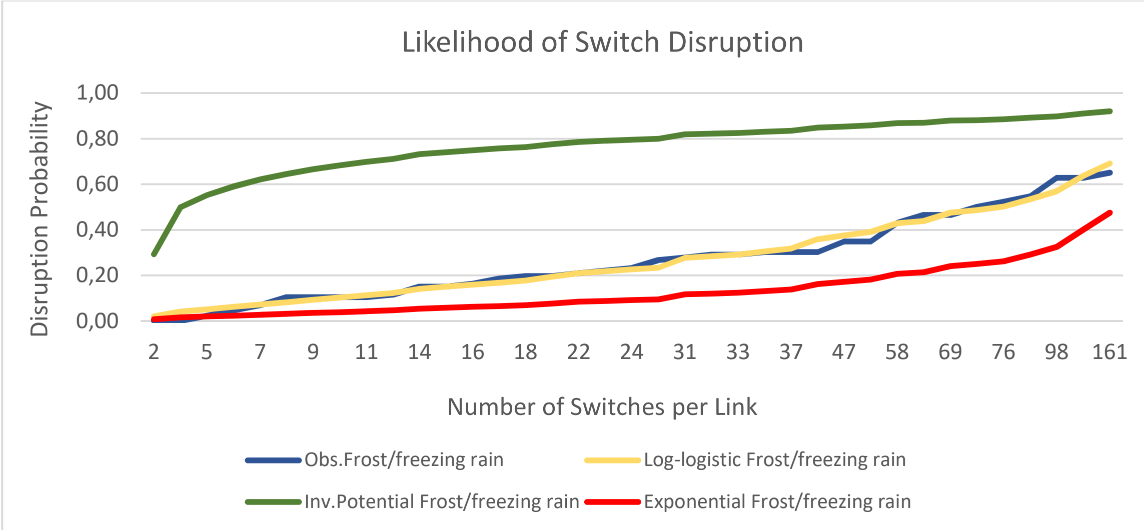


Figure 34 – Developed Functions Considering Links with Medium Train Frequencies for Frost/freezing rain

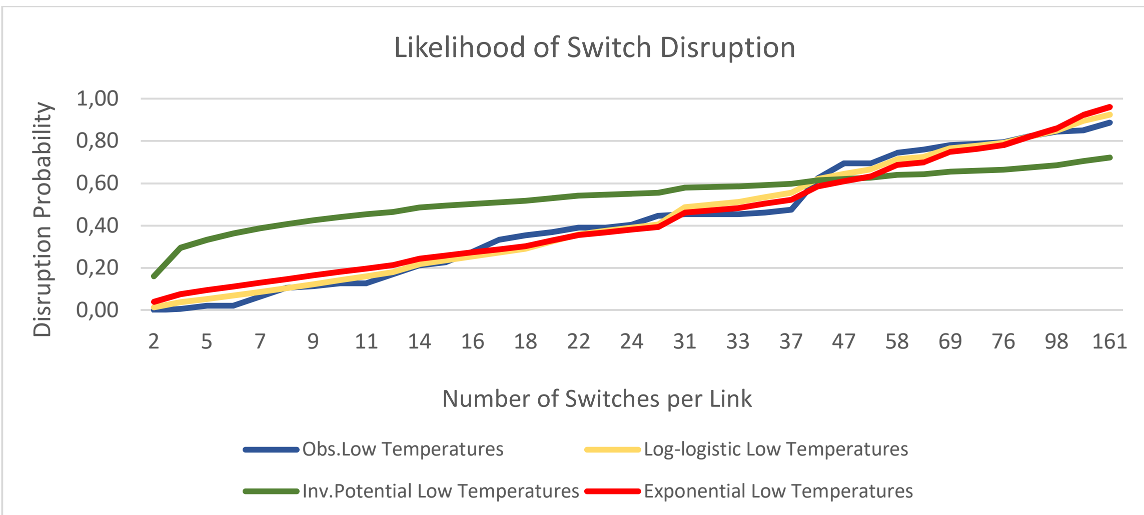


Figure 35 – Developed Functions Considering Links with Medium Train Frequencies for Low Temperatures

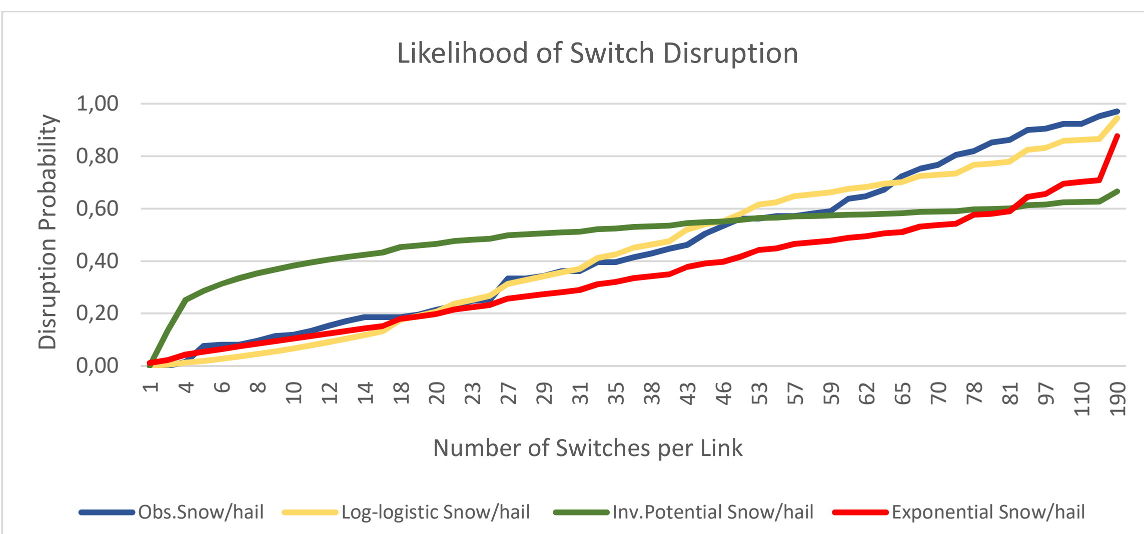


Figure 36 – Developed Functions Considering Links with High Train Frequencies for Snow/hail

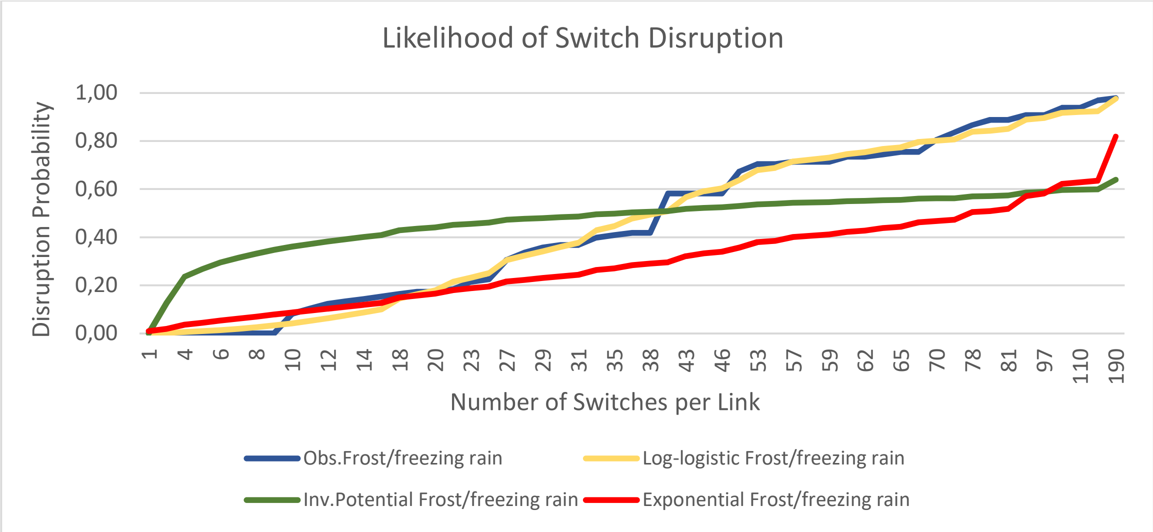


Figure 37 – Developed Functions Considering Links with High Train Frequencies for Frost/freezing rain

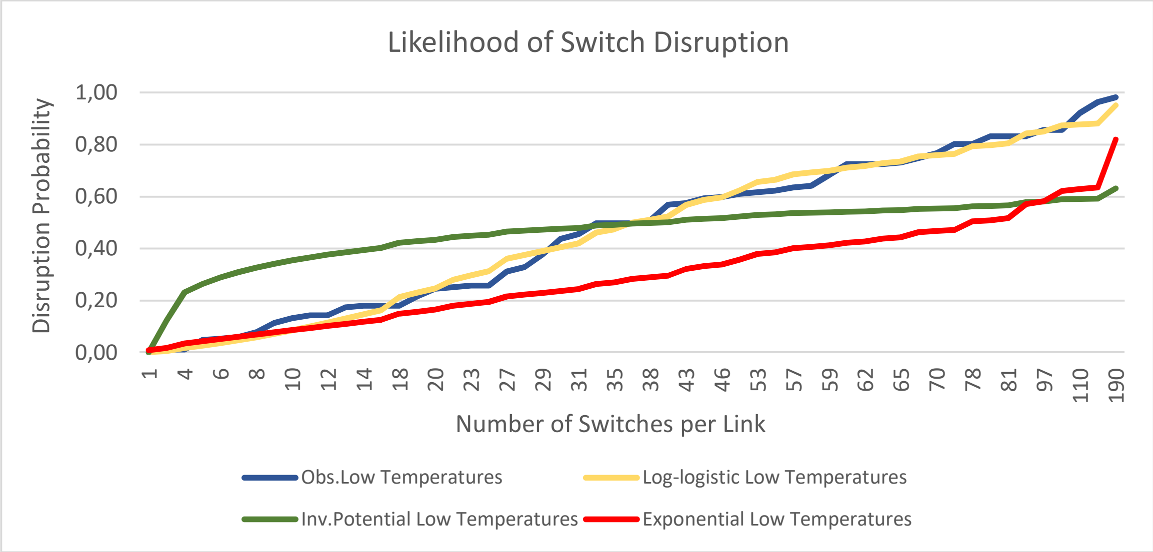


Figure 38 – Developed Functions Considering Links with High Train Frequencies for Low Temperatures

It can be visually verified throughout the graphs that the log-logistic model (yellow curve) presents the highest correlation with the observed values (blue curve), followed by the exponential function (red curve) and the inverse potential function (green curve). Therefore, this function was selected to represent the switch failure probability.

The used equation depends on the train frequency and the calculated parameters which are the presented in Figure 39.

The calculated cumulative probabilities represent the vulnerability of the rail section, which vary within 1 (most vulnerable) and 0 (least vulnerable). It can be noticed throughout the graphs that the higher the number of switches, the more likely the link will suffer a disruption. Also, the number of switches is different regarding the train frequency levels. While links with low frequencies have a maximum of 219 switches, medium frequencies present a maximum of 161 and high frequencies 190 switches. Links with no switches were considered not applicable for this study.

Low Train Frequencies	Snow/hail: a = 3,476; b = -0,678 Frost/freezing rain: a = 3,550; b = -0,832 Low Temperatures: a = 3,677; b = -0,911
Medium Train Frequencies	Snow/hail: a = 4,634; b = -1,194 Frost/freezing rain: a = 4,633; b = -1,071 Low Temperatures: a = 5,355; b = -1,545
HighTrain Frequencies	Snow/hail: a = 6,945; b = -1,868 Frost/freezing rain: a = 8,523; b = -2,336 Low Temperatures: a = 6,538; b = -1,810

Figure 39 – Encountered parameters for the log-logistic function.

Regarding the log-logistic function, an important finding is that the winter weather types (snow/hail, frost/freezing rain and low temperatures) have very closely related values (the variation fluctuates around 12%) with correlations between 0,953 and 0,980. This is important aspect considering investments in disruption mitigation strategies. As the vulnerabilities to each winter weather type are similar, the investment in an improvement will positively affect all winter categories. Having that in mind, new approaches in the system don't necessarily have to focus on specific winter types, providing more simple and effective actions. The implementation of improvements, new maintenance planning and arrangement of resources can follow one exclusive pattern.

As existing risk assessment literature suggests that usually the number of risk levels depends on the research goal. The number of ranges was based on Duvillard et al (2015), that uses five levels for determining risk assessment of infrastructure destabilisation: very low, low, medium, high, very high, which can be visualised in the produced switch failure probability maps within Figures 40a, 40b and 40c. Here, a map is presented for each winter weather type.

Due to the proximity of the switch failure probability levels throughout the different winter weather types, it was decided to unite the results to obtain a single value for the likelihood of disruption based on component characteristics. This was done by developing an average between the obtained switch failure probability levels. The new indicator can be visualized in the switch failure probability map in Figure 40(d).

The likelihood of disruption is the first step in calculating the vulnerability index. The next step will evaluate node potential for inclusion in the vulnerability assessment. The estimation of station importance is discussed in the following section (3.3.3). These values will enable the inclusion of the findings in the vulnerability index. Also, the estimation of node potential will permit the estimation of the most vulnerable routes in the network, underlining the impacts of switch disruption on network performance.

(a) – Switch Failure Probability for Snow/hail

(b) - Switch Failure Probability for Frost/freezing rain

Figure 40 – Switch Failure Probability Maps.

(c) – Switch Failure Probability for Low Temperatures

(d) – Switch Failure Probability for All Weather Conditions

Figure 40 – Switch Failure Probability Maps.

As mentioned, the most vulnerable geocodes (links) are near or in station areas. This is explained due to the increase of the number of switches in these locations, as it's generally within the stations areas that the trains change tracks and need higher flexibility of movement to access the platforms. The most vulnerable station area geocodes are presented in Table 2. These ten station areas are also the most vulnerable geocodes considering station and route links. Notice that the critical station areas are well spread throughout the country, presenting locations in the Northeast, South, Randstad North and Randstad South. All these station areas can be visualised in the Intercity station map in the appendix section.

Table 2 – Most Vulnerable Station Area Geocodes.

Station Area	Geocode	Number of Switches	Vulnerability Index
Amersfoort	506	190	0,957
Rotterdam Centraal	555	112	0,890
Eindhoven	618	110	0,887
Zwolle	603	108	0,883
Maastricht	520	97	0,859
Nijmegen	514	94	0,852
Groningen	501	81	0,811
Amsterdam Centraal	586	161	0,806
Haarlem	527	79	0,804
Arnhem	508	78	0,800

The geocodes presented in Table 3 are the most critical excluding station areas. Within the 20 most vulnerable links in the network, 18 are station areas, while only two are rail sections.

Table 3 – Most Vulnerable Route Section Geocodes.

Route Section	Geocode	Number of Switches	Vulnerability Index
Weesp Aansl. - Lelystad Industrieterrein	135	70	0,763
Barendrecht Vork - Rotterdam Maasvlakte	950	347	0,749
Rotterdam Lombardijen - Rotterdam Centraal	163	65	0,736
Boxtel - Eindhoven	54	59	0,697
Amsterdam Riekerpolder - Warmond	133	86	0,672
Moordrecht Aansl. - Rotterdam Kleiweg	132	54	0,659
Schiedam Centrum - Hoek van Holland Strand	115	60	0,573
Amersfoort Aansl. - Hattemerbroek	17	58	0,564
Roosendaal - Vlissingen	127	83	0,500
Woerden - Gouda	105	37	0,475

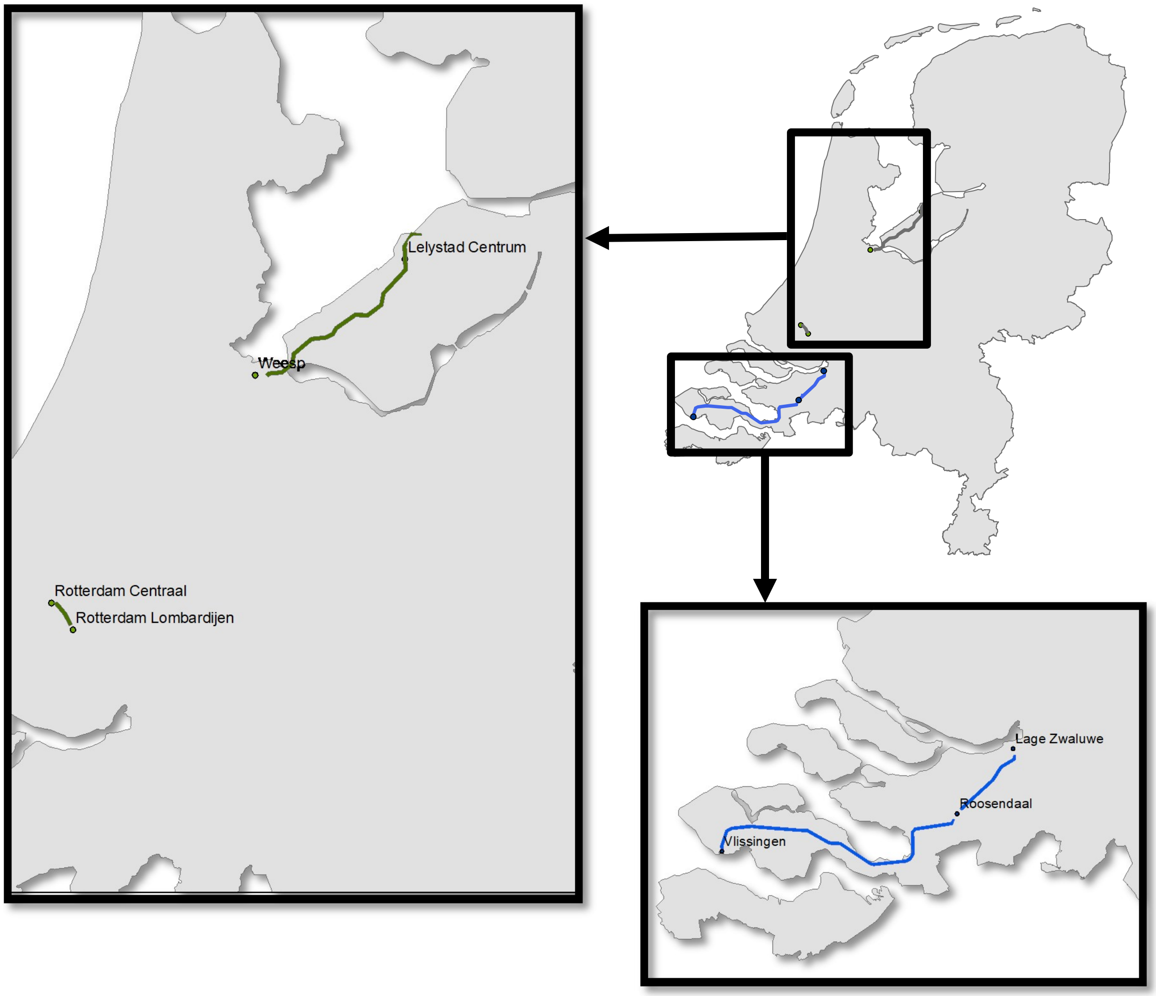


Figure 41 – Rail Tracks in Weesp and in Zeeland.

Links such as Roosendaal – Vlissingen, located in Zeeland are characterized by possessing low frequency train operations which can partially explain a bigger building up of snow/ice on the tracks during winter. Tracks with similar conditions (Lage Zwaluwe - Roosendaal e.g) with a higher frequency of trains presented lower vulnerability indexes which can be clarified due that the traffic partially removes snow and ice from the railway. High frequency train links with high vulnerability levels are also encountered. Weesp Aansl. - Lelystad Industrieterrein and Rotterdam Lombardijen - Rotterdam Centraal are located the coastal area within the Randstad and presented indexes of 0,7638 and 0,7363. These links can be visualized in Figure 41.

A correlation analysis comparing the vulnerability indicator, the distance to the coast and the train frequencies to understand if any correlations are present was carried out, but the results show very little correlation between the likelihood of disruption and the distance to the coast region. An explanation for higher disruption probabilities for low frequency links within the inner region can be that the amount of winter precipitation is greater in these locations, while the high frequency links demand a higher number of switches to operate.

The switch failure probability analysis is a valuable tool to understand the likelihood of switch disruption regarding winter weather conditions. These values can direct better mitigation plans and serve are an orientation for future investments. It is however fundamental also to understand the impacts that these disruptions have on the users. A busy route, for example is more critical to a disruption even if an unfrequently used one has higher vulnerability levels. The next section is the inclusion of the station importance factor in the indicator and the analysis of route vulnerability. These findings provide a more realistic and structured indicator for analysing switch vulnerability.

A map with the weighed sum of the switch failure probability was developed to analyse which regions tend to have higher likelihood of disruptions based on winter weather, infrastructure and train frequency (Figure 42). The averages were not considered because some regions have many links, while other have few bringing a level of bias to the values. As can be verified, the vulnerability to switches happens throughout the country, being the most critical regions in the Randstad, Southern and Northern-west areas. This is important to visualise the impacts and differences that arise from a prior analysis on the switch failure probability including the network indicators.

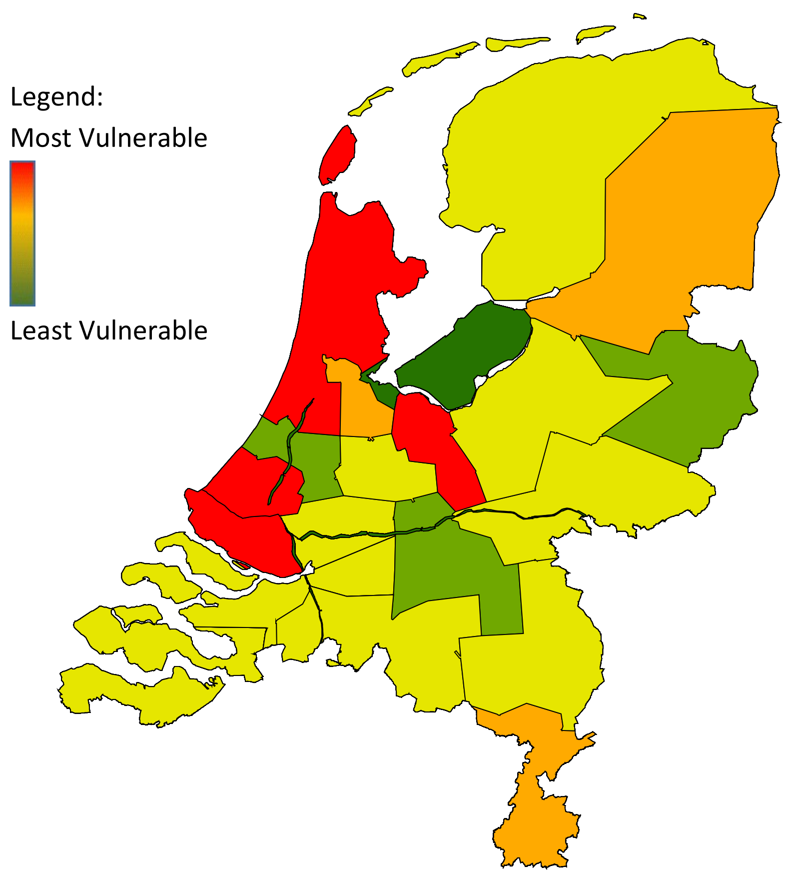


Figure 42 – Switch Failure Probability Levels per Trace.

Step 3: Impact Analysis on Network Performance

As explained, disruptions in a train network affect many parties. Operators need to quickly recover the track and spend resources on solving the problem, commuter modes suffer the impacts of more travellers and overcrowding and passengers need to wait patiently until the service is operational. The accessibility of the network directly impacts travellers, which need to use the system for reaching their destinations. In the Netherlands, the train system is widely used and plays a vital role in everyday commutation to work, social services and leisure.

The impact analysis phase of this report develops firstly an understanding on the node importance. In other words, the potential of the station and its surroundings are evaluated. Having the accessibility components from Geurs & van Wee (2004) in mind, three accessibility indicators were discussed: potential users, traveller ridership and station connectivity.

These indicators were estimated individually based on the literature review. For the potential users' indicator, for example, an estimation on the number of residents that can be benefited and use the transportation system was developed based on finding from Rietveld (2000), Gutierrez et al (2001) and (Hartholt, 2016). By analyzing the ranges of citizens that opted to use the rail system based on catchment areas from studies developed in the Netherlands, specific conditions were attributed to each station type (Intercity and All service). For the traveler ridership and station connectivity indicators, the values were collected from studies previously developed by (Hartholt, 2016).

Potential Users (land use component): The land use component is represented by potential train users around the station perimeter. As discussed by Geurs & van Wee (2004), the distance decay function represents the probability of one making or not a trip based on the distance. In other works, the probability of travelling diminishes as the distance increases. Using the same reasoning, users tend to use stations more frequently when there is one near their residence/work, while distant stations are less attractive. In that sense, buffers where created to estimate the number of users around a station area based on the number of inhabitants in the surroundings.

Traveller ridership (individual component): Representing the individual component, the second indicator is based on daily average ridership characterised by the number of station users. This means that station which have a high demand will be classified as more relevant for the system, providing a full understanding of the impacts on network performance. The values where obtained by a research on traveller ridership developed by Hartholt (2016).

Station Connectivity (temporal component): This indicator is related to how well the station is located within the network and represents the temporal component. This means the better the connectivity, the lower the in=vehicle travel time, waiting time and transfer penalty. Using the values obtained by Hartholt (2016) on closeness centrality, an indicator on station connectivity was included as a final weight for the understanding of the most important rail stations in the Dutch network.

In the sequence, the methods to estimate the indicators are explained in more detail.

3.3.2.1 Station Importance based on Potential Users

To estimate the number of potential users per station, catchment areas were defined based on the available literature. Data on populational density was collected on the Dutch Bureau of statistics (CBS) website and downloaded in shape format for covering the Dutch rail network.

Based on the Rietveld (2000), walking, cycling and public transport are the main transport modes used to access the station area, adding up to approximately 90% of commuters when considering home end and 92% when considering activity end transport. The mode of access and egress was used to better estimate the number of inhabitants that should be included in the analysis, therefore the estimation makes a grouping of the values and the catchment areas are considered using this combination. Having that in mind, the buffers were developed based on walking, cycling and public transport commuters (Table 4) as they represent most of the residents that are willing to use the rail system.

Table 4 – Train Access Distribution per Mode – Home End % and Activity End % (Rietveld, 2000).

Mode	1994 – Home end %	1994 – Activity end %
Walking	26%	10%
Cycling	37%	46%
Public Transport	27%	36%
Others	10%	8%

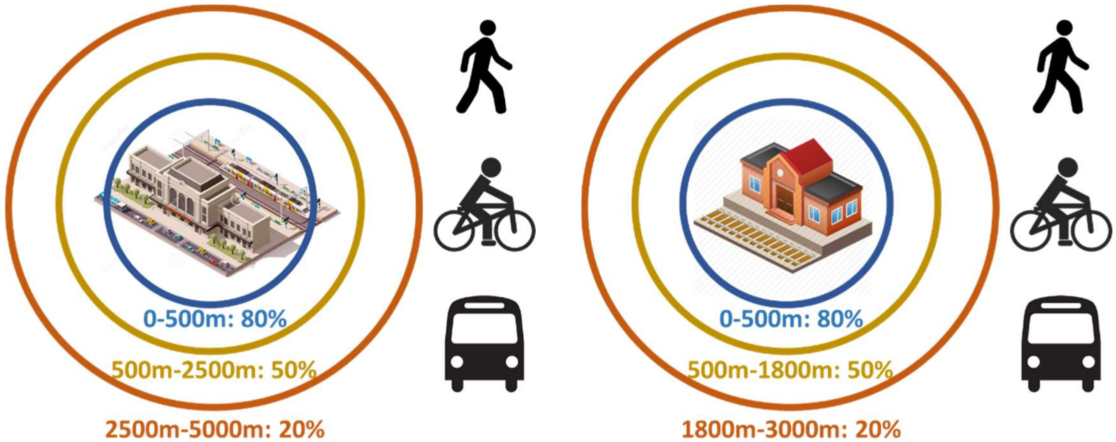
As mentioned, the estimated buffers were classified in two categories: Intercity stations and local service stations. Stations with overlapping buffers were not segregated as it is understandable that these inhabitants can be considered as potential users for more than one station. The details on the estimation of each band and buffer are presented in the following paragraph.

Intercity Stations: The largest and best-connected railway stations, which focus on intercity services within the Netherlands. Most trips are between large metropolitan areas from all regions within the country. Catchment areas around Intercity stations are known to be higher (Hartholt, 2016), so for this case the selected stations buffers were: 0m-500m, 500m-2500m and 2500m-5000m.

The first buffer (0m-500m) is based on the high chance of walking and biking commuters, the second (500m-2500m) is mainly founded on cyclists and the third (2500m-5000m) for the public transport modal. As 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 considers the large decrease of walking commuters and a small reduction 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 of 50% of the populational density. The last band is based on a small number of cycling users and the inhabitants that are willing to user public transport as an access mode. This value was selected to be 30% of the populational density. The scheme of the catchment areas for Intercity Stations can be analysed in Figure 43a.

Local Service Stations: These stations focus on sprinter services within the Netherlands. Most trips are all stop services in smaller station areas. Following (Hartholt, 2016), the catchment areas were somewhat reduced. These stations were also divided in three buffers, but with smaller circumferences: 0-500m, 500m-1800m and 1800m-3000m.

The percentages of potential users where maintained similarly to the ones adopted for intercity stations (80% for up to 500m, 50% for 500m-1800m and 30% for 1800m-3000m). The scheme of the catchment areas for local Service Stations can be analysed in Figure 43b.



(a) Intercity Stations *(b) All Service Stations*

Figure 43 – Station Catchment Buffer Areas (a) Intercity Stations; (b) Local Service Stations.

Within the stations in the Netherlands, the ones with the highest number of potential users is Dordrecht as this region presents the highest amount of residents within the buffer area. Koudum Molkwerum is the one with the lowest number, being the area with the least number of residents within the buffer area (129062 and 202 respectively). A map with the distribution of the stations considering the potential users indicator can be visualised in Figure 45. Also, a rank with the 5 most significant stations with the estimated weights is presented in Table 5.

3.3.2.2 Station Importance based on Traveller Ridership

According to Hartholt (2016), the number of reachable destinations of a station, train frequency and its accessibility levels are crucial factors when determining ridership. The author stathes that users are willing to travel further if the station offers a better quality of service.

Using data available by Hartholt (2016) and collected by virtual technology by the NS service provider, the average number of people that entered or exited a station (daily) was defined as the traveller ridership for this research. For this specific analysis, the values from 2014 were used as a weight for station importance. Unfortunately, the data is only for NS stations, but as the company is service provider of most of the network, it was decided that the data is adequate for this analysis. A map with the distribution of the stations considering the traveller ridership indicator can be visualised in Figure 46. Also, a rank with the 5 most significant stations with the estimated weights is presented in Table 6.

As the averages of traveller ridership from 2007 up to 2014 were made available, it is interesting to visualise the progress in the number of daily train passengers. As can be seen in Figure 44, the years with a reduction in number of passengers are related to 2010 and 2012. These specific periods coincide with the years with the worst performances in relation to winter weather.

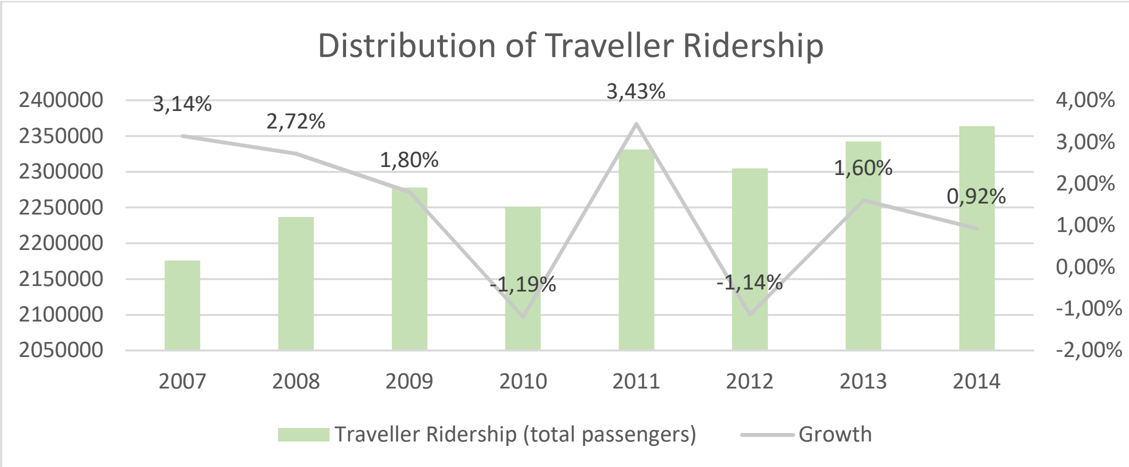


Figure 44 – Distribution of variation of traveller ridership from 2007 to 2014.

3.3.2.3 Station Importance based on Connectivity

Based on Hartholt (2016) the station connectivity indicator determines how well interconnected the station is in the rest of the network. A map with the distribution of the connectivity indicator can be visualised in Figure 47. Also, the 5 best scored stations are presented in Table 7. It is important to understand that the connectivity levels represent a weight of vulnerability, meaning better connected stations are more important when a disruption occurs.

Having the unit values for potential users and traveller ridership. A weighted form of each variable was determined to classify the most relevant station areas. This value is scaled from 0 to 1, being 1 the most important station in relation to the indicator. The station connectivity is already defined and included as a weight index. The classification ranges between very low (0,0-0,2), low (0,2-0,4), medium (0,4-0,6), high (0,6-0,8) and very high (0,8-1,0).

It is important to highlight that the node potential varies from station to station and classified indicator. Visualizing the developed maps on user potential, traveller ridership and station connectivity, it is noticed that potential users present a different pattern of criticality in comparison with traveller ridership and station connectivity.

While traveller ridership and station connectivity seem to concentrate the most critical stations in the Randstad, potential users presented a much different pattern. Potential users concentrate around the southern part of the Randstad (Dordrecht and Delft, for example) but also present high values in other regions, such as Groningen, Zwolle and Eindhoven. These might be indicators that the service provider can benefit and increase the number of passengers by investing in stations located in these regions.

Table 5 – Top 5 Stations in Relation to Potential Users.

Station	Number of Potential Users	Estimated Weight
Dordrecht	129062	1,000
Delft	98018	0,759
Den Haag HS	85157	0,660
Utrecht Centraal	78952	0,612
Den Haag Moerwijk	77249	0,598

Table 6 – Top 5 Busiest Stations in the Netherlands.

Station	Traveller Ridership (unit)	Estimated Weight
Utrecht Centraal	176292	1,000
Amsterdam Centraal	162103	0,920
Rotterdam Centraal	81811	0,464
Den Haag Centraal	76216	0,432
Leiden Centraal	71680	0,407

Table 7 – Top 5 best scores in Station Connectivity

Station	CCI
Utrecht Centraal	1,00
Schiphol	0,99
Duivendrecht	0,92
Amsterdam Bijlner ArenA	0,90
Leiden Central	0,90

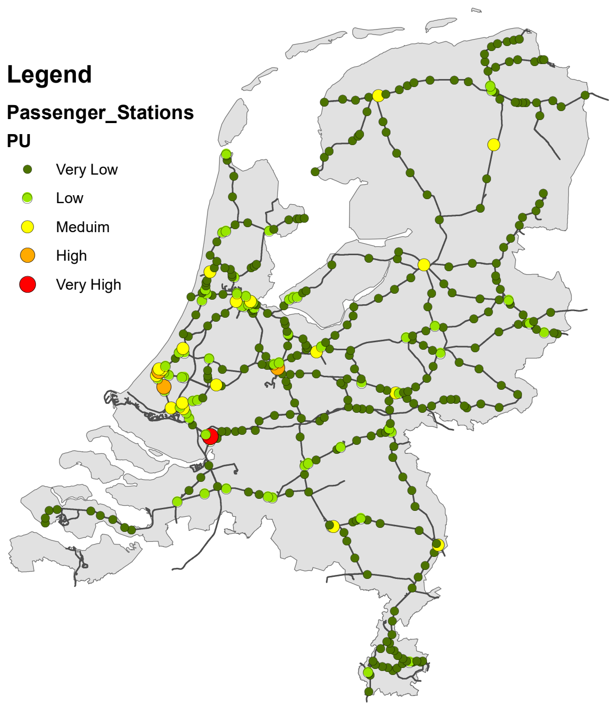


Figure 45 –Potential Users.

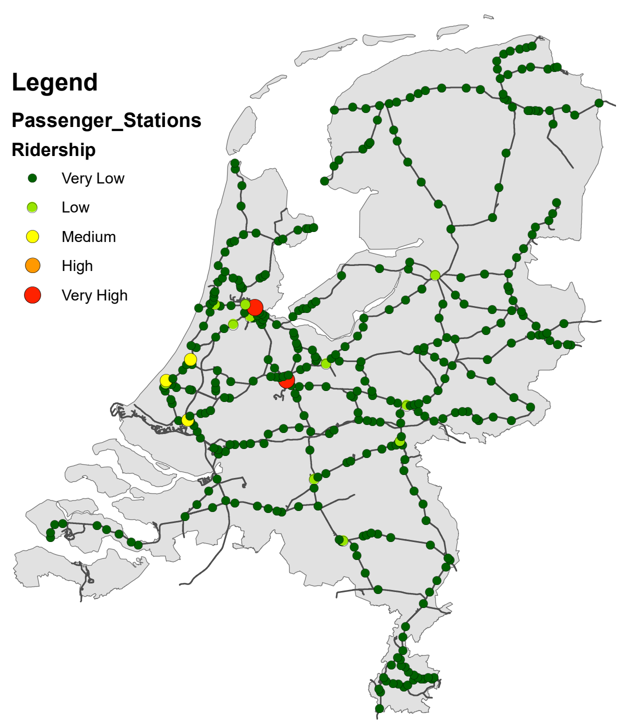


Figure 46 –Traveller Ridership.

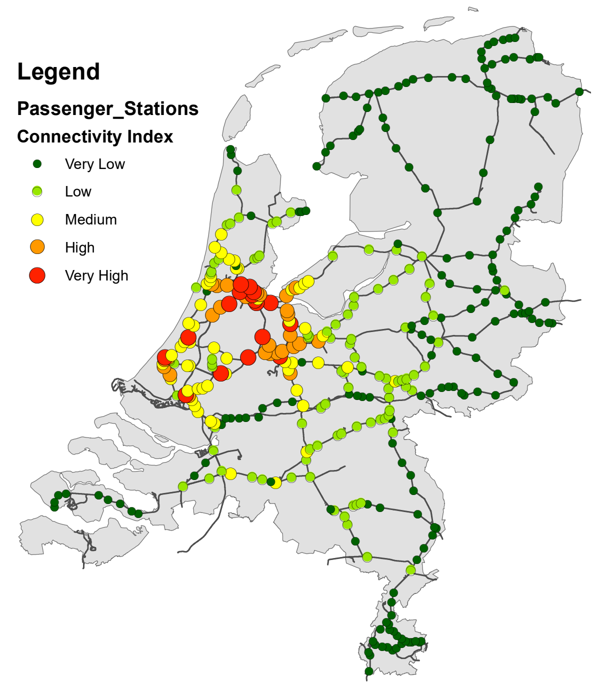


Figure 47 –Station Connectivity.

GIS Procedures

For Network Performance Analysis: Critical Routes

The first step in analysing the vulnerability impacts in a network performance perspective is to define all the origin-destination routes. This will allow the assessment of vulnerability levels for the routes and station potential per node, also needed to compound the final vulnerability index. For this, ArcGIS Network Analyst was used for building a chart of all links within each route. The software enables the simulation of all station to station courses, grouping the necessary links that need to be used during the trip (Figure 48). Analysing the routes and attributing switch disruption probability and node weights can also expose the most vulnerable ones within the network. These outputs will allow the determination of most critical train connections in the rail system. From this, strategies to enable appropriate recovery based on worldwide practices can be suggested.

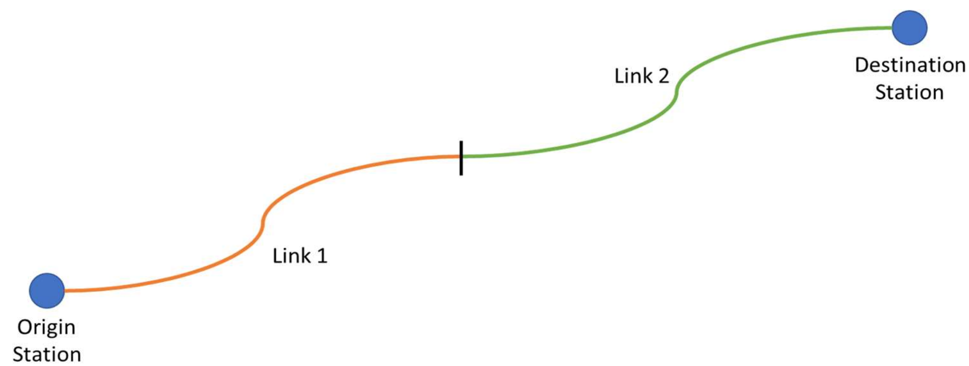


Figure 48 – Representation of the Identification of Links within a Route.

Within the network analyst tool from ArcGIS, two techniques can be used to analyse network performance: the OD cost matrix and the closest facility solver. These methods perform very similar analysis; the main difference is in the output and the computation speed. The OD cost matrix generates results more quickly but cannot return the true shapes of routes. The closest facility solver returns routes and directions but demands a substantial number of internal computer operations, which resulted in a longer processing time (http://www.esri.com). As there is the necessity of recognizing all the links within each route for developing a network performance indicator, the closest facility solver was defined for this activity. The tool relates incidents and facilities (in this case, origin and destination stations) and determines possible routes.

To provide a complete assessment, the combination of the components was estimated by calculating a route vulnerability factor in relation to potential users, ridership and connectivity in three levels: considering potential users and connectivity, considering ridership and connectivity and a grouping all three factors. It is interesting to analyse them separately to understand the implications of focusing only on current users compared to potential ones, although the usage of the results depends on the goals of improvement development within the rail network. As the operator has publicly announced the interest of increasing the number of daily train users the most suitable level would be to include both potential users and traveller ridership to the analysis. In addition, the usage of a complete approach can better direct investments as there is an interest in attracting more passengers. Equations 9, 10 and 11 represent the variables used for the calculation of route vulnerability.

$$Network\ Performance\ (Potential\ Users) = \sum VIij * PUij * CCij \tag{9}$$

$$Network\ Performance\ (Traveller\ Ridership) = \sum VIij * TRij * CCij \tag{10}$$

$$Network\ Performance\ (PU\ and\ TR) = \sum VIij * PUij * TRij * CCij \tag{11}$$

Where *VI* is the switch disruption probability (for the route), *PU* is the weighed number of potential train users (OD pair), *TR* the weighed traveller ridership in from the origin and destination stations and *CC* the connectivity component. *I* and *j* represent the origin and destination stations that are analysed.

For each route, the estimation is the multiplication of the switch disruption probability (weighted sum of all links within the route), potential users, traveller ridership and station connectivity components. A scheme for the calculation can be visualized in Figure 49.

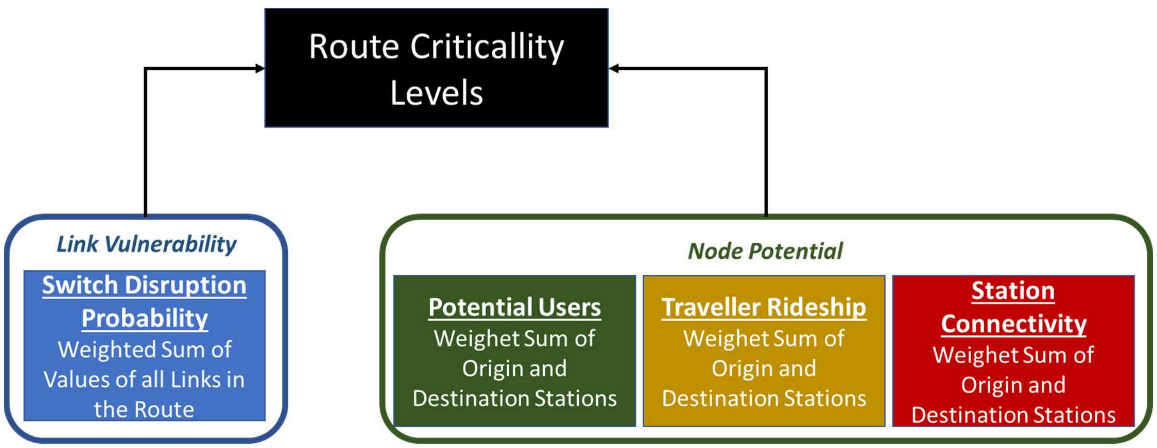


Figure 49 – Definition of Route Criticality.

The most important routes were encountered firstly based on potential users (Table 8) and on traveller ridership (Table 9) both considering the connectivity index of each origin and destination station. This represents the three phases of the network performance indicator. The combination of all three indicators results in an indicator that presents the route criticality. The top 5 are presented in Table 10. The correspondent figures, 50, 51 and 52 visually represent these routes. Due to the importance and high usage of trains in the Randstad region. All 5 most critical routes from each different perspective (potential users, ridership and connectivity) are located within this area.

It is important to highlight that these calculations consider any link that is used in the route, even if the connection is only truly partially used by the train. This can impact negatively the result. A highly vulnerable link that is considered but only a small fraction is used can result in a slightly higher value, for example. Also, the closest facility tool follows the smallest trajectory for the OD pair, not considering the train routes. At the end, some routes might have small variations in the final value.

Table 8 – Top 5 Critical Routes in Relation to Potential Users.

Route	Index
Dordrecht - Haarlem	1,000
Alkmaar - Dordrecht	0,836
Amersfoort Delft	0,779
Den Haag HS - Dordrecht	0,767
Amsterdam Lelylaan - Dordrecht	0,754

Table 9 – Top 5 Critical Routes in Relation to Traveller Ridership.

Route	Index
Amsterdam Sloterdijk - Nijmegen	1,000
Amersfoort – Amsterdam Sloterdijk	0,858
Amsterdam Sloterdijk - Eindhoven	0,803
Amsterdam Sloterdijk - Utrecht	0,797
Breda - Haarlem	0,769

Table 10 – Top 5 Critical Routes in the Netherlands.

Route	Index
Dordrecht - Haarlem	1,000
Amersfoort - Delft	0,819
Amsterdam Sloterdijk - Dordrecht	0,801
Amersfoort – Amsterdam Sloterdijk	0,761
Alkmaar - Dordrecht	0,757

Figure 50 – 5 Most Critical Routes based on Potential Users.

Figure 51 – 5 Most Critical Routes based on Traveller Ridership.

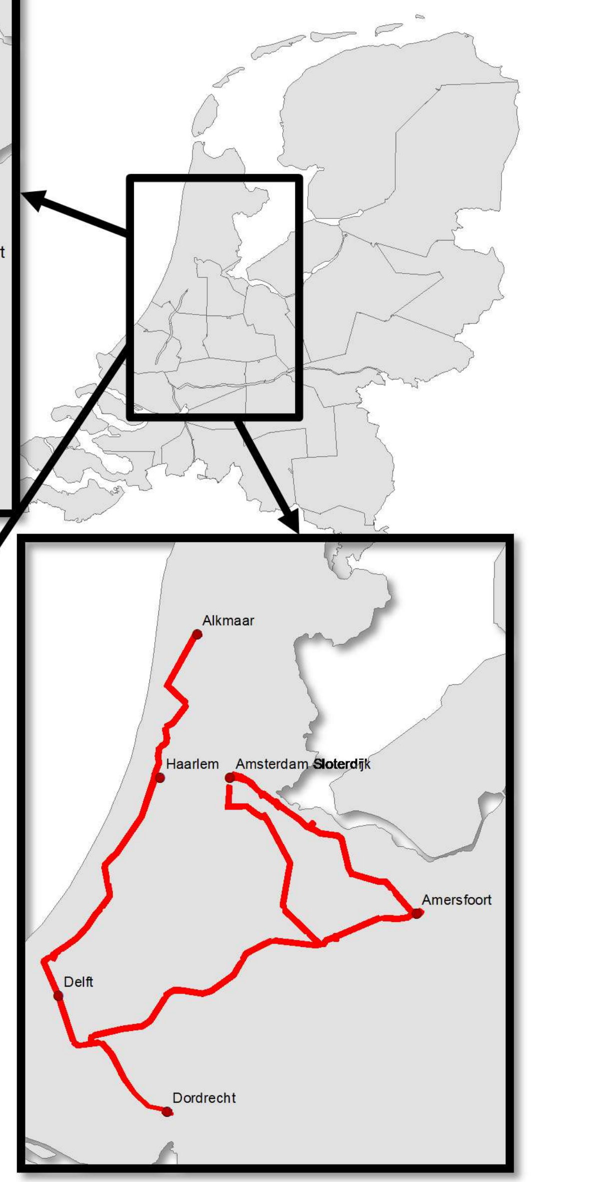


Figure 52 –5 Most Critical Routes in the Netherlands.

3.3.3 Results

Step 4: The Vulnerability Index and the Development of a Winter Risk Map

The last phase of the vulnerability assessment is the development of a risk map based on the findings of the previous stages. The objective is to provide a clear visualization of the most critical links in relation to winter weather by weighing the rail vulnerability indicator with the node importance. As some links are used by a higher number of routes, they were attributed an additional importance weight.

The determination of vulnerability indexes for each link followed by the understanding of the impacts on the network performance were the base for the classification of the connections in relation to risk of disruption. The winter risk map illustrates which sections of the network need to be carefully monitored based on their switch disruption probability levels and node potential. Having that in mind, the weighted averages of the calculated indicators were integrated in a single calculation (Equation 12).

$$Vulnerability\ Index = VI * NV * PV \tag{12}$$

Where *VI* is the already calculated vulnerability index per link based on weather, infrastructure and train frequency, *NV* the weighted average of node vulnerability *and PV* the potential vulnerability calculated by the weighted sum of the number of routes that use the link.

The used node vulnerability was based on potential users, traveller ridership and station connectivity as the goal is to provide outputs that also represent future rail demands. In other words, each link (with a predefined switch vulnerability) was weighted by the average of all origin and destination stations node potential indexes of the routes that use the link. Also, the potential vulnerability, which classifies the links that have the highest number of related routes, was included. This indicator represents the number of routes using a link, therefore the higher the number of routes that use the specified link, the higher the potential vulnerability. The index is based on the most used link (*PV*=1), which progressively diminishes as the number of routes going through a link reduces. To provide a suitable classification, the levels of vulnerability where used in the same distribution of the switch vulnerability (five levels of risk): very low, low, medium, high and very high. The final vulnerability indexes considering both link and node characteristics is presented in Figure 53.

It can be verified in the risk map that major connections linking the regions of the country to the Randstad present higher vulnerability levels. Sections such as Zwolle to Amersfoort, Lelystad to Amsterdam and inner connections around Gouda and Den Haag have a certain critical level. Similarly to the infrastructure vulnerability index, the risk map presented highest vulnerabilities in station areas. Amersfoort and Utrecht are the most critical, although other station areas outside the Randstad must be monitored such as Arnhem and Den Bosch (s'Hertogenbosch). Figure 53 also presents the weighted sum of the link values and provides a clear view of how the highest vulnerability levels shift to the Randstad. These regions must be monitored and controlled during winter events to avoid disruptions as the effects on users in addition to the criticality of the infrastructure have the highest levels. Also, new technological investments should be planed for supporting lower disruption levels and faster recovery.

Winter Risk Map

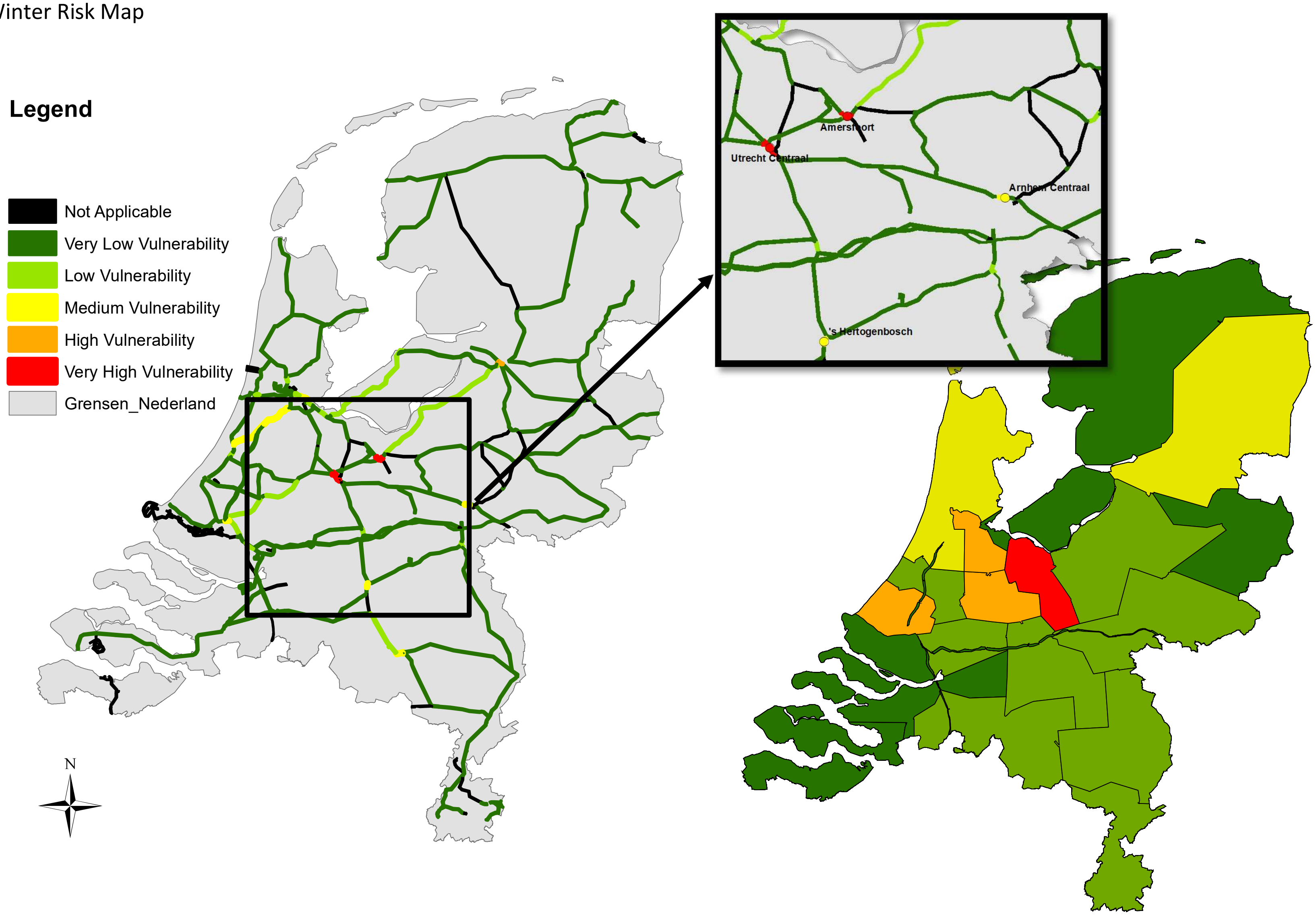


Figure 53 – Winter Risk Map.

3.4 Discussion

This research, which focused on rail vulnerability to winter, brings important insights on the most critical rail components and vulnerable locations within the season. The obtained results presented average low temperatures below 0 degrees Celsius and average relative humidity levels of over 80% as critical to the functioning of the system. These features might result in snow and frost events and even damage electrical connections within the components.

Switches are the most critical device during winter weather and were responsible for the majority of railway disruptions within the used dataset. These results are in accordance with the conclusions from Kloow (2011), which defined switches as being the most sensitive component in railway systems during winter.

The Randstad region presented the highest number and probability of disruptions, while the northern region has the highest ratio between switch disruptions and route km. Also, December and January are the most critical months and need heavy monitoring to mitigate winter-related issues.

Although Marteaux (2016) believes that severe weather conditions are likely to increase with climate change in the coming decades, winter has demonstrated a lower frequency tendency curve. As rain and storms were not analysed in this report, studies are suggested in this field to monitor the impacts related to these specific weather conditions.

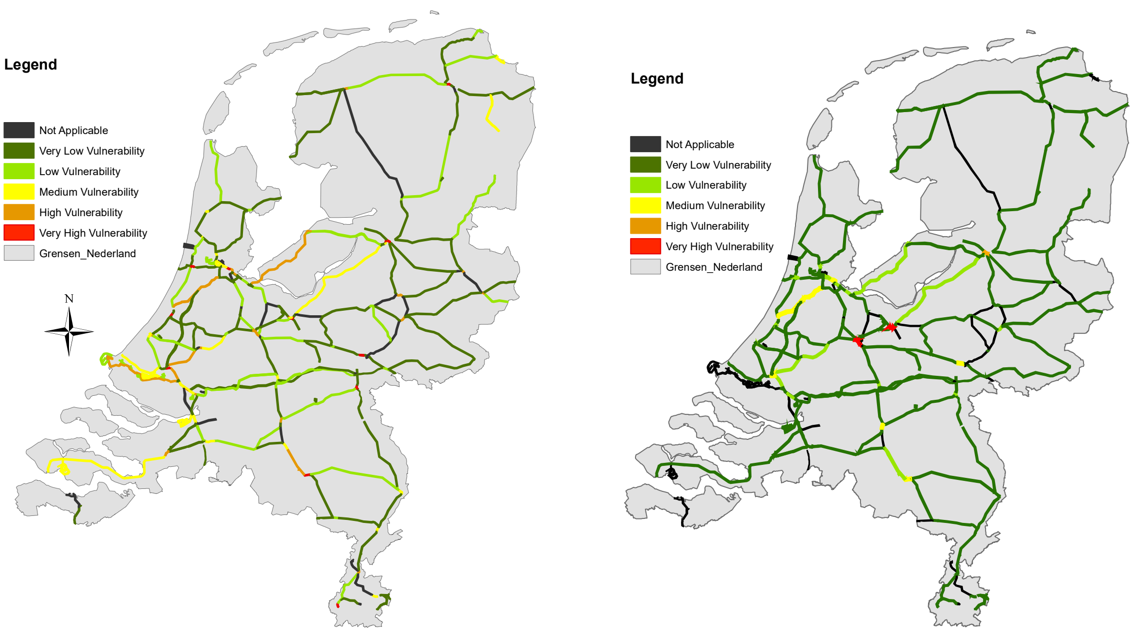
According to Rossetti (2007), snow, frost and hail can result in lengthy delays or even complete shutdowns in rail systems. As the malfunction in switches is mostly related to the jammed movable parts, trains can still operate if the device is fixed. In this case, rail flexibility is harmed, but the delay can be controlled and overcome with a structured recovery plan.

The used methodology to estimate switch disruption probability was based on studies developed by Erath et al (2009), Snæbjörnsson (1998) and Geurs & van Wee (2004). By developing a probabilistic model based on historical data, these values were estimated and attributed to every link within the network. As the goal was to understand the likelihood of switch disruption within this phase, this methodology proved suitable for presenting clear and realistic outcomes.

In order to include station importance in the vulnerability indicator, weighted values related to land use, individual and temporal components were considered. Following Geurs & van Wee (2004), the impacts caused in a network were analysed considering these accessibility components. The used methodologies were based on researches developed by Rietveld (2000), Gutierrez et al (2001) and (Hartholt, 2016), which proved adequate for encountering suitable values to include potential users, traveller ridership and station connectivity in the final indicator.

The route criticality closes the circle composed by the three risk management questions defended by Rausand (2011): What can go wrong? What is the likelihood of that happening? What are the consequences? In other words, a disruption may occur when severe winter events strike the Netherlands, the likelihood can be assessed using the vulnerability index and the consequences or impacts on the network can be evaluated by analysing route criticality. These results are important for understanding the link relevance within a network perspective.

Although the probability of switch failure has critical locations spread throughout the Netherlands, the network performance is deeply dependent on region attractiveness, meaning the most vulnerable connections are located within the Randstad region (Figure 54).



(a) Switch Disruption Probability Map *(b) Vulnerability Map*

Figure 54 – Comparison of Vulnerability (a) only Considering Switches and (b) Including Station Importance.

The decision of focusing investments in the Randstad during the *winterweer* program seem appropriate considering the results on link criticality. The region represents the highest number of opportunities, residents and services in the Netherlands, making the area economically and socially more attractive than the inner parts of the country.

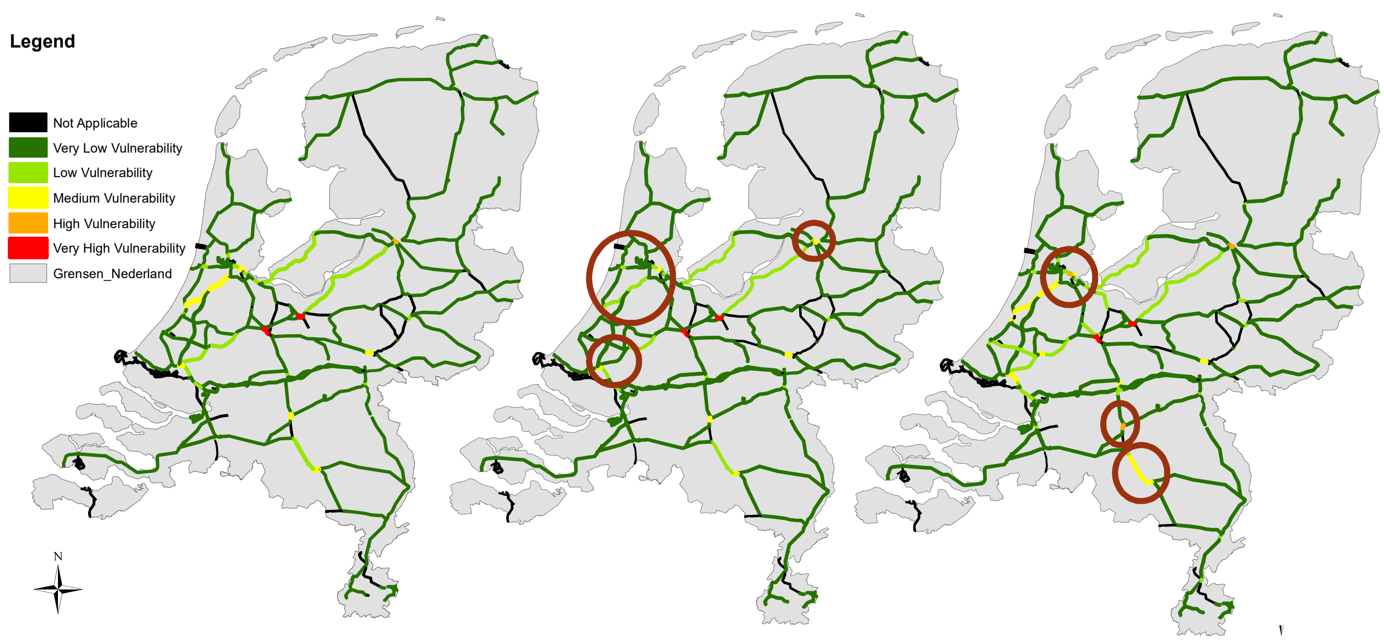
The currently applied switch disruption mitigation strategies are focused on planning and implementation of new technologies. The reduced timetable and fixation of critical switches has proven to have great outcomes when considering the diminishment of know-off effects. The drawback is the lowering of train flexibility, which goes against the goals of rail transport future development. The implementation of devices to avoid the building up of snow and ice are an interesting approach, but low temperatures is still the main issue and need a more directed mitigation strategy.

Overall there has been an improvement in switch performance with the *winterweer* program, but the impacts on traffic need to be monitored and evaluated to estimate gains in this field. A developed analysis considering the encountered vulnerability levels in different scenarios enabled a better understanding of the impacts that fixed switches and point heater have on disruption likelihood. These cases are described in the following section.

Developed Scenarios

Considering that the number of switches can be virtually reduced with investments in new technologies (point heaters for example) or switch fixation, two scenarios were used for analysing the mitigation approach: a 20% reduction in the number of switches and a 20% increase in the number of switches. The considered baseline was the developed vulnerability map. It is important to highlight that the scenarios affect the switch disruption probability and not the node potential. The result is a reduction and an increase in the vulnerability indexes, which are presented in sequence.

With the developed log-logistic function for each link in the network and the new number of switches, the switch disruption probability was recalculated and the vulnerability levels for the scenarios were defined. The scenarios are represented in Figure 55.



Baseline Scenario 1: 20% Switch Reduction Scenario 2: 20% Switch Increase

Figure 55 – Vulnerability Indexes for Developed Scenarios.

As can be noticed, in comparison with the baseline, the first scenario presented an improvement of the vulnerability. The connection Amsterdam-Sassenheim changed from medium to low vulnerability, while Rotterdam-Gouda changed from low to very low vulnerability. The station area of Zwolle also presented a change of classification, from high to medium vulnerability. For the second scenario, an overall worsening can be visualized. While the Amsterdam and S'Hertogenbosch station areas went from medium to high vulnerability, the connection between Boxtel and Geldrop changed from low to medium vulnerability and Den Haag to Gouda went from very low to low vulnerability. Most of the variations were maintained in the initial range (0,0-0,2 for very low; 0,2-0,4 for low; 0,4-0,6 for medium; 0,6-0,8 for high and 0,8-1,0 for very high vulnerability), which means the variation is subtle for low changes in the number of switches. The result evidences that the reduction of switches improves vulnerability while the increase intensifies the probability of disruptions during winter.

4. Limitations and Recommendations

Many are the limitations that can be listed within such a complex subject. The first and one of the most important ones is the necessity of clear orientation and training of the personnel responsible for registering winter weather related disruptions. The technicians must understand the relevance of their activity, be qualified to make the registration as complete and reliable as possible and receive feedback on future analysis of the produced data. These actions would improve the results of the investigation and better guide new inner strategies for rail performance development.

The need of additional information on disruptions is also pertinent. The system failure has currently a wide range of components, but does not describe in detail the type that came into collapse. Switches for example can be of many categories. Double, single or outside slips, crossover, wye, diamond and single-point are only a few examples. Each type will react differently to the weather events, as some will be more sensitive to these conditions than others. The classification would enable a more precise analysis with better and more accurate results. Terrain characteristics (slope, valley, wet lands) can also interfere in operability and could be included in the data collection.

Although the weather information is applicable for this case, it is important to recognize that the limitation in the number of distributed registration stations can bring a level of bias in the results. If a weather station registers snow in a specific location, a few kilometres form that place can be suffering only from low temperatures. To diminish this biasness, it is fundamental that new collecting points are implemented within the rail area, preferably near critical rail sections. In addition, the data should be quantified in more detail. A classification of heavy, medium and mild winter event for example, could support better findings in relation to the outcomes of the mitigation approaches.

As the switches have a fundamental role in rail flexibility, this device needs to be analysed in depth, and a balance between the operability and number of switches optimal for the Dutch case. As there are plans of increasing train frequency, it is recommended that the operability is maintained at a higher range and the winter disruption causes better investigated for an improved system in the future.

Finally, the propagation of a disruption is usually not a linear caused consequence. Rail disruptions that ended in great resource paradigms with extremely negative performance impacts resulted from a series of defects in the operation and management system. What began as a simple malfunction of a turn-out is usually aggravated by the criticality of the location, a deficient personnel resource system and a slow decision-making process. Mitigation strategies need to focus on all levels to diminish the impacts and increase recovery times.

Actions towards a more resilient system is the back bone of sustainable transportation. The modern world needs an improvement. Passengers travel further away expecting lower travel times every day and the rail sector needs to keep up with the development of a well-structure, planned and managed system. A list of suggestions for mitigating winter related disruptions is presented in item 07 of the appendix.

5. Conclusions

Although the rail sector has put in efforts to solve the inconsistencies on weather related rail disruption, they benefit from the support of academic and industry entities when overcoming barriers related to implementing new technologies and management strategies. The field is characterized by being conservative and operates in a traditional manner. Safety is a strong factor and the service providers require complete studies and analysis on specific operational situations.

Attributing vulnerability values to the links in the Dutch railways provides a clear understanding of how the system reacts to winter weather events and enables the estimation of likelihood of disruptions. The strategy needs to overlap significant aspects related to weather characteristics, rail infrastructure and the impacts on accessibility based on temporal, individual and land-use components. This indicator is a valuable tool for directing new investments and planning the mitigation strategies towards a better managed rail network. Vulnerability plays a significant role in rail network reliability. The determination of indicators that measure this aspect in combination with the analysis of network performance provided fundamental discernments on how to improve rail transportation services, reduce disturbances and decrease operational costs. The transport sector is at each day more competitive and an appropriate balance between costs, reliability, environmental impacts, comfort, safety and mobility put rail in a strategic position. The goal is to be attractive to users, encouraging the use of public transport for multimodal optimization.

Although there are areas throughout the Netherlands that presented high vulnerability levels, most of the critical links (based on infrastructure, potential users, traveller ridership and station connectivity) are concentrated in the Randstad region. The development of the Risk Map provides a clear visualization of the most critical links and allows the service provider a more directed planning of resources and better preparation of investment plans.

In relation to the developed winter disruption mitigation approach, a closer analysis on the conditions of the rail network before and after the implementation of the *Winterweer op het Spoor* program suggest an overall improvement in reliability monitoring and evaluation. Also, the choice of investing in technologies and strategies in relation to the railways movable parts seems the most adequate approach, as switches are by far, the most critical components. The program has brought positive results, but more analysis and research is fundamental for providing a diminishment of vulnerability in specific rail locations. Approaches focused on the timetable and switch fixation are important to avoid knock-off effects, but more investments on the improvement of rail components are fundamental to successfully increase train frequencies in the future. The results obtained through the risk map will support clearer findings and direct new evaluations, investigations and development plans.

Finally, although this research has limitations, the results can encourage collaboration between entities and enable an improved disruption data collection. Mutual interests of the rail operator and of meteorological facilities to invest in more detailed weather and component measurements. Suggestions on mitigation approaches are listed in appendix section item 07.

Finally, the research questions and answers can be analysed in the following paragraphs:

1) What are main characteristics of winter-related disruptions in the Dutch rail network?

The main weather features responsible for the malfunctions of rail components are high relative humidity levels (over 80%) and average temperatures under 0 degrees Celsius. Winter related disruptions mostly occur in the Randstad, specially within and around the Amsterdam region. The most critical months are December and January, with around 80% of total disruptions.

Each weather season has distinct impacts on the rail infrastructure. Lightning, for example, has mainly triggered problems in the power supply and the ICT (Information and Communication Technology) systems, while rain and storms strongly affect drainage systems. Snow, frost/freezing rain and low temperatures are strongly related to switch malfunctions (over 75%), while during other weather conditions switches barely enters the rank of most affected components (lighting – 2%, elevated temperatures – 5%, rain – 9% and storms – 4%).

2) Which railway infrastructure features are more sensitive to unexpected winter weather conditions and why?

Most failures occur due to the malfunctioning of switches, which are responsible for approximately 80% of the cases. These results are in accordance with the used literature.

A series of issues can arise when a switch is under severe winter weather conditions. Malfunctions can be a result of low temperatures, snow/hail or frost and ice. While snow and frost can hamper the movement of the tongue, causing a mechanical failure, low temperatures seem to have bigger impacts on the communication system. Disruptions related to low temperatures that effect inner connections within the switch motor have been frequently mentioned. The result is usually failures in the sending/receiving messages about the switch position to the central administration.

3) How can the likelihood of disruptions due to winter weather be estimated based on the encountered critical components?

A switch probability regression model was established based on type of winter weather (snow/hail, frost/freezing rain, low temperatures), number of switches on the link and train frequency (low, medium, high). A log-logistic function was selected for the assessment, as it presented the best fit within the used range compared to the exponential and inverse potential functions. The product of this first step was the assessment of the probability of disruptions related to switches for each link within the rail network. As the goal was to understand the likelihood of switch disruption within this phase, this methodology proved suitable for presenting clear and realistic outcomes.

4) What network performance indicators can be used to understand the impacts of disruptions caused by winter weather and which are the encountered impacts on the Dutch railways in the developed study case?

As the role of the rail network is to transport passengers, it was defined that the station (node) potential must be included as a weight in the vulnerability index. The station importance was estimated based on three indicators: potential users, traveller ridership and station connectivity. The first indicator represents possible users of the rail system by estimating the number of users based on the amount of residents within a station catchment area. The second indicator is the number of passengers that entered or exited each Dutch station (daily average) in 2014. The last one, station connectivity, is an indicator developed by Harthold (2016) which classifies how well the station is placed within the network. This indicator is based on the number of necessary transfers for reachability of the station, meaning the better connected the station, the higher the index value.

To understand the impacts on the network, and the importance of the studied stations, all possible routes within the network where analysed. The criticality of each route was calculated by assessing the node importance level (for the considered origin-destination - OD - pair) and the switch vulnerability sum of the links that compose the route. To define which links are to be considered in a route, a geographic information system (GIS) software for working with maps and geographic information was used. With ArcGis, the impacts of disruptions on accessibility were estimated using the Network Analyst tool.

The impact on network performance is the diminishment of trip flexibility, reducing the levels of accessibility of the rail users. As disruptions have developed to a reduced winter timetable, passengers need to deal with less trip options, busier trains and possible delays during winter events. The most critical encountered routes were Dordrecht - Haarlem, Amersfoort - Delft, Amsterdam Sloterdijk – Dordrecht, Amersfoort – Amsterdam Sloterdijk and Alkmaar – Dordrecht. All located within the Randstad region.

5) Which actions are currently being developed by NS and ProRail to decrease rail vulnerability (to winter weather) and are these actions focused on the most critical elements and in the most vulnerable regions?

Measures are being implemented on seven different levels as explained throughout the report. In relation to switches, the implementation of point heaters and the planning of fixed switches during winter events are the main ones used. As switches are the most critical element regarding winter weather disruptions and the highest number of occurrences happened in the Randstad, it can be stated that the mitigation strategy is in accordance with the calculated vulnerabilities. What can be added is that focusing on the reduced timetable and in fixing switches might bring development issues in the upcoming years. The number of passengers has increased gradually and the service provider has made public the goal of intensifying frequencies in the future. The increase of train frequencies can only be done with a structured timetable with no need of winter event reductions. A developed analysis considering the scenarios with a virtual decrease and increase in the number of switches (representing the implementation of fixed switches and point heaters) could have reduced the switch related disruptions in the past. This study supports that the investments in the mitigation program result in positive outcomes.

Vulnerability levels per link which consider the probability of switch disruption and the station importance are an important tool for directing investments in winter disruption mitigation strategies. The winter risk map can be used by the rail operators to identify critical regions, plan resources and implement new technologies. At the end, both service providers and passengers benefit as the rail transport organisation becomes a more robust and trustworthy system.

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Appendix

01. SEPTA – Potential Adaptation Strategies for Snow Events

Problem	Solution(s)	Department	Category	Barriers to Implementation	Fit within Existing Processes	Other Notes
Snow on tracks, stations, equipment, etc.	Put third-party contractors on call to facilitate snow removal	All	Maintenance	Low	SEPTA is already adopting this strategy	SEPTA is already adopting this strategy
	Salt rails, stations, and other key areas in advance	Bridges & Buildings, Track and Civil Engineering	Maintenance	Low	SEPTA is already adopting this strategy	SEPTA is already adopting this strategy
	Expand use of platform heaters	Bridges & Buildings	Capital planning	High	Could occur through regular station upgrade processes	SEPTA is currently piloting this strategy
Potential for power outages	Continue and enhance tree trimming program	Power	Maintenance	Low	Continuation or acceleration of existing program	SEPTA is already adopting this strategy
	Acquire backup power systems (permanent or temporary)	Power, others	Capital planning	High		SEPTA is already beginning to adopt this strategy
Dangerous working conditions	Closely monitor staff working on snow removal to prevent or respond to injuries and fatigue	All	Maintenance	Low	Continuation or enhancement of existing staff oversight efforts	SEPTA is already adopting this strategy
Increasing resource constraints from other weather-related events	Continue to plan for snow removal costs in budgets, in addition to other newer stressors	Policy and Administration	Capital planning	High	Incorporate into existing planning and budgeting processes	
Potential for service disruptions	Continue and improve customer communication	Policy and Administration	Operations	Low	Fits within existing communications framework	SEPTA has already begun to adopt this strategy

02. Winter Weather Correlations

Correlations

		Average wind speed (in 0.1 m / s).	Minimum average temperature (at 0.1 degrees Celsius)	Average pressure (in 0.1 hPa)	Average relative humidity (in percentage)	Snow 0 = no occurrence	Ice formation 0 = no occurrence	Low Temperature 0 = no occurrence
Average wind speed (in 0.1 m / s).	Pearson	1	,511**	-,296**	-,138**	,294**	-,270**	-,163**
	Sig. (bilateral)		,000	,000	,000	,000	,000	,000
	N	4170	4170	3476	4117	4170	4117	4170
Minimum average temperature (at 0.1 degrees Celsius)	Pearson	,511**	1	-,319**	,190**	,273**	-,302**	-,333**
	Sig. (bilateral)	,000		,000	,000	,000	,000	,000
	N	4170	4300	3476	4242	4297	4244	4300
Average pressure (in 0.1 hPa)	Pearson	-,296**	-,319**	1	-,281**	-,384**	,080**	,077**
	Sig. (bilateral)	,000	,000		,000	,000	,000	,000
	N	3476	3476	3476	3476	3476	3437	3476
Average relative humidity (in percentage)	Pearson	-,138**	,190**	-,281**	1	,239**	,192**	-,039*
	Sig. (bilateral)	,000	,000	,000		,000	,000	,011
	N	4117	4242	3476	4242	4242	4189	4242
Snow 0 = no occurrence	Pearson	,294**	,273**	-,384**	,239**	1	-,120**	,070**
	Sig. (bilateral)	,000	,000	,000	,000		,000	,000
	N	4170	4297	3476	4242	4297	4244	4297
Ice formation 0 = no occurrence	Pearson	-,270**	-,302**	,080**	,192**	-,120**	1	,071**
	Sig. (bilateral)	,000	,000	,000	,000	,000		,000
	N	4117	4244	3437	4189	4244	4244	4244
Low Temperature 0 = no occurrence	Pearson	-,163**	-,333**	,077**	-,039*	,070**	,071**	1
	Sig. (bilateral)	,000	,000	,000	,011	,000	,000	
	N	4170	4300	3476	4242	4297	4244	4300

**. The correlation is significant on a 0,01 level (bilateral).

*. The correlation is significant on a 0,05 level (bilateral).

03. Disruption Correlations

Correlations

		Duration Minutes	Train Frequencies	Disruptions/km track	Snow 0 = no occurrence	Ice formation 0 = no occurrence	Low Temperature 0 = no occurrence
Duration Minutes	Pearson	1	-,042**	-,051**	,034*	-,023	-,070**
	Sig. (bilateral)		,006	,001	,027	,143	,000
	N	4180	4180	4180	4177	4127	4180
Train Frequencies	Pearson	-,042**	1	-,101**	-,007	,014	-,017
	Sig. (bilateral)	,006		,000	,634	,364	,268
	N	4180	4300	4300	4297	4244	4300
Disruptions/km track	Pearson	-,051**	-,101**	1	-,029	,016	,111**
	Sig. (bilateral)	,001	,000		,061	,307	,000
	N	4180	4300	4300	4297	4244	4300
Snow 0 = no occurrence	Pearson	,034*	-,007	-,029	1	-,120**	,070**
	Sig. (bilateral)	,027	,634	,061		,000	,000
	N	4177	4297	4297	4297	4244	4297
Ice formation 0 = no occurrence	Pearson	-,023	,014	,016	-,120**	1	,071**
	Sig. (bilateral)	,143	,364	,307	,000		,000
	N	4127	4244	4244	4244	4244	4244
Low Temperature 0 = no occurrence	Pearson	-,070**	-,017	,111**	,070**	,071**	1
	Sig. (bilateral)	,000	,268	,000	,000	,000	
	N	4180	4300	4300	4297	4244	4300

**. The correlation is significant on a 0,01 level (bilateral).

*. The correlation is significant on a 0,05 level (bilateral).

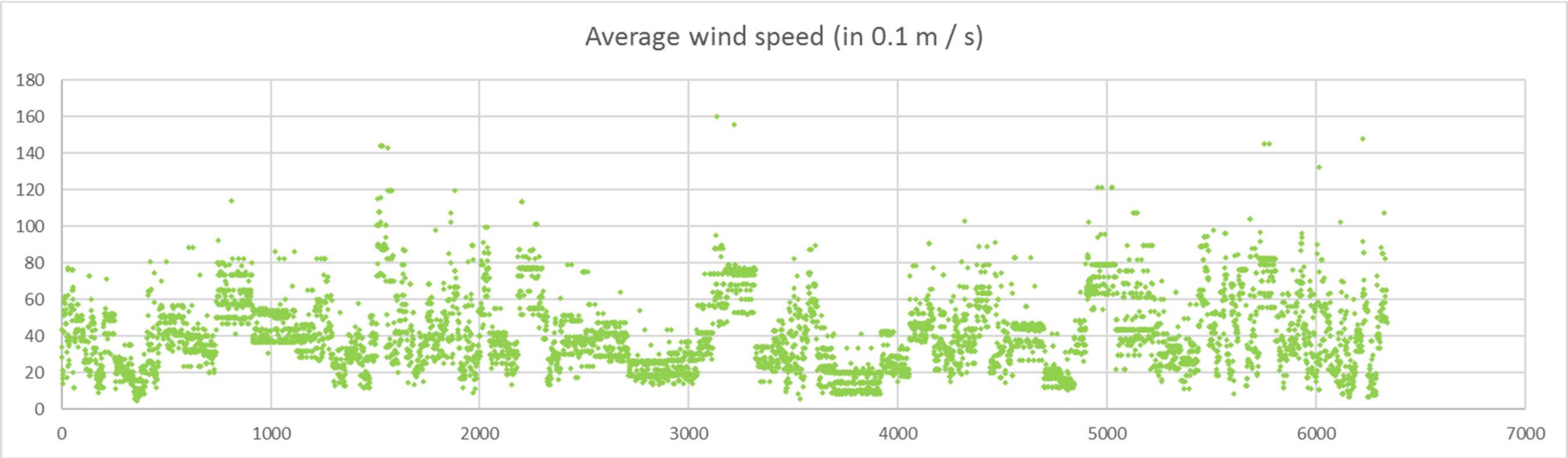
04. Distance to Coast Correlations

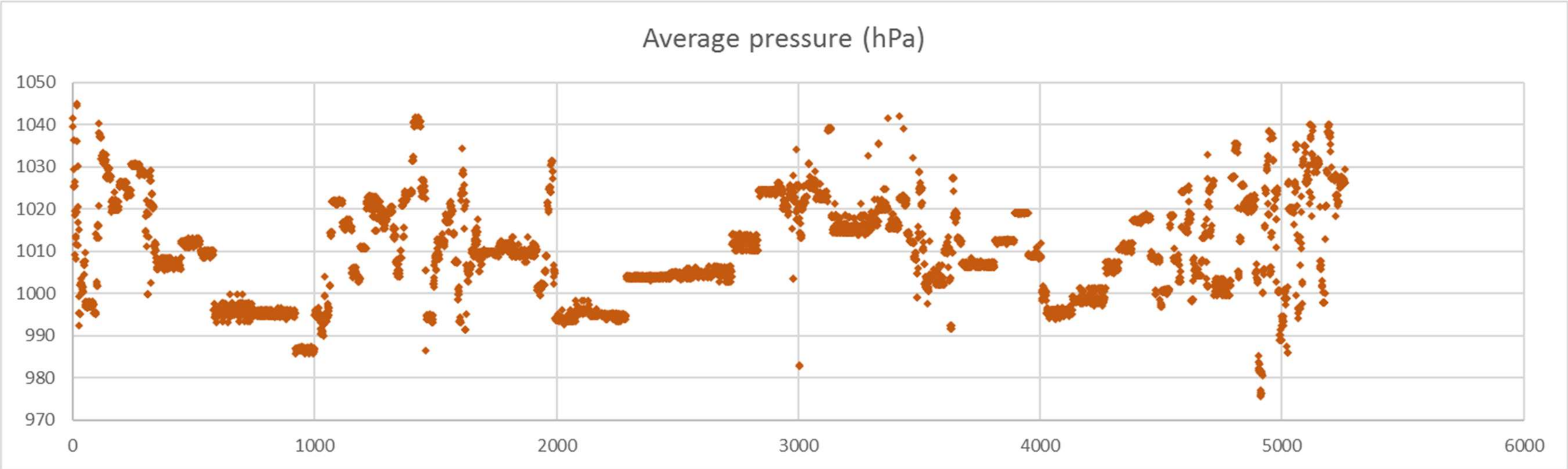
Correlations

		NEAR_DIST	VISnow	VIFrost	VILT	Train Frequency
NEAR_DIST	Pearson	1	-,021	,050	,036	-,234**
	Sig.		,741	,427	,562	,000
	N	259	259	259	259	259
VISnow	Pearson	-,021	1	,968**	,980**	,274**
	Sig.	,741		,000	,000	,000
	N	259	259	259	259	259
VIFrost	Pearson	,050	,968**	1	,953**	,209**
	Sig.	,427	,000		,000	,001
	N	259	259	259	259	259
VILT	Pearson	,036	,980**	,953**	1	,174**
	Sig.	,562	,000	,000		,005
	N	259	259	259	259	259
Train Frequency	Pearson	-,234**	,274**	,209**	,174**	1
	Sig.	,000	,000	,001	,005	
	N	259	259	259	259	259

**. The correlations is significant on 0,01 level (bilateral).

05. Additional Weather Characteristics during Winter Related Disruptions





06. Intercity Stations Dutch Rail Network

07. Suggested Approaches for the Winter Disruption Mitigation Program

Timetable – Level 1		
Period	**Actions**	**Category**
Immediately Before Event	Evaluate train lenght and communication of train extension to passengers based on forecast	Planning
	Maintain sharp and fast decision-making approaches	Operations
	Maintain well defined personnel responsibilities when defining the usage of the timetable	Operations
	Check availability and create connections with main responsible within the weather bureaus	Operations
During Event	Keep close and effective communication with weather bureaus for fast and effective decision making	Operations
	Have all main position in alert and available during the amended timetable	Operations
	Provide fast and effective communication with involved and responsible for updating traveller information	Operations
Long Term Planning	Improve communication process with weather bureaus for the inclusion of more details on winter characteristics	Planning
	Evaluate criteria for timetable alert	Research
	Include and analyse details on winter weather characteristics that trigger switch disruptions	Capital planning
	Develop amended table based on region criticallity	Planning
	Monitor and evaluate timetable necessity and performance	Planning
	Install additional weather measuring systems along the railway for more accurate data	Capital planning
	Sharpen decision-making process by developing a structured decision-making map including winter weather characteristics and the vulnerability per location	
	Diminish dependencies on winter timetable by focusing on other mitigation strategies	Planning
Asset and Vehicle Maintenance – Level 2		
Period	**Actions**	**Category**
Immediately Before Event	Ensure that the track is free of obstacles (no branches of bushes covered with snow hanging low and avoidance of ice formation at tunnel entrances)	Maintenance
	Put third-party contractors on call to facilitate snow/ice removal	Maintenance
	Salt rails, stations, and other key areas in advance	Maintenance
	Use of chemicals for melting snow	Maintenance
	Plan and train maintenance teams for asset and vehicle integrity evaluations before winter	
	Check functionality of point heaters	Maintenance
	Increase defrosting capacity and cover of the most important railway yards	Maintenance
	Deploy reaction teams and equipment (engines, rotary snow ploughs)	Management
	Prepare rolling stock and infrastructure for snow and cold weather (e.g. heating, removal of ice and snow, de-icing)	Maintenance
During Event	Manual cleaning of turn-overs (brushes, spades, blowers, excavators)	Maintenance
	Remove snow (snow blowing machines or vehicles, manually)	Maintenance

	Provide appropriate shelter for the rolling stock or cover sensitive parts (couplings, pantographs)	Management
	If applicable, keep vehicles moving across track overnight to reduce ice build-up	Operations
	Take measures to keep platforms free of snow and ice	Maintenance
	Closely monitor staff working on snow removal to prevent or respond to injuries and fatigue	Management
	Put third-party contractors on call to transport clients using different modes when necessary	Capital planning
Long Term Planning	Implement new technology with sensors to identify obstacles on critical segments	Capital Planning
	Invest in auxiliary equipment such as rubber spoilers and snow fences in critical segments	Capital planning
	Expand use of platform heaters	Capital planning
	Continue and enhance tree trimming program	Maintenance
	Acquire backup power systems (permanent or temporary) for critical regions	Capital planning
	Continue to plan for snow removal costs in budgets, in addition to other newer stressors	Capital planning
Material – Level 3		
Period	**Actions**	**Category**
Immediately Before Event	Check for sufficient spare equipment availability based on historical data	Planning
	Maintain a clear and well-defined process for the management and disposal of material based on past events	Operations
	Dispose warehouses and trained personnel within all critical regions	Operations
During Event	Provide fast and efficient material delivery	Operations
	Keep warehouses well maintained	Maintenance
	Keep track of used material	Management
	Keep track of used equipment	Management
	List issues that arise during process for future improvement	Management
	Keep track of material within warehouse to order additional parts in case necessary	Management
Long Term Planning	Analyse and define most used and critical components	Planning
	Develop a clear and well-defined process for the management and disposal of material based on past events	Planning
	Improve the process description for disposal of material	Planning
	Evaluate delivery times and spare part quality	Research
	Evaluate spare parts provider in relation to delivery speed and product quality	Research
	Evaluate overall performance with internal clients	Research
Management – Level 4		
Period	**Actions**	**Category**
Immediately Before Event	Check communication flow	Planning
	Update personnel on the decision-making process	Management
	Structure the integration and coordination with other measures.	Management
During Event	Keep track of process	Management

	Keep open communication with other areas	Management
	Follow defined plan	Management
Long Term Planning	Improve decision-operational treatment and adjustment	Planning
	Improving communication between the different organizations	Planning
	Improving standard measures and decision-making and implementation after disruptions	Planning
	Integration and coordination with other measures.	Planning
	Train personnel on the decision-making process	Capital planning
	Practice decision-making in crisis situations	Planning
	Enhancing structural operational evaluation and learning cycle	Planning
	Raise awareness and periodic exercising of emergency	Operations
Personnel – Level 5		
Period	**Actions**	**Category**
Immediately Before Event	Check on extra available staff for urgent matters	Operations
	Send out warning for winter condition	Operations
During Event	Provide support for critical management conditions	Operations
	Select personnel for direct handling of unexpected decisions	Operations
Long Term Planning	Train personnel for previewed winter scenarios	Capital Planning
	Invest in communication technology and training	Capital planning
	Develop pilots for checking the communication within the winter mitigation team	Capital planning
Traveller Information – Level 6		
Period	**Actions**	**Category**
Immediately Before Event	Verify accuracy of traveler information in social media and provide announcements	Operations
	Verify accuracy of travel information at stations and on national channels	Operations
During Event	Provide information on the situation, the expected recovery times and possible alternative journeys (+ forecasts)	Operations
Long Term Planning	Improve travel information at stations and on all national channels on a meta-level, including frequent updates.	Capital Planning
	Improve stability and availability of travel information such as Info Plus signs and redundancy	Capital planning
Customer Satisfaction – Level 7		
Period	**Actions**	**Category**
Immediately Before Event	Monitor the spread of information on possible winter events	Operations
	Check on additional staff (volunteers) ready to guide customers	Operations
During Event	Provide convenient waiting rooms and coffee/tea for stations with delay issues	Management
	Verify quality of received travel information to customers	Management
	Dispose of extra personnel to support passengers specially	Management
Long Term Planning	Invest in marketing in favour of patience and understanding of the customers in winter disruptions focusing on the importance of safety and good travel experiences	Capital Planning
	Develop, update, run and evaluate a yearly survey on customer satisfaction	Capital planning

08. Probabilistic Analysis – T-tests for the Exponential Function

Low Frequencies

Snow/hail

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,249402	0,203147
Variance	0,028374	0,043668
Observations	38	38
Hypothesized Mean Difference	0	
df	71	
t Stat	1,062318	
P(T<=t) one-tail	0,145846	
t Critical one-tail	1,6666	
P(T<=t) two-tail	0,291691	
t Critical two-tail	1,993943	

Frost/freezing rain

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,330753	0,322507
Variance	0,050151	0,078611
Observations	38	38
Hypothesized Mean Difference	0	
df	71	
t Stat	0,141667	
P(T<=t) one-tail	0,443872	
t Critical one-tail	1,6666	
P(T<=t) two-tail	0,887744	
t Critical two-tail	1,993943	

Low Temperatures

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,355378	0,358336
Variance	0,061943	0,087207
Observations	38	38
Hypothesized Mean Difference	0	
df	72	
t Stat	-0,04722	
P(T<=t) one-tail	0,481233	
t Critical one-tail	1,666294	
P(T<=t) two-tail	0,962467	
t Critical two-tail	1,993464	

Medium Frequencies

Snow/hail

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,340168	0,347909
Variance	0,049946	0,055585
Observations	37	37
Hypothesized Mean Difference	0	
df	72	
t Stat	-0,14495	
P(T<=t) one-tail	0,442576	
t Critical one-tail	1,666294	
P(T<=t) two-tail	0,885151	
t Critical two-tail	1,993464	

Frost/freezing rain

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,269013	0,130922
Variance	0,033548	0,012627
Observations	37	37
Hypothesized Mean Difference	0	
df	60	
t Stat	3,90898	
P(T<=t) one-tail	0,000119	
t Critical one-tail	1,670649	
P(T<=t) two-tail	0,000238	
t Critical two-tail	2,000298	

Low Temperatures

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,425532	0,43428
Variance	0,080711	0,069181
Observations	37	37
Hypothesized Mean Difference	0	
df	72	
t Stat	-0,13745	
P(T<=t) one-tail	0,445529	
t Critical one-tail	1,666294	
P(T<=t) two-tail	0,891059	
t Critical two-tail	1,993464	

High Frequencies

Snow/hail

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,447273	0,345412
Variance	0,08537	0,044638
Observations	55	55
Hypothesized Mean Difference	0	
df	98	
t Stat	2,095089	
P(T<=t) one-tail	0,019371	
t Critical one-tail	1,660551	
P(T<=t) two-tail	0,038742	
t Critical two-tail	1,984467	

Frost/freezing rain

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,462709	0,29897
Variance	0,109407	0,036337
Observations	55	55
Hypothesized Mean Difference	0	
df	86	
t Stat	3,180806	
P(T<=t) one-tail	0,001022	
t Critical one-tail	1,662765	
P(T<=t) two-tail	0,002043	
t Critical two-tail	1,987934	

Low Temperatures

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,470768	0,29897
Variance	0,086868	0,036337
Observations	55	55
Hypothesized Mean Difference	0	
df	92	
t Stat	3,629822	
P(T<=t) one-tail	0,000233	
t Critical one-tail	1,661585	
P(T<=t) two-tail	0,000466	
t Critical two-tail	1,986086	

Probabilistic Analysis – T-tests for the Inverse Potential Function

Low Frequencies

Snow/hail

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,249402	0,797056
Variance	0,028374	0,037483
Observations	38	38
Hypothesized Mean Difference	0	
df	73	
t Stat	-13,1552	
P(T<=t) one-tail	3,02E-21	
t Critical one-tail	1,665996	
P(T<=t) two-tail	6,04E-21	
t Critical two-tail	1,992997	

Frost/freezing rain

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,330753	0,647025
Variance	0,050151	0,035613
Observations	38	38
Hypothesized Mean Difference	0	
df	72	
t Stat	-6,65733	
P(T<=t) one-tail	2,35E-09	
t Critical one-tail	1,666294	
P(T<=t) two-tail	4,71E-09	
t Critical two-tail	1,993464	

Low Temperatures

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,355378	0,603512
Variance	0,061943	0,033642
Observations	38	38
Hypothesized Mean Difference	0	
df	68	
t Stat	-4,94747	
P(T<=t) one-tail	2,61E-06	
t Critical one-tail	1,667572	
P(T<=t) two-tail	5,21E-06	
t Critical two-tail	1,995469	

Medium Frequencies

Snow/hail

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,340168	0,658749
Variance	0,049946	0,017844
Observations	37	37
Hypothesized Mean Difference	0	
df	59	
t Stat	-7,44283	
P(T<=t) one-tail	2,4E-10	
t Critical one-tail	1,671093	
P(T<=t) two-tail	4,81E-10	
t Critical two-tail	2,000995	

Frost/freezing rain

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,269013	0,766185
Variance	0,033548	0,017182
Observations	37	37
Hypothesized Mean Difference	0	
df	65	
t Stat	-13,4269	
P(T<=t) one-tail	1,03E-20	
t Critical one-tail	1,668636	
P(T<=t) two-tail	2,06E-20	
t Critical two-tail	1,997138	

Low Temperatures

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,425532	0,535587
Variance	0,080711	0,015485
Observations	37	37
Hypothesized Mean Difference	0	
df	49	
t Stat	-2,1584	
P(T<=t) one-tail	0,017912	
t Critical one-tail	1,676551	
P(T<=t) two-tail	0,035824	
t Critical two-tail	2,009575	

High Frequencies

Snow/hail

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,447273	0,494143
Variance	0,08537	0,016048
Observations	55	55
Hypothesized Mean Difference	0	
df	74	
t Stat	-1,0915	
P(T<=t) one-tail	0,139297	
t Critical one-tail	1,665707	
P(T<=t) two-tail	0,278593	
t Critical two-tail	1,992543	

Frost/freezing rain

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,462709	0,469768
Variance	0,109407	0,014907
Observations	55	55
Hypothesized Mean Difference	0	
df	68	
t Stat	-0,14848	
P(T<=t) one-tail	0,441202	
t Critical one-tail	1,667572	
P(T<=t) two-tail	0,882405	
t Critical two-tail	1,995469	

Low Temperatures

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,470768	0,463044
Variance	0,086868	0,014591
Observations	55	55
Hypothesized Mean Difference	0	
df	72	
t Stat	0,17983	
P(T<=t) one-tail	0,428896	
t Critical one-tail	1,666294	
P(T<=t) two-tail	0,857791	
t Critical two-tail	1,993464	

Probabilistic Analysis – T-tests for the Log-logistic Function

Low Frequencies

Snow/hail
Low Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,249401914	0,251005128
Variance	0,028373823	0,023932302
Observations	38	38
Hypothesized Mean Difference	0	
df	73	
t Stat	-0,043212273	
P(T<=t) one-tail	0,482825151	
t Critical one-tail	1,665996224	
P(T<=t) two-tail	0,965650302	
t Critical two-tail	1,992997126	

Frost/freezing rain
Low Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,330753	0,337188
Variance	0,050151	0,044917
Observations	38	38
Hypothesized Mean Difference	0	
df	74	
t Stat	-0,12864	
P(T<=t) one-tail	0,448995	
t Critical one-tail	1,665707	
P(T<=t) two-tail	0,89799	
t Critical two-tail	1,992543	

Low Temperatures
Low Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,355378	0,365632
Variance	0,061943	0,054477
Observations	38	38
Hypothesized Mean Difference	0	
df	74	
t Stat	-0,18527	
P(T<=t) one-tail	0,426761	
t Critical one-tail	1,665707	
P(T<=t) two-tail	0,853522	
t Critical two-tail	1,992543	

Medium Frequencies

Snow/hail
Medium Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,340167754	0,341838873
Variance	0,049945754	0,048276839
Observations	37	37
Hypothesized Mean Difference	0	
df	72	
t Stat	-0,032434152	
P(T<=t) one-tail	0,487107786	
t Critical one-tail	1,666293696	
P(T<=t) two-tail	0,974215573	
t Critical two-tail	1,993463567	

Frost/freezing rain
Medium Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,269013	0,270391
Variance	0,033548	0,032491
Observations	37	37
Hypothesized Mean Difference	0	
df	72	
t Stat	-0,03261	
P(T<=t) one-tail	0,487036	
t Critical one-tail	1,666294	
P(T<=t) two-tail	0,974072	
t Critical two-tail	1,993464	

Low Temperatures
Medium Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,425532	0,42948
Variance	0,080711	0,078101
Observations	37	37
Hypothesized Mean Difference	0	
df	72	
t Stat	-0,06026	
P(T<=t) one-tail	0,476059	
t Critical one-tail	1,666294	
P(T<=t) two-tail	0,952119	
t Critical two-tail	1,993464	

High Frequencies

Snow/hail
High Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,447272727	0,434435672
Variance	0,085369828	0,085296299
Observations	55	55
Hypothesized Mean Difference	0	
df	108	
t Stat	0,230448082	
P(T<=t) one-tail	0,409089778	
t Critical one-tail	1,659085144	
P(T<=t) two-tail	0,818179557	
t Critical two-tail	1,982173483	

Frost/freezing rain
High Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,462709	0,458309
Variance	0,109407	0,108302
Observations	55	55
Hypothesized Mean Difference	0	
df	108	
t Stat	0,069925	
P(T<=t) one-tail	0,472191	
t Critical one-tail	1,659085	
P(T<=t) two-tail	0,944383	
t Critical two-tail	1,982173	

Low Temperatures
High Frequencies
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0,470768	0,42948
Variance	0,086868	0,078101
Observations	55	37
Hypothesized Mean Difference	0	
df	80	
t Stat	0,679666	
P(T<=t) one-tail	0,249339	
t Critical one-tail	1,664125	
P(T<=t) two-tail	0,498678	
t Critical two-tail	1,990063	