Passenger punctuality

Assessing the impact of disruptions

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by

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Summary

During the last decades, the focus of public transport reliability measures has been shifting from the operators' perspective to the passengers' perspective. During this shift, the original vehicle punctuality got passenger punctuality as a counterpart from passengers' perspective. The passenger punctuality should fit better to the experience of the passenger. In the Netherlands, passenger punctuality is measured based on smart card data. These data allow to determine the delay of each passenger under normal conditions. During disruptions, however, passengers behave in ways that can not be automatically detected in the current calculation method. For example, a passenger that needs to take a bus, due to a disruption, to reach its final destination may appear in the data as punctual. This is because the train part of its journey could be made in time. However, the train part was not the complete planned journey in this case. It is also possible that a passenger postpones or cancels its trip due to a disruption. Such a passenger will not appear in the data as unpunctual, while it did experience hindrance from the disruption. It is currently unknown what the impact is of these scenarios on the passenger punctuality metric. Therefore, the objective of this research sounds:

> **Objective**
> Assess the unkown part of the impact of disruptions on passenger punctuality and evaluate the current calculation method.

This is a relevant objective from both a practical and a scientific perspective. Inside the business, passenger punctuality is used as a Key Performance Indicator by both the Dutch main railway operator NS and infrastructure manager ProRail. As KPI, the passenger punctuality has on the one hand a supervision function from the Dutch government, which grants the concession for the rail network. On the other hand, it has a steering function on all planning levels in both organizations in order to improve service reliability. From a scientific perspective, there is little knowledge about the impact of disruptions on service reliability, based on empirical passenger data. By filling this gap, this research contributes to the field of public transport service reliability, enabling to test disruption mitigation measures in real-life. In order to achieve the research objective, the report follows a number of subquestions, divided in three categories: state of practice and research, method and application.

State of practice and research

The state of practice describes passenger punctuality in its function as KPI of NS and ProRail. The definition of the KPI is based on the philosophy that the operator promises possible journeys to the passenger. If the journey can not be made as planned, it is considered as unpunctual. In the definition of the KPI, this rule applies from an arrival delay of 5 minutes or 15 minutes (supervision thresholds). The percentage of passengers within a time interval that made a punctual journey is called the passenger punctuality. The KPI has two functions. In the first place, the government uses it as supervision instrument. The government grants concessions to use and maintain the infrastructure on the condition that this is done in an appropriate way. If the KPI norms are not accomplished, both organizations pay a fine. In the second place, the KPI can be used to indicate weak spots and to steer improvements.

The state of research has been discussed by reviewing available definitions and methods for measuring passenger service reliability. The current method used by NS and ProRail, called passenger punctuality '17, is built-up in several modules. These modules process check-in/check-out and vehicle location data to passenger delays. Regarding disruptions, this method probably fails in measuring detouring, postponing and canceling passengers in an accurate way. The previous method by NS and ProRail, called passenger punctuality '15, is based on planned and realized passenger arrivals and transfers. The number of planned arrivals and transfers is deducted from passenger counts and estimated transfer rates. Realized arrivals and transfers are derived from vehicle location data. The punctuality is calculated based on data from 35 measuring stations. Since this method is based on demand prognoses, canceling and postponing passengers are also taken into account in case of disruptions. The Danish railways have used several generations of passenger delay models in the past.

The 1.5 generation models assign the expected passenger demand to the realized timetable. It is assumed that passengers arrive to the station at their planned departure time. Regarding disruptions, assigning expected demand to the realized timetable allows to assess for postponing and canceling passengers. Expecting passengers to arrive at the station at their planned departure time seems to be a reasonable assumption. For the London Underground, a method has been developed that calculates the Reliability Buffer Time: the buffer time a passenger should add to the planned travel time in order to obtain a reliable forecast of the real travel time. Realizing that this measure is strongly affected by incidents, they also developed an alternative measure that indicates the impact of disruptions by calculating the RBT with exception of disrupted days. This method is based on AFC data and, although an attempt is made to cope with the impact of disruptions, the same problems exist as in the passenger punctuality '17 method. All in all, there is no 'best' way of measuring passenger service reliability. Re-assigning the expected demand in undisrupted conditions to the realized timetable seems to be a good method to capture detouring, postponing and canceling passengers.

Method

The Journey Pattern Reconstruction (JPR) method has been developed in order to cope with the limitations of the passenger punctuality '17 method concerning detoured, postponed and canceled trips. This method makes a reconstruction of the observed journey pattern during a disruption, based on the expected demand and the realized timetable. Figure 1 displays the approach that is followed to get to this reconstruction. It starts with selecting a disruption case that is expected to have a considerable impact on passenger punctuality that is not yet measured. Then, the demand is determined for all possible journeys in disrupted and undisrupted conditions, based on the punctuality data. Using the disruption data in combination with the timetable, it can be determined if a journey is hindered by the disruption or not. If a journey is hindered, three alternative journey advises are generated that are allowed to use any (transit) mode. Based on these alternatives and the demand in disrupted and undisrupted conditions, a reconstruction is made of the observed journey pattern during and after the disruption. This is done by assigning the expected passenger demand to the generated alternatives including the alternative to cancel the trip. The assignment process is carried out by formulating a linear program that minimizes the absolute difference between the journey pattern reconstruction and the observed journey pattern. In the reconstruction, it is exactly known what alternative the expected passengers chose, so that the number of detouring, postponing and canceling passengers can be determined. Based on these numbers, the passenger punctuality can be recalculated. Besides, journey patterns during disruptions and final delays can be studied.

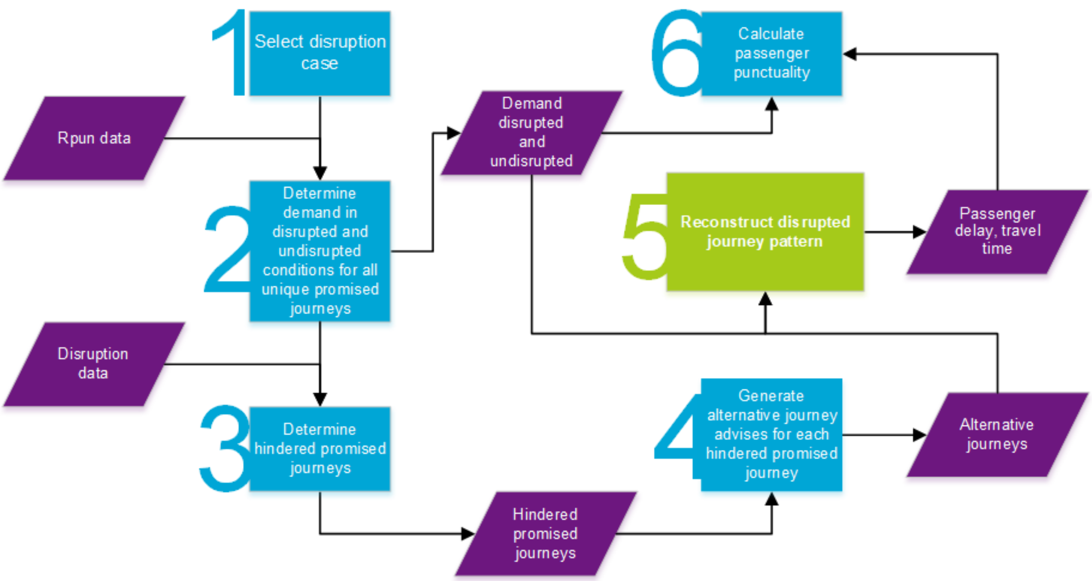


Figure 1: Impact assessment approach

Application

Six disruption cases have been selected in a strategic way, so that a maximum amount of information could be obtained. These cases vary in the part of the day they occurred and the number of detour possibilities in the NS network. One additional case was studied that concerns an exceptional severe disruption. Table 1 gives a summary of the results. Figure 2 shows the resulting journey patterns after applying the JPR method.

Table 1: Summary of the case studies results

Label	**Morning peak, medium detour possibilities**	**During the day**	**Evening peak**	**Few detour possibilities**	**Much detour possibilities**	**Exceptional large disruption**
Total hindered passengers	16298	22054	10864	5112	19354	47448
Total passengers detouring	3417	7218	5206	1268	8755	5686
Total passengers postponing	1541	2070	352	166	243	1504
Total passengers canceling/detouring only by other modes	10797	11425	4909	3522	10037	37821
Passenger punctuality '17	92.91%	92.47%	88.34%	94.83%	93.09%	91.93%
Recalculated passenger punctuality	91.69%	90.71%	87.68%	94.40%	91.11%	86.71%
Delta passenger punctuality	-1.22%	-1.76%	-0.67%	-0.42%	-1.98%	-4.68%

It appears that, during the morning peak, more passengers cancel their trip than during the day and the evening peak. This can be explained by the fact that people may choose to work at home if there is a large disruption in the morning peak. When a disruption occurs during the evening peak, people want to get home from work, which makes canceling a much less attractive option.

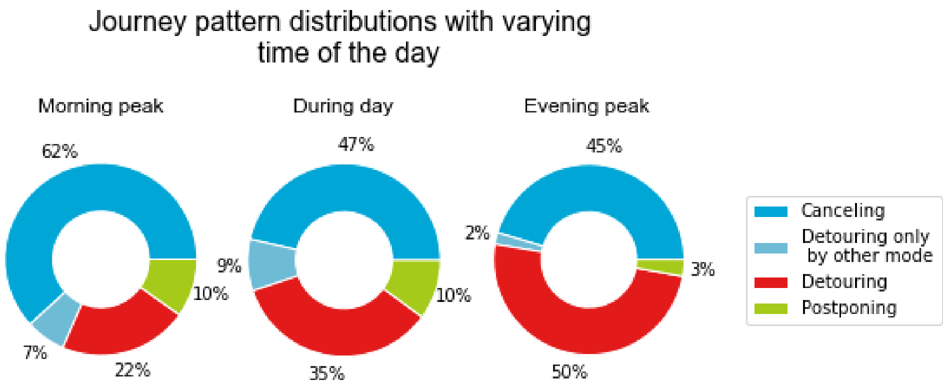
When varying in the availability of detour possibilities, it appears that if there are few detour possibilities in the NS network, passengers travel by bus only or traverse the disrupted trip leg by another mode. Therefore, the detour rate in cases with few detour possibilities in the NS network is not necessarily low. The opposite does appear to be true: in cases with lots of detour possibilities in the NS network, the detour rate is higher than in the other cases.

During an exceptional severe disruption, canceling and detouring using only other modes appear to be the most used alternatives. Due to the complete shut-down of the rail network in the area, it is even hardly possible to take the train, so this is a logical result.

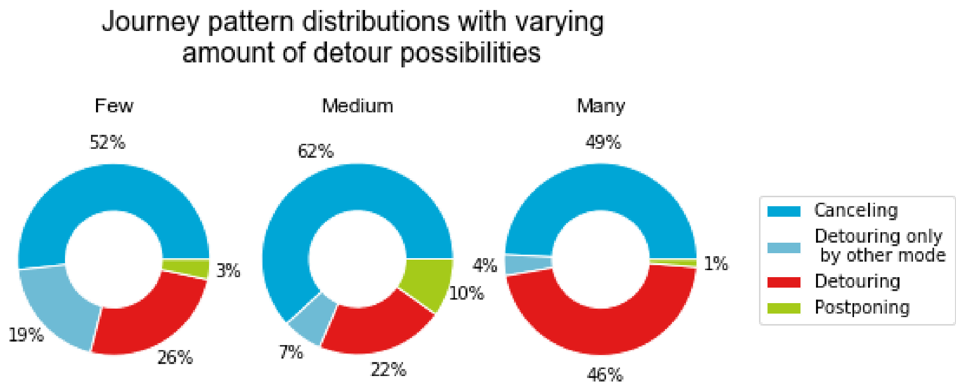
The unknown part of the impact of disruptions on passenger punctuality appears to range from lower than 0.5% to higher than 4.5%. This impact roughly corresponds with the number of passengers that are hindered by the disruption. This is a logical finding, because each hindered passenger has by definition one negative contribution to the population of the recalculated KPI, whether they detour, postpone or cancel their trip.

Conclusions

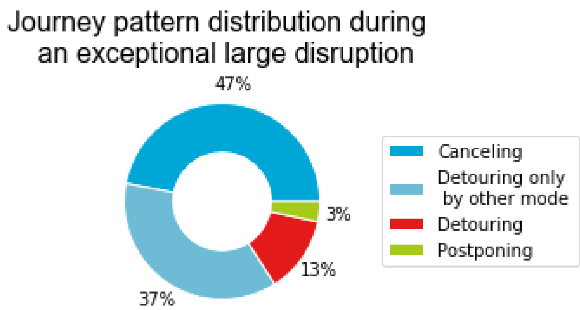
The key finding of this thesis is that disruptions probably have a considerable impact on passenger punctuality that is not captured in the current calculation method. Assuming that the KPI plays an important role in steering the organizations involved, it is advised to explore ways to improve its accuracy. At some points, the designed JPR method is still limited. One of the main limitations is that there is currently no accurate forecast of passenger demand available. Developing a model that predicts the demand would not only improve the JPR method, but can also be used in other studies. Another limitation lies the fact that the journey advise generator only returns three alternatives per request. Not always is there a postponing alternative or there is only one. This might be the reason why postponing alternatives appear to be relatively unpopular. Adding postponing alternatives to the alternatives sets, may improve the accuracy of the method. A final suggestion for future research is to take a better look into the available definitions and methods for determining passenger services reliability in order to find out which fits best to the experience of the customer.



(a) Journey pattern distributions with varying time of the day



(b) Journey pattern distributions with varying amount of detour possibilities



(c) Journey pattern distribution in during an exceptional large disruption

Figure 2: Journey pattern distributions for the selected case studies

Preface

"*Anyone who stops learning is old, whether at twenty or eighty. Anyone who keeps learning stays young.*"

—Henry Ford

Dear reader,

Before you lies my thesis titled: ”Passenger punctuality: assessing the impact of disruptions”. It has been written to complete the masters’ program Transport, Infrastructure and Logistics at Delft University of Technology. I started my research in April and finished writing in November, 2018.

This project came about after the suspicion was risen that the passenger punctuality metric as used by ProRail and NS might not be as accurate as desired during disruptions. Around that time, I informed if there was an opportunity to perform a graduation research project at ProRail. The aforementioned suspicion formed my opportunity and I was granted an internship to work on the project.

I want to thank my supervisors for keeping me on the right track and for their great ideas in finding the route. From TU Delft, Rob Goverde, Oded Cats and Maarten Kroesen have played an important role to get this thesis to the scientific level a masters’ thesis requires and deserves. From ProRail and NS, I want to thank Vincent Weeda, Jan-Martijn Egbers, Mischa van der Haar and Jesper Haverkamp for providing all the practical guidance I needed including their valuable feedback.

After my supervisors, I want to thank my wife, family, friends and fellow students for supporting and motivating me not only during this graduation project, but also during the preceding study years.

I wish you a pleasant reading.

A.T. den Heijer
Rotterdam, November 2018

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Glossary

AFC Automatic Fare Collection, the system that collects the fares based on check-ins and check-outs. 3, 11

CICO Check-In-Check-Out, the data that contains all journey information from the AFC system. 6

GTFS General Transit Feed Specification, a general format for publishing transit timetables. 15

JPR method Journey Pattern Reconstruction method, the method that is developed in the current research to reconstruct the observed journey pattern of a disrupted day. 14, 23

KPI Key Performance Indicator, a variable that is used to analyze the performance of an organization, brand or product. 1, 5, 17, 35

OD Origin-Destination. 6

OTP OpenTripPlanner, an open source application that is used to generate alternative journey advises. 15

Passenger punctuality a public transport service reliability measure, determined from the passengers perspective. 1, 5, 13, 23, 35

Peer day is a day before or after a disruption day on which the estimation of the undisrupted demand is based. 14

Promised journey is a journey that could be made according to the journey planner two days before departure. 6, 14, 26, 37

Smart card a card that is used by passengers to enter the departure station, which automatically collects the fare when the passenger leaves the final station. 1, 6

1
Introduction

This chapter introduces the research topic and defines the problem in section 1.1. In section 1.2, the relevance of the subject is explained from both a scientific and a practical perspective. Section 1.3 describes the research approach and the report structure. Eventually, section 1.4 walks through the report, indicating what is described in each chapter.

1.1. Problem definition

This section defines the problem and estimates the size of it. In the last subsection, the objective is formulated that covers the problem and the scope of the project is defined.

1.1.1. Research topic

Punctuality is one of the most important indicators for public transport service performance and reliability [15]. It can be divided into two types: vehicle and passenger punctuality. Previously, most public transport operators in several networks only measured vehicle punctuality based on vehicle delays. However, vehicle punctuality does not directly reflect passenger punctuality; small vehicle delays can imply many failed transfers leading to large passenger delays. Therefore, during the last decade, the focus has been shifting from vehicle punctuality to passenger punctuality in order to better reflect the experience of the passenger [18]. Passenger punctuality can be determined in different ways (see chapter 2). The current calculation method by NS[1] and ProRail[2] in the Netherlands is based on smart card data containing time and location of check-in and check-out in combination with train location data. Under regular conditions, this is enough information to calculate the delay of a trip. During disruptions however, it is much more challenging to make an adequate calculation of the passenger punctuality.

1.1.2. Problem introduction

Passenger punctuality is defined by NS and ProRail as the percentage of passengers that reach their final destination within 5 and 15 minutes from the planned arrival time. This measure is used as a KPI[3] in both these companies. It is suspected that the impact of (large) disruptions is not sufficiently and adequately accounted for in the current indicator definition. This is because there are several cases in which it is hard to determine if a passenger reached its destination in time. When a passenger takes the planned route and reaches its destination with or without a delay, the current method is able to calculate the delay of this passenger. It can also happen that a passenger needs to take a detour, possibly using replacement modes. In this case, the passenger has to check-in or -out at another station than planned. The journey by train may then appear punctual in the data, but may be not in reality, since the journey is not completely captured in the data. Other possibilities are that passengers postpone or cancel their trip due to the disruption. These passengers either do not appear in the data at all or with a punctual journey, although they did experience hindrance. The described scenarios probably lead to a bias in

[1] Nederlandse Spoorwegen: Dutch railway operator. See appendix A for more information.
[2] Dutch rail infrastructure manager. See appendix A for more information.
[3] Key Performance Indicator (KPI): a variable that is used to analyze the performance of an organization, brand or product.

the calculation of the KPI. It is therefore desired to gain better insight into the impact of disruptions on travel behavior as well as on the passenger punctuality as KPI.

1.1.3. Size of the problem

A rough estimation of the impact of disruptions on passenger punctuality is made by Wolters [27]. This is done by taking an example case in which a certain track is disrupted. The number of check-outs at the stations along this track under disturbed conditions is compared to the mean number of check-outs on the 15 workdays around this day. For 3 different disruptions, the impact is estimated to be 0.05 to 0.12 percentage point on the passenger punctuality of that particular day. It is expected that the true impact is even larger than estimated here since only executed check-outs are taken into account, while missed or delayed check-ins are also part of the passenger punctuality. There are also passengers postponing or canceling their trip, which are not taken into account. Furthermore, the impact probably also depends on other factors like the duration of the disruption and the length of the disturbed track. In the past 12 months, 650 high-impact infrastructure failures took place [11]. If we assume that, on average, 2 disruptions occur every day, the yearly passenger punctuality is overestimated by 0.1 to 0.24 percentage point. This seems to be a negligible difference, but in the passenger punctuality KPI, small differences matter. For the previous 12 months, the passenger punctuality was 92.5%, while the norm value is 90.4% [11]. The difference between these values is only 2.1%, so a bias of 0.1 to 0.24 percentage point matters.

1.1.4. Objective and scope

As stated in the problem definition, the main research problem is that there is a part of the impact of disruptions on passenger behavior and punctuality is currently unknown. The quality of the current KPI calculation method partly depends on this impact. The objective can therefore be formulated as follows.

> **Objective**
> Assess the unknown part of the impact of disruptions on passenger punctuality and evaluate the current calculation method.

In the first place, passenger delays due to disruptions will be analyzed. Then, an estimation will be made of the impact of disruptions on the KPI value in order to gain better insight into the KPI. Based on the total impact, the quality of the current KPI calculation method can be evaluated. Given the knowledge gained, it must be assessed if the current calculation method is still reasonable.

The result will consist in the first place of a calculation and analysis of passenger journey pattern and factors that affect passenger behavior during disruptions. In the second place, the impact of disruptions on the passenger punctuality KPI will be calculated and analyzed. Based on these results, the quality of the KPI will be evaluated. In the end, this will lead to a number of general conclusions regarding passenger behavior during disruptions and the impact of disruptions on passenger punctuality during a longer period. Besides, recommendations will be made regarding the current KPI calculation method.

The issue of adapting the calculation method of the KPI lies beyond the scope of this project. Only developing a new algorithm or changing the existing algorithm would require a whole new project, which clearly cannot be executed within the time boundaries of the current project. However, the methods used to find the impact of disruptions on passenger punctuality may form the basis for such a plan.

Another question that is not explicitly asked in this thesis is the question if the passenger punctuality KPI sufficiently reflects the perception of the passenger. This is regarded as a more behavioral question that is not directly related to the impact of disruptions. Moreover, it is debatable if the KPI would sufficiently reflect the passengers' perception, even if it would perfectly represent reality. It is common property that human perception deviates from reality as well. In addition, there is already a dedicated KPI for measuring client satisfaction.

1.2. Relevance

The proposed research is relevant in two ways. First, it will make a contribution to the scientific field of research into service reliability of public transport systems. This section will present the state of research at this point. With this analysis, it becomes clear why the proposed topic is of scientific value. Furthermore, the project will give better insight into the passenger punctuality KPI for the railway operator and infrastructure manager. The second part of this section introduces the KPI from their point of view, indicating its function and the reasoning behind it.

1.2.1. State of research

Service reliability has always been a hot item in public transport systems research. The importance of this subject has been studied by Brons and Rietveld [12], Peek and van Hagen [21]. They find that service reliability is of large importance to the customer. Metrics have been developed in order to quantify service reliability, among which are trip time variability, punctuality and regularity [23, 26]. As stated in chapter 1.1, punctuality is one of the most important of these metrics.

During the last decade, the focus of service reliability research has shifted from the supply-side to the demand-side [20]. This trend has been catalyzed by emerging technologies for Automatic Fare Collection (AFC). New passenger-oriented metrics for service reliability and in particular punctuality, have been developed by Trépanier et al. [24]. For a full overview of the possibilities for analysis using smart card data, see the reviews by Ghofrani et al. [17], Pelletier et al. [22].

Metrics have become more passenger-oriented in order to fit better to the perception of the customer. Based on smart card data, the difference between planned travel time and realized travel time can be calculated very accurately. However, as already introduced in section 1.1, there are some cases in which this is not yet possible, in particular during disruptions. Therefore, it is currently unknown what the impact is of disruptions on passenger punctuality.

Methods for determination of the impact of disruptions have been developed in the context of validation of control measures, see for example Cats and Jenelius [13], Ghaemi et al. [16], Zhu and Goverde [29]. However, these methods are designed for model-based settings, but not for working with real data. If a method can be developed for calculation of passenger punctuality during both regular and disrupted conditions, it will be possible to test these measures in real-life.

A valuable contribution to this area is made by Cats et al. [14]. Here, link exposure and vulnerability are combined into a network risk analysis. Vulnerability is defined as welfare loss due to a disruption and calculated through assigning passengers to the disrupted network. For this research, empirical disruption data have been used in order to find the probability of a disruption to occur. In the present study, empirical passenger data is also taken into account.

Yap et al. [28] developed a transfer inference algorithm that holds under both regular and disturbed circumstances. This research took place in an urban public transport network with passengers checking in and out on-board. In this situation, the challenge was to infer realistic transfers between vehicles, since a fixed threshold obviously does not work in disturbed conditions. This research also reveals that different configurations of AFC systems yield different problems in processing the gathered data.

Given the state of research, there is currently no method to assess the impact of disruptions on service reliability based on smart card data. Developing such a method will open up opportunities for studying the effects of disruptions and measures to mitigate them.

1.2.2. Passenger punctuality in practice

Passenger punctuality is used by public transport operators to quantify service reliability, which is an important performance indicator. Passenger punctuality can be analyzed per line or per station in order to identify weak spots in the network. Doing so, valuable information is obtained about locations that need measures to improve performance, so that the performance of the whole network can be improved. Because of these features, passenger punctuality is an important steering instrument at all levels in the organization of public transport agencies. Finding a method for assessing the impact of disruptions will help in short-term to real-time planning of mitigation measures. But also at the more strategic level, it is helpful to know where disruptions have the largest impact on network performance. In short, assessing the impact of disruptions on passenger punctuality will be of value to all planning levels in public transport.

1.2.3. Conclusion

Based on the information in this section, it can be concluded that the proposed research into the impact of disruptions on passenger punctuality has sufficient scientific and practical relevance. The scientific gap lies in the lack of insight into the impact of disruptions on service reliability. Filling this gap will make it possible to evaluate disruption mitigation measures in real-life situations. This research will contribute to the value of the KPI by providing better insight into the impact of disruptions, which will support planning from strategic to real-time level.

1.3. Approach

In section 1.1, the objective is formulated as follows: "assess the unknown part of the impact of disruptions on passenger delay and punctuality and evaluate the current calculation method". This section drafts the questions that will lead to the achievement of the objective. For each question, a brief explanation is added on how it is answered. At the same time, the questions are divided into chapters to set up the structure of the report.

Research questions

1. State of practice and research
   - How is the passenger punctuality KPI currently defined, what is the reasoning behind it and what function does it fulfill?
     Literature research and talks with experts. At the methodological side, the passenger punctuality is well documented. However, when it comes to the philosophy behind it, there may come more information available through talks with experts. These talks take place in an informal setting.
   - How do the available methods for passenger punctuality take disruptions into account?
     Literature research, assessment based on the four scenarios as identified in section 1.1. Methods may be found in literature, but also in documentation by public transport agencies. Both these fields should be checked for relevant information.
2. Method
   - How can passenger hindrance be determined during disruptions, concerning detoured, postponed and cancelled trips?
     A new method must be designed to assess for passenger delay and punctuality during disruptions. Information from the available methods may serve as input for this step.
3. Application
   - What is the impact of disruptions on passenger punctuality?
     The designed method is used to analyze a disruption case and then to assess the impact of a larger set of disruptions on passenger punctuality.

1.4. Reading guide

The next chapters will follow the structure that is introduced in the research questions in section 1.3. Chapter 2 describes the state of practice and research, answering the first two subquestions. Passenger punctuality is discussed in its function as KPI in the Dutch railway sector as well as a general measure for service reliability. Several methods will be reviewed with emphasis on how (large) disruptions are handled. Inspired by the available methods, a new method is developed in chapter 3 that reconstructs the observed journey pattern in disrupted situations in order to determine the impact of the disruption on the passenger punctuality of that day. This method is applied to several sets of disruption cases in chapter 4. The results are analyzed in order to determine the influence of several factors on passenger behavior during disruptions. Chapter 5 recalls the key findings of the research and derives the policy implications. The limitations of this research are identified, which lead to directions for future research.

2

State of practice and research

In order to create a practical and scientific basis for this thesis, this chapter will provide more background information on the state of practice and research. In section 2.1 the passenger punctuality KPI as used by NS and ProRail is described in detail. Section 2.2 describes the state of research regarding methods for calculation of passenger punctuality.

2.1. Passenger punctuality KPI

This section answers the following subquestion:

> How is the passenger punctuality KPI currently defined, what is the reasoning behind it and what function does it fulfill?

The answer will be based on the documentation of passenger punctuality by NS and ProRail.

Philosophy

According to specialists, the definition of the passenger punctuality KPI is based on the philosophy that the transport agency made a promise that has to be fulfilled. In other words, NS and ProRail promise that a passenger can travel between station A and station B within a certain time from a given departure time. If that passenger could make that journey as promised, the journey can be considered as punctual. If that was not possible, the journey is considered as unpunctual.

KPI definition

Based on this philosophy, the passenger punctuality KPI is defined as the percentage of punctual journeys out of the total amount of journeys made. A punctual journey is defined as a journey with a delay lower than a certain threshold. Currently, the KPI is measured with thresholds of 5 and 15 minutes. For example, if a journey is made with a delay of 8 minutes, it is not punctual in the 5 minutes punctuality, but in the 15 minutes punctuality, it is punctual.

Function

The function of the passenger punctuality is twofold. Firstly, the KPI has a supervision function. In the Netherlands, NS is the railway operator and ProRail is the Infrastructure Manager on behalf of the Ministry of Infrastructure and Water Management. The exact role of these organizations is explained in appendix A. The NS has permission to operate trains on the main rail network (Hoofdrailnet, HRN) via a concession that is granted for the time period between 2015 and 2025 [3]. ProRail is charged with the infrastructure management via a concession over the same time period [4]. Part of these concessions is a review based on KPI's of which the passenger punctuality is one. Both ProRail and NS are ordered a fine if the targets set with respect to these KPI's are not accomplished. Therefore, NS and ProRail strive for keeping the passenger punctuality at a high level. Better insight into the properties of the KPI will be helpful in doing so.

The second function of the passenger punctuality is to help steering the organizations in satisfying their clients. When analyzing the KPI, the areas can be identified where more attention is needed.

This can be on all planning levels, from long-term strategic planning to real-time operational control. The product of this research may provide valuable insights into the impact of disruptions, so that the activities to decrease this impact can be better focused.

2.2. Passenger punctuality calculation methods

This section answers the second subquestion:

> How do the available methods for passenger punctuality take disruptions into account?

The goal of this section is to find available methods for passenger punctuality that may be helpful to find a more accurate value for passenger punctuality during disruptions. Therefore, the current calculation method by NS and ProRail will be analyzed, followed by the previously used method and other methods found in literature or at other public transport agencies. The required knowledge of each method is input, process, output and how it copes with disruptions. Concerning disruptions, four scenarios can be identified from a passengers' point of view: the journey is made as planned with or without a delay; a detour is taken by train or any other mode; the journey is postponed; the journey is cancelled. Based on these scenarios, a method can be assessed.

2.2.1. Passenger punctuality '17

Since 2017, passenger punctuality is calculated by the NS and ProRail using smart card data. This method will be called "Passenger punctuality '17". The input data for this method comes from CICO (Check-In Check-Out) data, the journey planner and the realization data. Based on the CICO data, frequent Origin-Destination (OD) pairs are determined. Then, the first module combines the frequent OD's and the data from the journey planner into promised journeys. For the promised journeys, the realization is determined using the realization data. Journeys that could not be made, can be rescheduled in module 3 which is not in place yet. When the realization for all promised journeys is known, they are combined with the CICO data. Based on this combination, a data set is generated. Figure 2.1 shows a simplified flow chart of this method.

Determine frequent OD's

Input: CICO data
Process: every quarter of a year, the frequent OD's are extracted from the CICO data. All journeys on the 100 days before determination are taken into account. A frequent OD is defined as an OD that is traveled at least a hundred times and on at least 20 days of these 100 days.
Output: frequent OD's

Module 1 // Request promised journeys

Input: frequent OD's, journey planner
Process: for the frequent OD's, all advised journeys from the journey planner are requested for the time period the punctuality is calculated for. Every journey is divided in journey parts if one or more transfers are required.
Output: promised journeys, journey parts

Module 2 // Determine realization

Input: promised journeys, journey parts, realized train movements, *rescheduled journeys, journey parts*
Process: the execution of the promised journey is determined per journey part. If there are no deviations in all parts of a journey, the journey is marked 'realized'. If there are deviations on one or more journey parts, it is first determined if the train on this part departed with a delay of 15 minutes or more. If this is the case, the whole journey is left for rescheduling. If the departure delay is less than 15 minutes, the next question is if the train reached the destination of the journey part. If this is not the case, the journey needs to be rescheduled. If the train reached the destination of the journey part and it is the final journey part, the journey is realized. If the particular journey part is not the final part, it must be determined if the transfer could be made. If this was possible, the next journey part is controlled. If this was not possible, the journey must be rescheduled. A flowchart of this process can be found in 2.2.
Output: realized journeys

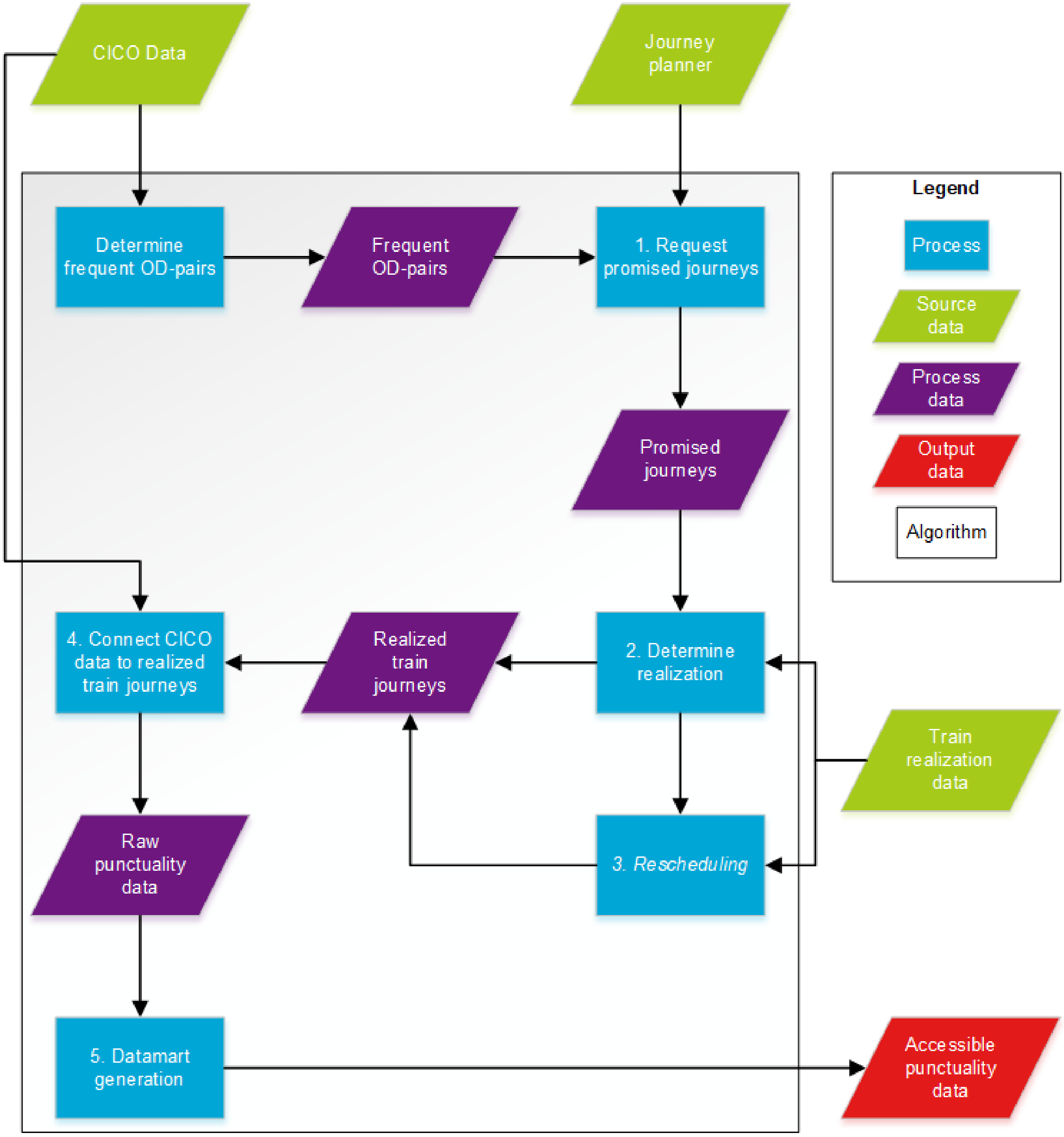


Figure 2.1: Simplified flow chart passenger punctuality

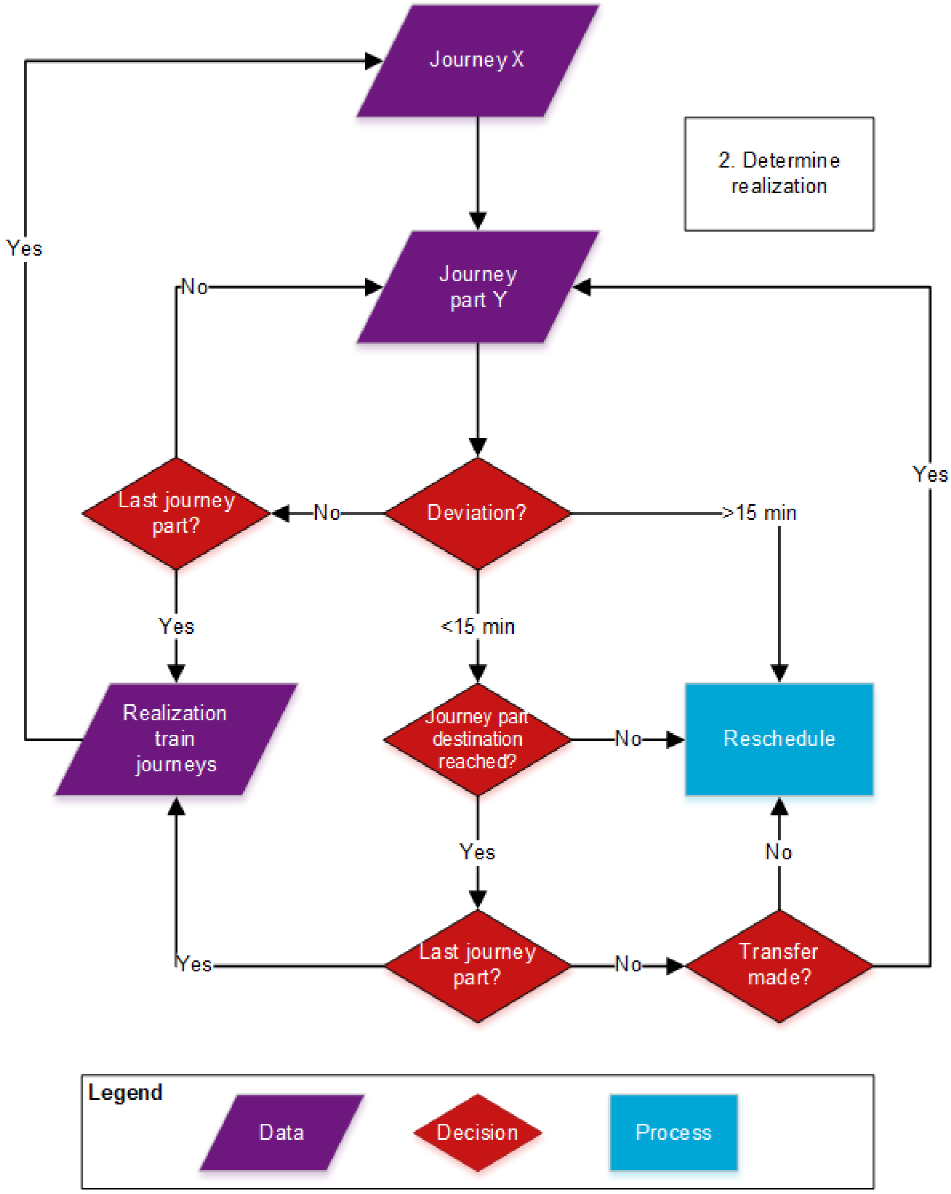


Figure 2.2: Flowchart of module 2. Determine realization

Module 3 // Rescheduling
Input: unrealized journeys
Process: unrealized journeys are rescheduled based on their planned departure time and the train realization data
Output: alternative realization
Remark: this module is not in place (yet), because first, it is analyzed how the KPI functions in its current form.

Module 4 // Connect journeys made to realized journeys
Input: CICO data, operator realized journeys, *boarding/alighting margins*
Process: every journey from the CICO data is connected to a realized journey based on check-in station and time and check-out station. For each journey, the first possible promised journey is taken. If the journey was not realized, the arrival time is defined as the check-out time minus an alighting margin (i.e. the time between alighting and check-out for an average passenger, station specific).
Output: passenger realized journeys

Module 5 // Dataset generation
Input: passenger realized journeys
Process: a new dataset is generated including for every passenger journey the journey ID, promised arrival time, realized arrival time, amount of delay minutes, delay reason and delay category. From this dataset, the passenger punctuality can be calculated.
Output: dataset

Punctuality calculation
Given the amount of delay minutes, it can be determined if a passenger had a delay of more than 5 or 15 minutes. These thresholds are the intervals for which the passenger punctuality is calculated. The punctuality is defined as the percentage of passengers that reached their final destination with a delay of less than 5 or 15 minutes. It is calculated by equation 2.1.

$$PP_5 = \frac{P_{delay<5}}{P_{total}} \tag{2.1}$$

Where PP_5 is the 5 minutes passenger punctuality, $P_{delay<5}$ is the amount of passengers with a delay smaller than 5 minutes and P_{total} is the total number of passengers. The 15 minutes passenger punctuality is calculated in the same way, but with the amount of passengers with a delay smaller than 15 minutes.

Disruption handling
Concerning disruptions, this method only captures passengers that follow their planned route and arrive with or without a delay. If the third module for rescheduling would be in place, passengers taking a detour by train would also be captured. Currently, no passengers taking a detour are captured, nor passengers postponing or canceling their journey. These passengers may appear in the data as punctual. Passengers that cancel their journey do not appear in the data at all, although they probably experienced hindrance from the disruption.

2.2.2. Passenger punctuality '15

The "Passenger punctuality '15" is the calculation method of passenger punctuality previously used by ProRail and NS. This method is based on demand prognoses in combination with the realized timetable at 35 measuring stations. The calculation of the passenger punctuality is based on equation 2.2.

$$PP'15 = \frac{A_{realized} + T_{realized}}{A_{planned} + T_{Planned}} \tag{2.2}$$

Here, PP is the passenger punctuality, $A_{planned}$ and $A_{realized}$ are the planned and realized passenger arrivals, $T_{planned}$ and $T_{realized}$ are the planned and realized transfers. These variables are explained in the following paragraphs.

Planned passenger arrivals
The planned passenger arrivals is the number of train arrivals on 35 measuring stations weighted with the expected number of passengers per train. The prognoses are based on passenger counts by conductors. If there is no prognosis for a certain train line, a default value of 150 passengers is used. The way the prognoses are made is clearly dubious, since they are not based on subjective measurements, but instead on estimations by conductors.

Realized passenger arrivals
The realized passenger arrivals is the number of passenger arrivals that is realized within 5 minutes from the planned arrival time. Train arrival times are measured at 35 stations. The number of realized passenger arrivals is the sum of trains that arrived within 5 minutes from the planned arrival time, weighted with the number of passengers on those trains. A large drawback of the methods for calculating the planned and realized passenger arrivals is that if one journey passes multiple measuring stations, it is also taken into account multiple times. E.g. if a train makes a journey from Rotterdam to Utrecht, it passes Gouda. The passengers on this train are counted both in Gouda and in Utrecht. Besides, the amount of 35 measuring stations is far beneath the total of 400 railway stations in the network.

Planned transfers
Planned transfers is the number of executed connections weighted with the number of passengers transferring. Connections are measured if they meet the following conditions:

- More than 300 passengers per working day make the transfer, according to the prognoses;
- The planned transfer time is 7 minutes or less;
- The planned transfer time is at least the design norm, which is based on the number of platforms that need to be crossed to make the transfer.

The prognosis of planned transfers is made by taking a percentage of arriving passengers that is expected to transfer. If there is no prognosis available, a default value of 1 planned transfer is used.

Realized transfers
Realized transfers is the number of planned transfers that could be made in the realized timetable, according to the conditions as discussed in the previous paragraph. If one of the trains in a connection did not run, the connection is considered as not executed and left out of the punctuality calculation. This is another drawback of this method, because punctuality is overestimated, since unrealized transfers are left out of the calculation.

Disruption handling
Regarding disruptions, this method has both benefits and drawbacks. The calculation is based on passenger prognoses instead of observed demand on a disrupted day. The benefit of this method is that passengers that take a detour, postpone or cancel their trip are taken into account in the passenger punctuality. However, it is not known what actually happened to the passenger. A large drawback is that this method is relatively inaccurate due to the limited amount of measuring stations and the manual passenger counts on which the prognoses are based. Still, the idea of using expected passenger demand may be useful for determination of the impact of disruptions on passenger punctuality.

2.2.3. Rail Net Denmark passenger delay model
The Danish railways have an extensive history when it comes to delay modeling. Nielsen et al. [20] reviews three generations of passenger delay models and develops a fourth. In the 1.5 generation, a passenger delay model by Ildensborg-Hansen [19] is discussed.

Calculation method
In the model by Ildensborg-Hansen, the passenger delay is determined by assigning a time-space OD-matrix to the realized timetable. It is assumed that passengers arrive according to the normal timetable. From this point, full knowledge of the delays in the network is assumed, so passengers are assigned to the optimal route. The total delay is obtained by taking the difference between the planned and realized arrival time, weighted by the demand in the OD-matrix.

Disruption handling

Similar to Passenger punctuality '15, this method uses normal passenger demand to calculate delays. This way, passengers that take a detour, postpone or cancel their trip, are taken into account in the passenger punctuality. By rescheduling these trips based on the realized timetable, it is assumed that all passengers make their trip by taking a detour (or postponing if that is the fastest option). Rescheduling is a good option, especially when assuming that passengers arrive at the station at the planned arrival time.

2.2.4. Method by Uniman et al.

Another method for passenger punctuality measurement was developed by Uniman et al. [25]. This method is based on AFC data and applied to the London Underground. The measure is based on the buffer time a passenger should add to the normal travel time in order to obtain a reliable forecast of the travel time.

Calculation method

This Reliability Buffer Time (RBT) is calculated for a certain time period at OD level using equation 2.3.

$$RBT_{OD} = (95th \text{ percentile travel time} - \text{median travel time}) \tag{2.3}$$

Thus, for a certain period the travel times are taken for a given OD-pair. The RBT is obtained by taking the difference between the 95th and 50th percentile of these travel times.

The RBT can be obtained at line level using equation 2.4.

$$RBT_{line} = \frac{\sum_{OD \in line} Vol_{OD} * RBT_{OD}}{\sum_{OD \in line} Vol_{OD}} \tag{2.4}$$

This equation gives the weighted average of the RBT at OD level.

Uniman et al. [25] realized that reliability is strongly affected by incidents, so another measure was developed, namely the Excess Reliability Buffer Time. It is defined as the amount of RBT that is caused by disruptions and calculated using equation 2.5.

$$ERBT = RBT_{overall} - RBT_{typical} \tag{2.5}$$

Where $RBT_{overall}$ represents the overall RBT and $RBT_{typical}$ is the RBT with exception of the disrupted days. The latter is the baseline RBT.

Disruption handling

This method provides a way to find the impact of disruptions on service reliability. However, it assumes that the RBT on disrupted day is reliable, making the same assumptions as those that are made in the Passenger punctuality '17. Since this method also uses AFC data, it has exactly the same problems.

Table 2.1: Systematic comparison of available passenger-oriented service reliability metrics

Method	Data source	Calculation base	Outcome	Disruption handling
Passenger punctuality '17	Smart card	Realization first possible promised journey	Passenger punctuality interval	Only journeys fully made by NS trains
Passenger punctuality '15	Manual count	Realized arrivals and transfers	Passenger punctuality interval	Assign expected demand to the realized timetable
Railnet Denmark	Automatic count	Route choice model	Passenger delay	Assign expected demand to the realized timetable
Uniman et al.	Smart card	Travel time percentiles between stations	Reliability Buffer Time	Only journeys that are fully made by underground

2.3. Conclusion

The passenger punctuality KPI is built upon the philosophy of fulfilling the promise that is made to the passenger. This means that a passenger which could not make its journey as planned can be considered as unpunctual. The actual definition of the passenger punctuality KPI measures punctuality in terms of delays greater than 5 and 15 minutes. The function of the KPI is two-sided: on the one hand, it is a supervision measure. On the other hand it has a steering function.

Several methods for quantification of service reliability have been reviewed. The results are summarized in table 2.1. The method by Uniman et al. also uses smart card data, but has also no solution to the disruptions problem. Other methods re-assign the expected demand of an undisrupted day to the realized timetable on the disrupted day. This may be a suitable method to model passenger delays more accurate during disruptions. It must then be assumed that on a disrupted day, passengers arrive at the station at their planned departure time. This method is still restricted to the rail network, while it is expected that, during disruptions, passengers will also use other modes to reach their destinations. Therefore, it would be interesting to incorporate other modes in the re-assignment of the demand.

Another conclusion that can be drawn is that there is no standard way of defining passenger punctuality; each researcher and public transport operator handles its own definition of it. This fact raises the question what a good definition of passenger punctuality is and which of the definitions is best. These questions are beyond the scope of this research, but it may be worth the effort to find an answer to these questions in future research.

3
Method

The following subquestion will be answered in this chapter:

> How can passenger hindrance be determined during disruptions, concerning detoured, postponed and cancelled trips?

This chapter describes the method that will be used to find the impact of disruptions on passenger punctuality as well as the data that is required. First, the impact assessment approach will be described in section 3.1. The data required for this method are specified in section 3.2. Section 3.4 concludes with a short summary.

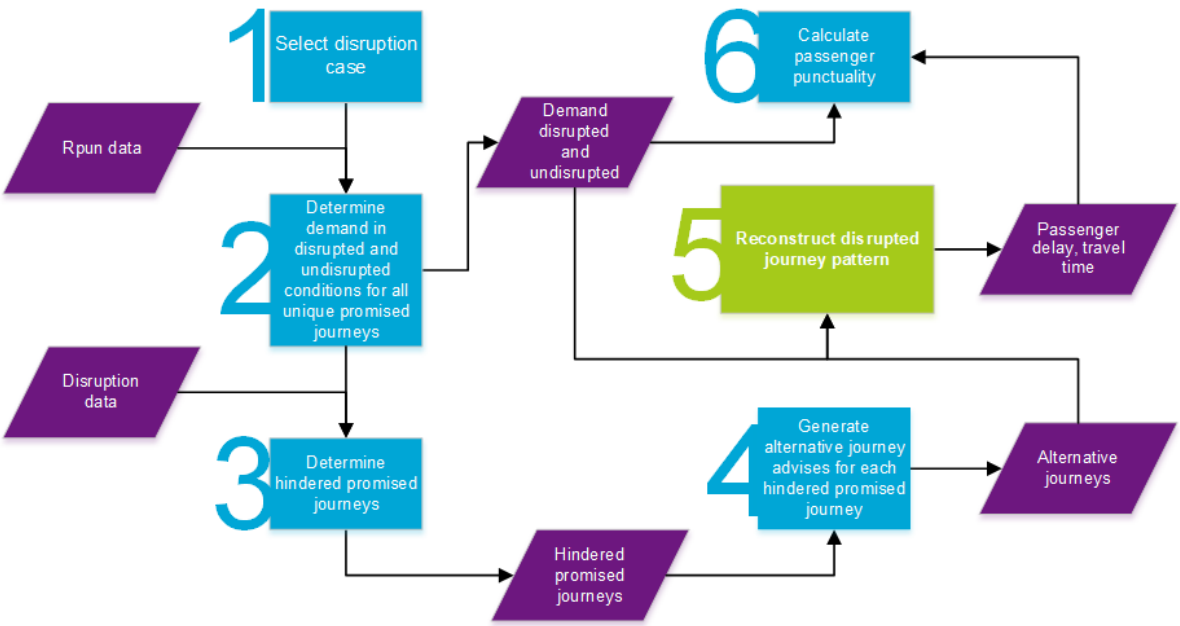


Figure 3.1: Impact assessment approach

3.1. Impact assessment approach

This section describes the approach that is followed in order to come to an estimation of the impact of disruptions on passenger punctuality that is not accounted for in the current calculation method. An overview is given in the flowchart in figure 3.1. The central part of the approach is step 5, where the observed journey pattern of the disrupted day will be reconstructed. The steps 1-4 prepare and generate the data that is needed for this process. Step 6 translates the output of step 5 to insightful results. Because the center of the method is the reconstruction of the disrupted journey pattern, this method will be called the Journey Pattern Reconstruction (JPR) method in the remainder of this report. The majority of the data operations will be performed using Python. Where this is not the case, it is clearly indicated. All steps are automated as far as possible. Only at switch points between Python and other applications, some manual actions are required. Other applications used are Java and R.

3.1.1. Case selection

A disruption case is chosen that is expected to have considerable impact on passenger punctuality that is not measured in the current calculation method. Disruptions can be described by characteristics like location, time of the day and duration. Cases must be selected that differ at only one characteristic, so that the influence of that characteristic on the impact of disruptions on punctuality can be determined. Per characteristic, three cases will be studied in order to find possible relations. In order to confirm these findings, more cases need to be examined.

3.1.2. Determine demand in disrupted and undisrupted conditions for all promised journeys

The passenger punctuality data is requested for the disruption day and the same day in the four weeks before and after if possible and reasonable (otherwise, shifting a few weeks is allowed). The latter are called peer days and are used to determine the expected demand on the disrupted day. The punctuality data contains all information regarding punctuality per passenger journey, see section 3.2.2. The punctuality data for the disruption day represents the observed demand. The peer days are used to deduct the expected demand for the undisrupted situation. The data are grouped by promised journey in order to determine how many passengers are observed on the disrupted day and on the peer days. The amount of passengers on the disrupted day is defined as the observed demand in disturbed conditions, $q^{disturbed}$. Then, the expected demand in undisturbed conditions, $\hat{q}^{undisturbed}$, is calculated by taking the median of the demand on the peer days. $q^{disturbed}$ and $\hat{q}^{undisturbed}$ are determined for each promised journey on which passengers are observed on at least one of the peer days or the disruption day.

3.1.3. Determine hindered promised journeys

The output of this step should be a list of promised journeys that could not be made due to the disruption. This list is used in step 4 to generate alternative journeys. The process of selecting hindered promised journeys is displayed in figure 3.2.

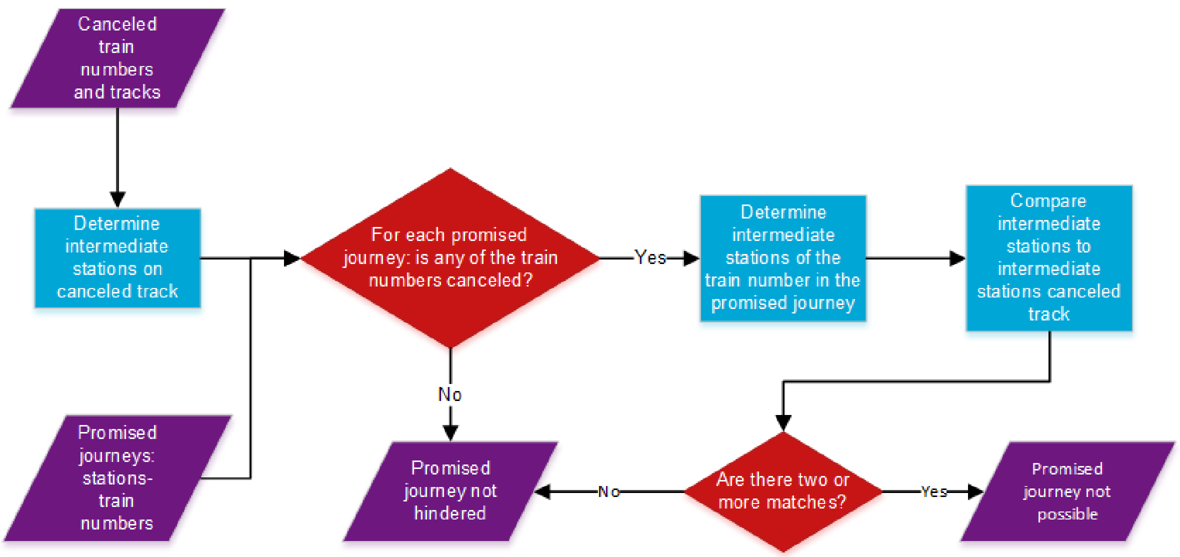


Figure 3.2: Hindered promised journeys selection process

The disruption data is requested for the selected case. It is desired to know the canceled train numbers and corresponding tracks in order to determine the affected promised journeys. A promised journey is described by an origin station, a destination station, transfer stations (if any) and train numbers between the stations. Using the timetable, it can be determined which stations a train would have passed on the disrupted track part. Then, for each promised journey it is checked if there if any of the train numbers used was canceled on the disrupted day. If this is true, the intermediate stations of this train number are determined for the promised journey. These stations are compared to the intermediate stations of the disrupted track part. If there are two or more matches, it can be concluded that the promised journey has been hindered by the disruption. The result of these steps is a list of affected promised journeys including their origin, destination and departure time.

3.1.4. Generate alternative journey advises for each hindered promised journey

In order to be able to make a reconstruction of the observed journey pattern on the disrupted day, it is required to know what alternatives passengers have between their origin and destination from their planned departure time. Therefore, alternative journeys are generated for each hindered promised journey. This is done with the help of the open source application OpenTripPlanner (OTP) based on transit data from the General Transit Feed Specification (GTFS) of the Netherlands. This is a format in which most public transport operators of the Netherlands publish their timetables, which is free to use. By excluding the disrupted links from the planning network, alternative journey advises can be generated. Excluding links from the GTFS data is done with the help of the open-source GTFS Transformer application by OneBusAway [10]. Requests to OTP are carried out by an R function, found at [9] and edited to suit better to the specific needs of this research. Originally, this function only returned some trip information. It has been edited to return all trip information in JSON format, so that it can be exported to Python and further processed there. By default, the OTP generates three advises per request, including the most evident travel options. The result of this step is a set of three alternatives for each hindered promised journey.

3.1.5. Reconstruct observed disrupted journey pattern

The observed disrupted journey pattern is reconstructed by assigning the expected demand in undisrupted conditions per hindered journey to the alternatives that were generated in step 3. The option to cancel the whole journey is added to the set of alternatives per hindered journey. It is assumed that each passenger has either chosen one of the alternative travel options or canceled its trip.

Now, the expected demand of the hindered promised journeys must be distributed over the alternatives in such a way that the differences between the resulting journey pattern and the observed journey pattern on the disrupted day are minimized. In order to compare the reconstruction to the observation, the alternative journeys must be connected to existing promised journeys. For example: if a journey is partly made by bus due to the disruption, only the train part of this journey appears in the passenger data. Another example is if a passenger decides to take a detour to the final destination. It is then assumed that the passenger is already checked in at the departure time of the original journey, so a passenger which chose this alternative appears in the passenger data with the original promised journey. Therefore, it must be investigated for each alternative travel option how a passenger which took this option has appeared in the passenger data. The full process of connecting the alternative travel options to existing promised journeys is displayed in figure 3.3.

Some assumptions are made in this process that may affect the quality of the model. The first is that passengers that take a detour are expected to check in at their planned departure time. However, especially during larger disruptions, there are also passengers that are informed of the disruption before they depart to the station. In this case, it is not expected that a passenger checks in at its planned departure time, but this is assumed in the model for simplicity reasons.

The second assumption is that passengers check out and in again when they postpone their journey when the disruption is almost solved, even when the delay is only 15 minutes. A passenger which is delayed by only 15 minutes probably checks in at its planned departure time and waits till the first train after the disruption runs. The result of this assumption is that passengers are assigned to the promised journey of the postponed journey instead of their planned journey. The precise effect of these assumptions on the quality of the model is unknown. More knowledge regarding information availability and accessibility and passenger behavior is needed to get insight into this effect.

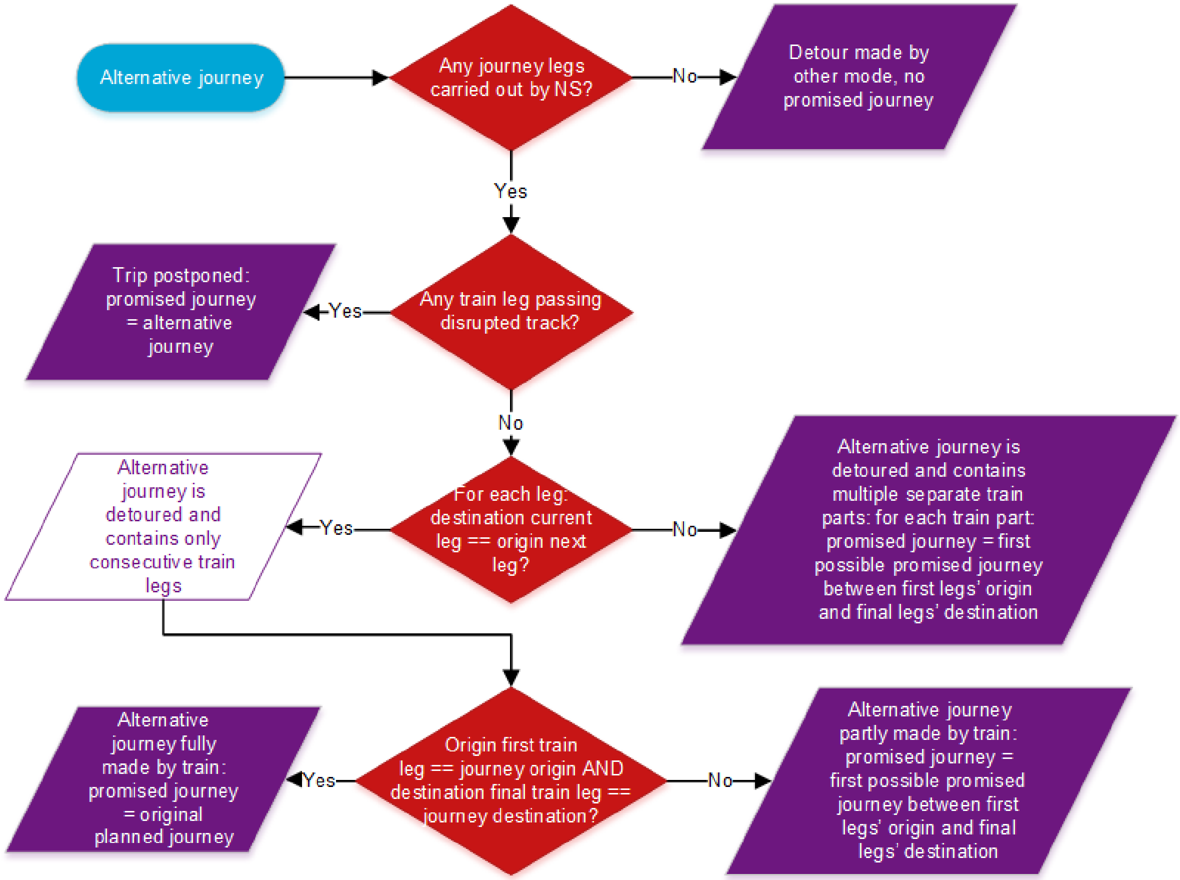


Figure 3.3: Connecting alternative journeys to existing promised journeys

A linear program is formulated in order to make the reconstruction of the observed journey pattern. The following variables have been used in the problem formulation.

Variable	Description
$\hat{\mathbf{q}}^{reconstruction}$	Decision variable, assigned demand per alternative
$\hat{\mathbf{q}}^{alternative,undisrupted}$	Demand per alternative promised journey in undisturbed conditions, 0 for hindered promised journeys
$\mathbf{q}^{disrupted}$	Demand per alternative promised journey in disturbed conditions
$\hat{\mathbf{q}}^{hindered,undisrupted}$	Expected undisrupted demand per hindered promised journey
$T^{alternative}$	Transformation matrix to transform the assigned demand per alternative to the assigned demand per unique alternative promised journey
$T^{hindered}$	Transformation matrix aggregate the assigned demand per alternative to the assigned demand per hindered promised journey
N	Number of unique alternative promised journeys

The problem can be described mathematically with the following set of equations.

$$\min |\Delta| = \sum_{i=1}^{N} |(T^{alternative} * \hat{\mathbf{q}}^{reconstruction})_i + \hat{\mathbf{q}}_i^{alternative,undisrupted} - \mathbf{q}_i^{disrupted}| \tag{3.1}$$

$$\text{subject to } (T^{hindered} * \hat{\mathbf{q}}^{reconstruction})_i = \hat{\mathbf{q}}_i^{hindered,undisrupted} \ \forall\ i \tag{3.2}$$

$$\hat{\mathbf{q}}_i^{reconstruction} \geq 0 \ \forall\ i \tag{3.3}$$

The problem formulation sounds as follows. For each hindered promised journey, there is a set of four alternatives, including the alternative to cancel the trip. The expected demand in undisrupted conditions for these promised journeys must be assigned to the alternatives. For example: the hindered promised journey between Arnhem and Utrecht of 7:31 has an expected undisrupted demand of 80 passengers. There are four alternatives for this journey. The sum of the number of passengers that is assigned to each of these alternatives must be equal to 80. This is also the first constraint of the problem as described in equation 3.2. In this equation, the left hand side calculates the sum of assigned passengers per hindered promised journey. This number must be equal to the expected demand for that hindered promised journey in undisrupted conditions.

Now, the goal is to assign the expected undisrupted demand to the alternatives in such a way that it creates a new journey pattern that is a reconstruction of the observed journey pattern of the disrupted day. Therefore, the alternative journeys must be aggregated on unique existing promised journeys on which they will appear in the punctuality data. For example: the journeys between Arnhem and Utrecht of 7:31 and 7:46 can both be postponed till 8:31. This is one alternative for two hindered promised journeys. Therefore, the passengers that are assigned to this alternative from any hindered promised journey must be added up. Then, the demand that was already expected on this promised journey must also be added. Not only the passengers that postponed their trip between Arnhem and Utrecht till 8:31 will take this option, but also the passengers that already planned to take this train. When these steps are taken, the reconstruction of the journey pattern is complete and can be compared to the observed journey pattern of the disrupted day. For each unique alternative promised journey, the observed demand of the disrupted day is subtracted from the reconstructed demand. The sum of the absolutes of these values is taken as measure for the difference between the observed and the reconstructed journey pattern. The objective function in equation 3.1 tells to minimize this value.

The second constraint in equation 3.3 is the non-negativity constraint that forces all decision variables to be non negative.

Because passengers are not divisible, it would be logical to constrain the decision variables to be integer. However, this does not yield feasible solutions, so the decision variables will be floats and be rounded later on.

Several solver packages for solving linear programs are available in Python via the CVXPY package [8]. Two solvers have been tested: GLPK and ECOS_BB. It appears that, when using the GLPK solver, a larger share of the hindered passengers emerges in the results, while the optimization values are equal. Therefore, it has been decided to use the GLPK solver.

In the process that linked the alternative journeys to the existing promised journeys, it was already determined if an alternative was to detour or postpone a journey. After the reconstruction, it can be directly calculated how much passengers took a detour, postponed or canceled their trip. This is the basis for the recalculation of the passenger punctuality.

3.1.6. Passenger punctuality and delay calculation

Based on the results of the journey pattern reconstruction, the passenger punctuality percentage can be recalculated. The recalculation equation is formulated in equation 3.4. In this equation, q stands for the observed numbers in the current punctuality calculation and r stands for the reconstructed numbers. The base for the recalculation equation is formed by the normal punctuality calculation: number of punctual passengers divided by the total number of passengers for a certain time interval. The number of punctual passengers is corrected by subtracting the number of passengers that detoured or postponed their trip and is registered on a punctual promised journey; passengers that are already registered unpunctual should not be counted again. The total number of passengers is corrected by adding the number of passengers that is detouring their trip only by other modes or canceling. Then, the number of passengers that took a detour with two separate train parts must be subtracted from the total number of passengers, so that they are taken into account once instead of twice.

$$pp^{recalculated} = \frac{q^{punctual} - r^{detour,punctual} - r^{postpone,punctual}}{q^{total} + r^{canceling} + r^{detour,othermode} - r^{detour,double}} \tag{3.4}$$

In this calculation, postponing and canceling are considered unpunctual. This is in line with the philosophy of the passenger punctuality KPI, see section 2.1; the promised journey these passengers planned to take could not be made. With the outcome of this equation, the most important result is obtained. Other results that are suitable for analysis can be found in the distribution of passengers over alternatives.

After recalculating the punctuality of the disrupted day, the delays can be deducted from the alternative arrival times, planned departure times and number of assigned passengers per alternative journey. Based on this, the total passenger delay, average delay per passenger and societal costs can be calculated. Then, the delays can be distributed over intervals of 5 minutes in order to gain insight into the delay distribution.

3.1.7. Calculating disruption impact already captured

In order to know the total size of the impact of disruptions on passenger punctuality, an estimation must be made of the part of the impact that is already captured in the current calculation method. In order to make this estimation, a method is used that is similar to the method that was used to detect hindered promised journeys in section 3.1.3. There are two differences. Here, all trains that are directly affected by the obstruction measure are taken into account. Besides canceled trains, these can also be returned or rerouted trains. The other difference is that only the disrupted day is taken into account, because we want to know the number of passengers that is already registered unpunctual during the disruption. With these changes, the flowchart in figure 3.2 is walked through. The result is a list of hindered promised journeys on the disrupted day including their total delay. By filtering the journeys with a delay larger than 5 minutes, it can be determined what part of the impact of disruptions on passenger punctuality is already captured in the current calculation method. An estimation of the passenger punctuality with these journeys excluded is made by adding them to the nominator of the punctuality equation. This equation is displayed in equation 3.5 where $q^{punctual}$ is the number of passengers that is counted punctual by the current calculation method. The number of passengers that is counted unpunctual due to the disruption, $d^{unpunctual}$, is added. The sum of these is divided by the total number of passengers on the disrupted day, q^{total}.

$$pp^{exclude\_disruption} = \frac{q^{punctual} + d^{unpunctual}}{q^{total}} \tag{3.5}$$

3.2. Required data

This section introduces the available data sources, which are: disruption data, passenger punctuality data, and the planned timetable.

3.2.1. Disruption data

The first data source contains the disruption information. These data are put together from the obstruction measure (versperringsmaatregel, VSM) database and the planned timetable. Only two columns are required: the cancelled train number and the cancelled track. See table 3.1.

Table 3.1: Disruption data

Train number	Track	Action
36xx	Ah-Zp	Cancel
76xx	Ah-Dr	Reroute
...	...	

The first two entries of the train number represent the train series. In this case, the first train series is the 3600 between Zwolle and Den Bosch via Arnhem and Zutphen. The last two entries represent the index number of a specific train. The directions of the train are divided by odd and even numbers, so the 3601 runs in the opposite direction of the 3602. This way, each train has a unique train number.

3.2.2. Passenger punctuality data

The passenger punctuality database contains all trip information for a sufficient time period, including the punctuality according to the current calculation method. Passenger punctuality is often abbreviated to *rpun* in coding environments. Table 3.2 gives an overview of the columns that are used in the model.

The itinerary column gives the origin station, destination station, transfer stations if any and the train numbers that are used between the stations. Besides that, the table compares the promised departure and arrival time to the realized departure and arrival time and gives the check-in and -out times.

Table 3.2: Passenger punctuality

Itinerary	Origin	Destination	Planned departure time	Delay
Nm-3022-Ah	Nm	Ah	7:43	4.7
Ut-539-Zl-1839-Mp	Ut	Mp	11:48	6.3
...	...	...	...	...

3.2.3. Planned timetable

The planned timetable contains all train numbers that are planned for a day. For these train numbers, all control points are listed. See an example of the relevant columns in table 3.3. The displayed train number is 2230 between Amsterdam central station and Vlissingen.

Table 3.3: Planned timetable

Train number	Control point
2230	Asd
	Sgbr
	...
	Hlm
	Zspl
	...
	Vs
...	...

3.2.4. GTFS

The process of generating alternative journey advises is based on Dutch public transport timetables published in General Transit Feed Specification (GTFS) format. This is a format developed by Google to be a common format between public transport operators and developers [5]. Most Dutch transit agencies also publish their timetables in this format. These data are used as input for the OpenTripPlanner. The GTFS data is in fact a set of eight files that each contain different data. There are files that define the agencies, the calendar dates for which the timetable is used, additional feed data, routes, stops and trips. These data are combined into one file that keeps all intermediate stops and stop times.

3.3. Example method walk-through

One example case is worked out in order to make the developed method more imitable. This is the disruption case between Utrecht and Arnhem that took place on April 12, 2018. Here, the full track was obstructed due to a collision with a person. Because this is an example case, there is no further reasoning behind the case selection.

Determine demand First, the passenger demand per promised journey for the disrupted day is determined in disrupted as well as in undisrupted conditions. Therefore, the passenger punctuality data is obtained for the disrupted day, including the same day in the four weeks before and the four weeks after. These data are grouped by promised journey in order to determine the passenger demand per promised journey per day. The expected demand in undisrupted conditions is now obtained by taking the median of the demand of the peer days. The observed demand on the disrupted day is already obtained by grouping the data.

Determine hindered promised journeys Next, it is determined per promised journey if it was hindered by the disruption. This is done by taking the canceled train numbers and comparing them to the train numbers used in a promised journey. Each promised journey contains a deducted itinerary existing of stations and train numbers used between the stations, for example: 'Ed-3123-Ah' for a journey between Ede-Wageningen and Arnhem. In this case, train number 3123 has been canceled from

Utrecht. Therefore, the promised journey with this itinerary must be further investigated. In order to do that, the origin station, destination station and train number are combined with the timetable data to obtain the intermediate waypoints. This is also done for the canceled train for the specific track part. Then, both sets of start stations, end stations and intermediate waypoints are compared. If there are two or more matches, it is concluded that this promised journey is affected by the disruption. If there is only one match, the destination station of the journey is equal to the first station of the canceled track, so the promised journey is not affected. The result of this step is a list of hindered promised journeys, including their demands.

The list of hindered promised journeys is prepared for export to R for generating alternative journey advises. The OpenTripPlanner uses lat/lon coordinates for specifying origin and destination locations. The station coordinates are added from an available list of station locations.

Generate alternative journey advises Before alternative journey advises can be generated, the GTFS data must be obtained and edited. These data are freely accessible via the internet. In order to exclude the canceled trains and tracks from the journey planner, the GTFS data must be edited. This is done using the open-source application OneBusAway [10]. This application takes the following query and uses it to trim the trips.

```
{”op”:”trim_trip”, ”match”:{”file”:”trips.txt”, ”trip_id”:”77999005”},
”to_stop_id”:”54974”, ”from_stop_id”:”381627”}
```

The trip_id and stop_id's are found in the stop_time file in the GTFS dataset based on the train numbers and station names. The GTFS transformer application runs in Java and returns an edited GTFS dataset based on the modification queries that are feeded into it.

At this point, both the demand data and the GTFS data are ready for generating alternative journeys. This is done using an online available R script [9] that automates the requests to the locally launched OTP client. The original R script translates the OTP output to JSON format and deducts the most important journey information. This script is edited so that the output in JSON format is returned. The resulting JSON string contains all relevant information about the three journey alternatives, from general departure and arrival times to specific trip leg information like leg origins, destinations and trip numbers (both for train and for other modes). This output can be used in Python to extract the journey information needed.

Reconstruct observed journey pattern In Python, an alternatives list is created that takes each entry from the list with hindered promised journeys four times; for each hindered promised journey, there are three journey alternatives plus one canceling alternative. For each of these alternative journey entries, the promised journey(s) are added on which an alternative journey is expected to appear in the punctuality data. This is done following the flow chart in figure 3.3, which is expected to speak for itself. At the same time, two data fields are added that indicate if a journey is postponed or if a journey is made by only other modes than NS trains (in the latter case, passengers will not appear in the punctuality data). The last data field that is added is the realized arrival time of the alternative journey to enable us to calculate the final delay.

Again, an example from the Arnhem-Utrecht case is taken to make things a bit clearer: three alternative journeys have been generated for the hindered promised journey between Arnhem and Utrecht at 06:31 am. A summary of these alternatives is displayed in the table below. To start with the first

Departure time	Arrival time	Duration [min]	Itinerary	Modes
06:51	08:16	85	Ah-3621-Ht-3922-Ut	NS train, NS train
06:40	08:24	104	Ah-3614-Dv-1722-Ut	NS train, NS train
09:45	10:21	36	Ah-3130-Ut	NS train

alternative journey and walk through the process of connecting it to an existing promised journey, it is first asked if any of the journey legs is carried out by NS. This is the case, so the next question is if any of the train legs traverses the disrupted track. Here, it is checked if the train numbers belong to a series that has been canceled. If so, it is checked if this trip leg indeed traverses the track part that was obstructed (earlier). If that is true, it is assumed that the journey is postponed. If not, as in this case (none of the train numbers belong to a series that has been canceled), it is checked for each train leg if the destination of that train leg is the same as the origin of the next train leg. If not, it is concluded that there are two separate train parts in this alternative journey: some other mode(s), e.g. the bus have been used to connect those two train legs. If, for all train legs, the destination is the same as the origin of the next train leg, the alternative appears to be detoured and to contain only consecutive train legs, which is the case here. This does not yet mean that no other modes have been used in this journey, but that the train legs in this alternative are consecutive. The next question is, thus, if the full journey has been made by train: is the origin of the first train leg the same as the journeys' origin and is this also true for the final train legs' destination? Then, the journey is fully made by train, which is true in this case. Then, the promised journey on which a passenger appears in the punctuality data on the disrupted day is expected to be the original planned journey, since it is assumed that passengers arrive at their planned departure time. If the journey is not fully made by train, the promised journey becomes the first possible promised journey between the first train legs' origin and the final train legs' destination. For the first alternative journey in this example, the promised journey on which it will appear in the punctuality data is the journey between Arnhem and Utrecht at 06:31 am. For the second alternative journey, it is roughly the same: it contains trip legs carried out by NS, the train legs do not traverse the disrupted track part, all NS train legs are consecutive and the journey is fully carried out by NS. Therefore, this alternative is also captured in the data on the promised journey between Arnhem and Utrecht at 06:31 am. For the third example, things become different: there is a journey leg carried out by NS, but this train leg traverses the disrupted track part. Therefore, it is concluded that this journey has been postponed and that the passenger checked in again at the planned departure time of the postponed journey. Therefore, the promised journey connected to this alternative will be the journey between Arnhem and Utrecht at 09:45 am. For the connected promised journeys, it is also looked up how many passengers have been observed on the disrupted day and how many were expected in the undisrupted situation. If the promised journey to which the alternative journey is connected is hindered on the disrupted day, the expected passenger demand is set to zero; in the reconstruction of the observed journey pattern, passengers that are assigned to this alternative will be added to this value, so it can not be equal to the original expected demand. The process as explained above yields the following results.

Origin	**Destination**	**Departure time**	**Realized arrival time**	**Observed disrupted**	**Expected undisrupted**	**Post-poned**	**Other mode**
Arnhem	Utrecht	06:31	08:16	9	0	False	False
Arnhem	Utrecht	06:31	08:24	9	0	False	False
Arnhem	Utrecht	09:46	10:21	49	34	True	False

Next, the promised journeys that are connected to the alternative journeys are filtered so that a list of unique promised journeys remains. This is done because multiple alternatives may appear in the punctuality data with the same promised journey. In the reconstruction, the passengers that take these alternatives must be added up.

Now, the input matrices for the optimization program can be created. The first is the vector with decision variables for all alternative journeys, which has a length of 13992 entries in this case. The second is a matrix to transform the decision variables to the expected demand. This is a binary matrix that consists of all alternatives in the rows and all hindered promised journeys in the columns. There are ones at the places where the alternative belongs to the hindered promised journey. The next vector represents the expected demand on an undisrupted day for these hindered promised journeys. Then, there is another vector containing the expected undisrupted demand for all unique promised journeys from the alternatives, with zeros for hindered promised journeys. There is also a corresponding transformation matrix for this vector. The last vector contains the observed disrupted journeys for the unique promised journeys from the alternatives.

With these matrices, the linear optimization program is formulated as described in section 3.1.5. Finally, the journey patterns, delays and passenger punctuality can be calculated according to section 3.1.6.

3.4. Conclusion

A method has been developed that reconstructs the observed journey pattern in order to derive passenger travel behavior. This is done by taking all passengers that are hindered by a disruption and generating alternatives for them. Then it is determined if a passenger chose a specific alternative, how would it have appeared in the punctuality data? If this is a promised journey where more passengers are observed on the disrupted day than on a normal day, it is assumed that the passenger indeed chose this alternative. The goal of the method is to assess the part of impact of disruptions on passenger punctuality that is not captured in the current calculation method. Therefore, it is desired to know how much passengers made a detour, postponed or canceled their trip. The method is first applied to a single disruption case in order to test the concept. When the method appears to be solid, it can be applied to a set of disruption cases that is expected to have impact on the passenger punctuality. Then, it can be analyzed what factors influence the impact of disruptions on passenger punctuality.

4

Application, results and analysis

The method as described in chapter 3 is applied to several cases in order to test the well functioning of the method and to obtain results that help answer the main research question. Section 4.1 presents the selected cases. The results that were obtained are given in section 4.2 and analyzed in section 4.3.

4.1. Case selection

As described in chapter 3, each disruption can be described by properties that are expected to have influence on the journey pattern and thus the impact of the disruption on passenger punctuality. In order to draw conclusions on the influence of such properties, multiple cases must be studied, preferably only varying with respect to a single property. Cases are selected from the disruption log that also registers the measures that were taken, including the trains that were canceled. After the reasoning that decides what cases should be selected, the case selection also depends on the availability of the desired cases. Therefore, it is not always possible to find a case that exactly matches the desired properties. The current set of cases is expected to be suitable for the purposes of this research. It is decided to vary the cases with respect to the time of the day and with respect to the availability of detour possibilities. These factors are of interest because they are expected to have a certain impact on passenger behavior during disruptions, but this has never been confirmed by real data studies. Besides, an extra case is selected in which a very large disruption took place. The first combination of cases concerns disruptions in the morning peak, during the day and in the evening peak. The second combination of cases concerns disruptions on trajectories where few, medium and a lot of detour possibilities are available. These combinations will be further explained in the following subsections. Section 4.1.3 describes the large disruption case. Because of the time consumption of applying the JPR method to a case and the limited set of suitable cases, only one case has been selected per specification. More cases need to be studied in order to draw more generic conclusions, but for this research, it is expected to be enough to recognize patterns. Regarding the time consumption of running the JPR method for a case, this depends on the case size, but lies between 2 and 3 hours per case when running flawless. Including time for solving minor errors, half a day is needed on average per case from step 2 till step 6. The time consumption could probably be decreased by using a computer with higher processor and memory capacity. The potential time gain of this measure is unknown.

4.1.1. Cases varying in time of the day

For the cases varying in time of the day, three cases have been selected on the track Arnhem-Utrecht. This track is found with 21 collisions in the top-5 of track parts where the most collisions with persons took place [7]. For this track there is a medium amount of detour possibilities. See figure 4.1 at the end of this section for a specification of the location of this trajectory. The three cases are concerning collisions with persons, causing a complete obstruction of the corridor. These cases occurred on Monday, January 22, Thursday, April 12 and Friday, June 1, all 2018. The times of the day are respectively evening peak, morning peak and during the day. For the first two cases, the number of cancelled trains is 50 and 46. For the last case, this is 117. It is assumed that the number of cancelled trains influences the number of hindered passengers, but not their travel behavior.

Label	Morning peak	During the day	Evening peak
Date	2018-04-12	2018-06-01	2018-01-22
Track	Ah-Ut	Ah-Ut	Ah-Ut, Ah-Rhn
Duration	3:11	2:24	3:54
Canceled trains	50	46	117

4.1.2. Cases varying in available detour possibilities

The cases varying in availalbe detour possibilities are chosen at different locations in the network. The first case is the case Arnhem-Utrecht in the morning peak as described in the previous subsection. The second case took place on Wednesday, May 30 between Zwolle and Meppel. The track Zwolle-Meppel is the only rail connection to the North of the Netherlands, which makes it a very vulnerable part of the network. There are few detour possibilities, which is expected to cause more passengers to postpone or cancel their trip, instead of taking a detour. The third case in this set took place on Wednesday, February 28 between Leiden Centraal and Schiphol Airport. For passengers between Amsterdam and Leiden/The Hague/Rotterdam, it is easy to take the route via Haarlem; this route does not lead to additional travel time, except for a few minutes of waiting time. For passengers between Schiphol and Leiden, the route by train via Amsterdam Sloterdijk takes 2 to 4 minutes less than the direct bus route: 49-51 versus 53 minutes. It can, therefore, be assumed that the unknown impact of this disruption on passenger punctuality is limited. The locations of these cases in the network are displayed in figure 4.1.

Label	Few detour possibilities	Medium detour possibilities	Much detour possibilities
Date	2018-05-30	2018-04-12	2018-02-28
Track	Zl-Mp	Ah-Ut	Ledn-Shl
Duration	3:44	3:11	2:23
Canceled trains	52	50	37

4.1.3. Exceptional large disruption case

Since an important interest of this research is the unknown impact of large disruptions on passenger punctuality, a last case is selected that is expected to have a large impact on punctuality. It concerns an exceptional large signal and switch failure that begun at Schiphol Airport, but has spread to the whole Amsterdam area with implications throughout the whole national network. During this disruption, a total of 484 trains has been cancelled around Amsterdam and in other parts of the network. It was not possible to travel from and to Amsterdam for several hours.

Label	Exceptional large disruption
Date	2018-08-21
Track	Asd
Duration	7:10
Canceled trains	484

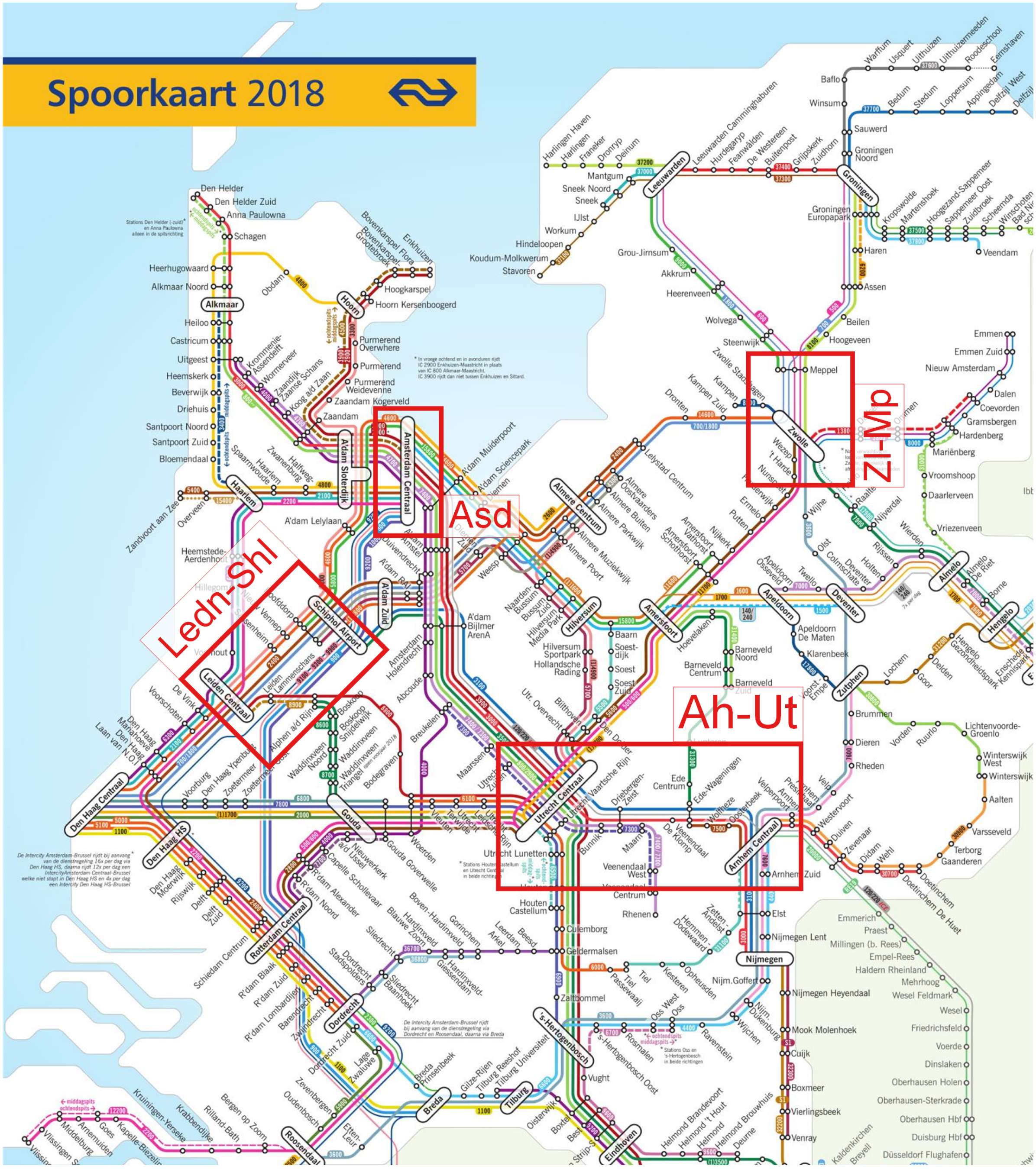


Figure 4.1: Location in the network of the selected cases [6]

4.2. Results

The JPR method is applied to the cases as specified in section 4.1. The numeric results are listed in table 4.1.

Table 4.1 starts with the case study labels, which can be found in the descriptions of the cases. Per case, the results can be divided in several blocks. The first block represents the total number of passengers that were hindered by the disruption. Due to some shortcomings in the method, not every hindered passenger is found in the reconstruction. Therefore, the number of passengers that has been reconstructed is also displayed.

The second block is about the passengers that take a detour. The first entry represents the total number of passengers that takes a detour in the reconstruction and its share of the total number of passengers in the reconstruction. Two subgroups follow representing the number of detouring passengers that is registered punctual, the number of passengers that take a detour with separate train parts and their shares of the total number of passengers that take a detour. A detour with separate train parts is a detour with, for example, first a train leg, then a bus leg and finally another train leg. In this case, a passenger appears twice in the punctuality data, which should be corrected for.

The third block represents the postponing passengers, first calling the total number of postponing passengers and its share of the total number of passengers in the reconstruction and then the number and share of these passengers that are registered punctual.

In the fourth block, the passengers are displayed that travel only by other modes or cancel their trip. Both these passengers do not appear in the data, which is the reason they are taken together. Because they are exchangeable, the sum of these values is also showed. The percentages in this block represent the shares of the total number of passengers in the reconstruction.

The fifth block represents the total number of passengers and the total number of punctual passengers on the disrupted day according to the current passenger punctuality calculation method.

In the sixth block, the passenger punctuality is calculated according to the current calculation method and according to the reconstruction. Then, the difference between these is given. Then, the part of the impact that is already captured by the current calculation method is shown. The last row of this block sums both impact parts up to the total impact.

The seventh block represents the outcomes of the optimization programs. The optimization value is the sum of the squared differences between the observed journey pattern and the reconstruction of it per promised journey. The number of unique promised journeys in the reconstruction is called in order to calculate the average deviation between the observed and reconstructed journey pattern per unique promised journey.

Block eight contains delay numbers, beginning with the total delay that is not captured by the current calculation method, including the number of passengers that contribute to this delay. Then, the total delay that is already captured by the current calculation method and the corresponding number of passengers. These numbers are added to each other in the third set of lines. Finally, the average delay per passenger and the percentage of delay that was already captured are calculated.

Table 4.1: Case studies results

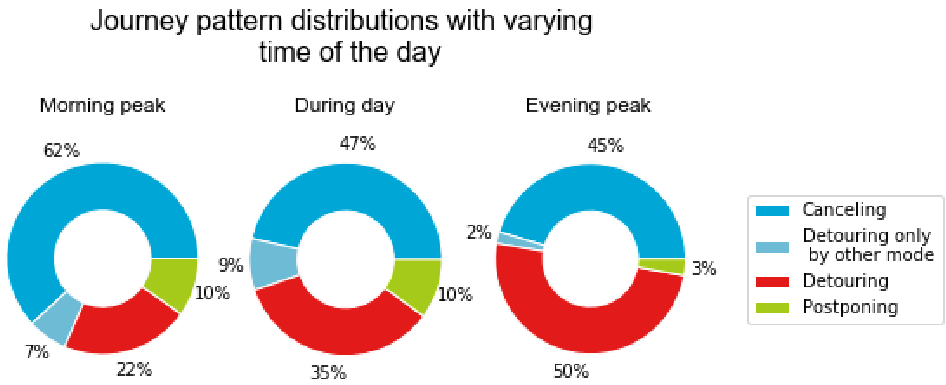
	Label	Morning peak, medium detour possibilities	During the day	Evening peak	Few detour possibilities	Many detour possibilities	Exceptional large disruption
1	Total hindered passengers	16298	22054	10864	5112	19354	47448
	Total passengers in reconstruction	15755 96.67%	20713 93.92%	10467 96.35%	4956 96.95%	19035 98.35%	45011 94.86%
2	Total passengers detouring	3417 21.69%	7218 34.85%	5206 49.74%	1268 25.59%	8755 45.99%	5686 12.63%
	-registered punctual (F)	*3339 97.72%*	*6805 94.28%*	*2873 55.19%*	*1192 94.01%*	*8618 98.44%*	*5074 89.24%*
	-with separate train parts (G)	*65 1.90%*	*36 0.50%*	*50 0.96%*	*37 2.92%*	*7 0.08%*	*8 0.14%*
3	Total passengers postponing	1541 9.78%	2070 9.99%	352 3.36%	166 3.35%	243 1.28%	1504 3.34%
	-registered punctual (H)	*1511 98.05%*	*1761 85.07%*	*240 68.18%*	*132 79.52%*	*225 92.59%*	*1248 82.98%*
4	Passengers detouring only by other modes	1060 6.73%	1791 8.65%	395 3.43%	958 19.33%	670 3.52%	16636 36.96%
	Total passengers canceling	9737 61.80%	9634 46.51%	4550 43.47%	2564 51.74%	9367 49.21%	21185 47.07%
	Sum of above values (I)	10797 68.53%	11425 55.16%	4909 46.90%	3522 71.07%	10037 52.73%	37821 84.03%
5	Total passenger demand disrupted day (M)	1207096	1070797	1104651	1090365	909717	835571
	Total punctual passengers disrupted day (N)	11214933	990207	975900	1033939	846853	763662
6	Passenger punctuality '17 (N/M)	92.91%	92.47%	88.34%	94.83%	93.09%	91.39%
	Recalculated passenger punctuality ($(M-F-H)/(N+I-G)$)	91.69%	90.71%	87.68%	94.40%	91.11%	86.71%
	Delta passenger punctuality	-1.22%	-1.76%	-0.67%	-0.42%	-1.98%	-4.68%
	Impact already captured	-0.36%	-0.67%	-0.35%	-0.09%	-0.53%	-1.74%
	Total impact	-1.57%	-2.44%	-1.01%	-0.51%	-2.51%	-6.43%
7	Optimization value (A)	6218	7831	2695	1009	8722	10717
	Unique promised journeys in optimization program (B)	3742	2719	5990	1496	4188	7457
	Average deviation per unique promised journey (A/B)	1.66	1.31	0.99	0.67	2.08	1.44

Table continued on next page

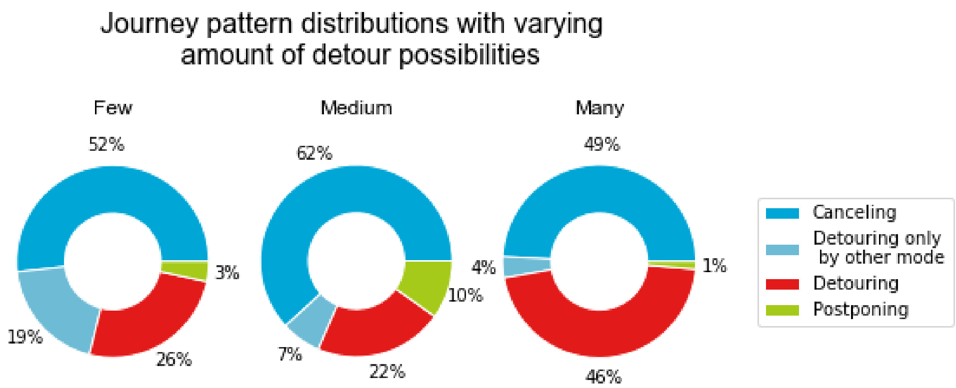
	Label	Morning peak, medium detour possibilities	During the day	Evening peak	Few detour possibilities	Much detour possibilities	Exceptional large disruptoin
8	Delay uncaptured (min.)	372194	511249	308725	224997	401199	1363598
	Passengers uncaptured	6018	11088	5936	2396	9680	24258
	Delay captured (min.)	187087	274623	139146	51663	106855	629764
	Passengers captured	4304	7207	3813	943	4865	14579
	Total delay (min.)	559281	785872	447871	276660	508054	1993362
	Total passengers	10321	18295	9749	3339	14545	38837
	Average delay (min.)	54.2	43.0	45.9	82.9	34.9	51.3
	Percentage delay captured (%)	33.5	34.9	31.1	18.7	21.0	31.6

4.3. Analysis

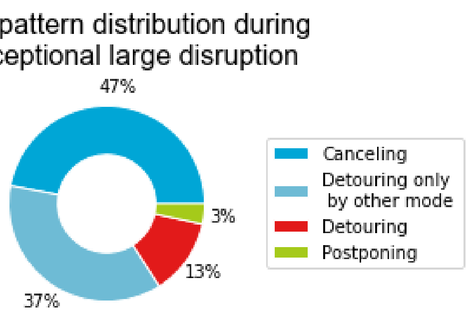
The goal of the research is to assess the unknown impact of disruptions on passenger punctuality. In order to reach that goal, disruption cases have been selected based on factors of interest. These factors are time of the day and availability of detour possibilities. Five cases have been analyzed, which will be discussed in sections 4.3.1 and 4.3.2. In addition to these cases, one exceptional large disruption case has been studied, which will be discussed in section 4.3.3. Section 4.3.6 discusses other findings based on the six case studies. Figure 4.2 represents per set of cases and per case the distribution of passengers over the detour, postpone and cancel alternatives.



(a) Journey pattern distributions with varying time of the day



(b) Journey pattern distributions with varying amount of detour possibilities



(c) Journey pattern distribution during an exceptional large disruption

Figure 4.2: Journey pattern distributions for the selected case studies

4.3.1. Variation in time of the day

By varying in time of the day, it is expected that passengers during the morning peak are more prone to canceling than passengers later on the day. More and more employers offer their employees the opportunity to work at home, so if there is a large disruption, it will be no problem to cancel the trip. Passengers in the evening peak are expected to go home from work and therefore be less prone to canceling their journey, because staying at work is no option. Journeys during the day are expected to be less work-related or to be work-related and important. The cancellation rate for these trips is expected to be somewhere in between the cancellation rates in the morning and evening peak. These hypotheses are confirmed by the representation of the results in figure 4.2a. It appears that the cancellation rate for a disruption in the morning peak is 69%. For a disruption during the day, this is decreasing to 55%. During the evening peak, only 47% of the passengers appears to cancel their trip when a disruption occurs. Another finding is that in the morning peak and during the day, 10% of the passengers are postponing their trip, while this is only 3% during the evening peak. There are two possible clarifications for this effect. One is that passengers during the evening peak are less willing to wait and are more willing to take a detour that takes more travel time if that puts the arrival time forward. The second is that the frequency for most connections decreases to two trains per hour instead of four after the evening peak. This makes postponing a trip to after the evening peak more difficult and less attractive.

4.3.2. Variation in availability of detour possibilities

For the cases with variation in availability of detour possibilities, it is expected that the amount of postponing and canceling passengers will increase with a decreasing availability of detour possibilities. However, for the case with few detour possibilities, it appears that the detour rate for this case is higher than for the case with medium availability of detour possibilities. This result can be explained by the fact that, in the case Zwolle-Meppel an obvious detour alternative between e.g. Leeuwarden and Zwolle is to take the NS train between Leeuwarden and Meppel and to take the bus between Meppel and Zwolle. This detour takes about 90% more time than the undisturbed travel time, but it is one of the best alternatives when the disruption is taking much time. Because of the unavailability of detour possibilities by NS trains between Zwolle and Meppel, it also appears that there are more attractive alternatives that only use the bus or take the train, the bus and then again the train (separate train parts in table 4.1. This is why the share of passengers detouring only by other modes is 19%, which is significantly higher than in the other cases. The share of passengers detouring with separate train parts is also with almost 3% the highest of all cases. For the case with many detour possibilities, it appears that 46% of the passengers detours their trip, which is, as expected, much more than in the other cases.

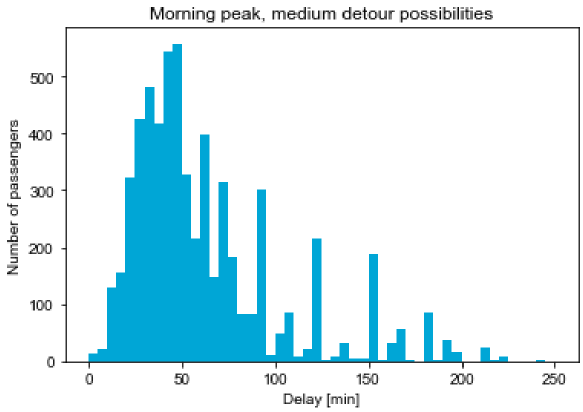
4.3.3. Exceptional large disruption

For the exceptional large disruption, the resulting decrease in passenger punctuality between the current calculation method and the model used is 4.68%. In this case, a lot of journeys are probably canceled, because it was impossible to travel by train in the environment of Amsterdam. This is also the explanation for the low detouring rate. This is the percentage of journeys that is detoured (partly) by train. However, when there is hardly any train traffic possible, it also becomes hard to make a detour partly by train. A lot of journeys may also be made by only using other modes. This is a reasonable effect, because when excluding the train from the Amsterdam public transport network, a fairly extensive network remains. Another option for the stranded passengers was to try to get a ride. The NS launched a hashtag on Twitter named '#treinpoolen' (carpooling for the train), where car drivers could offer empty seats to stranded passengers. It is unknown how many passengers could find a ride, but it can be assumed that it is a small share of the number of hindered passengers. The low postponing rate can in this case be explained by the fact that the disruption was solved late during the night.

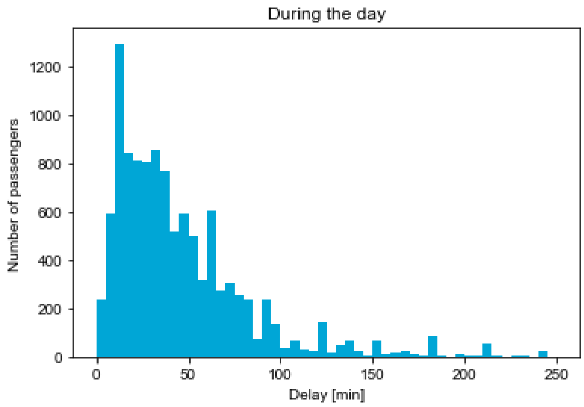
4.3.4. Delay and delay distributions

Figure 4.4 displays the average delay per passenger in minutes. The first remarkable result is that the average delay during the day and in the evening peak is almost equal, while during the morning peak, the average delay is 10 minutes higher. As stated in section 4.3.1, it appears that during the morning peak, less passenger decide to take a detour. Maybe, the passengers that take a detour are also accepting a higher delay, causing the average delay to increase.

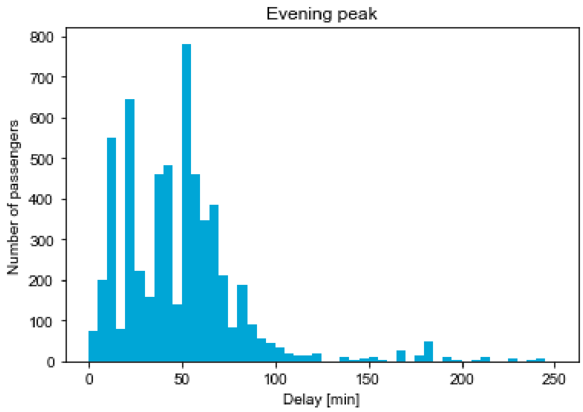
The next remarkable result is that the availability of detour possibilities seems to influence the aver-



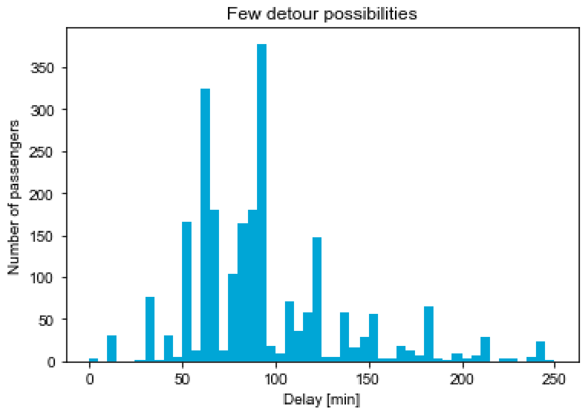
(a) Delay distribution during a disruption in the morning peak with medium detour possibilities



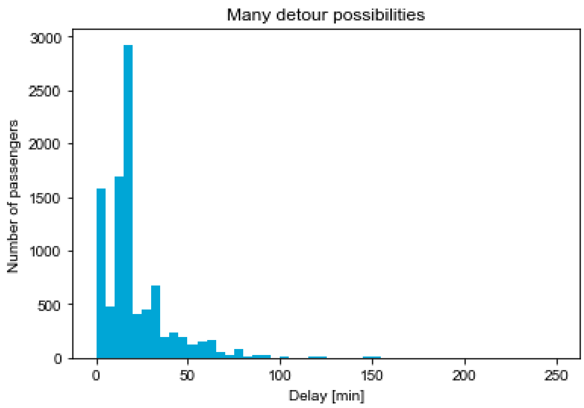
(b) Delay distribution during a disruption during the day



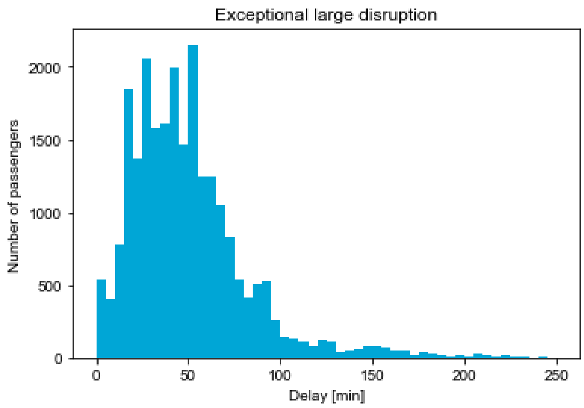
(c) Delay distribution during a disruption in the evening peak



(d) Delay distribution during a disruption with few detour possibilities



(e) Delay distribution during a disruption with many detour possibilities



(f) Delay distribution during an exceptional large disruption

Figure 4.3: Delay distributions for the selected case studies

age delay per passenger. The average delays for the cases varying in availability of detour possibilities from few to many are respectively 82.9, 54.2 and 34.9 minutes. So, although these cases do not show peculiarities where it comes to impact on passenger punctuality, the average delays do so. For the cases studied, the average delay per passenger decreases with an increasing availability of detour possibilities. As already indicated in section 4.3.2, the Zwolle-Meppel case does not only have few detour possibilities, but the detour possibilities that are available also imply a much higher travel time.

Probably, this is a general fact, that fewer detour possibilities also means detour possibilities with higher travel times.

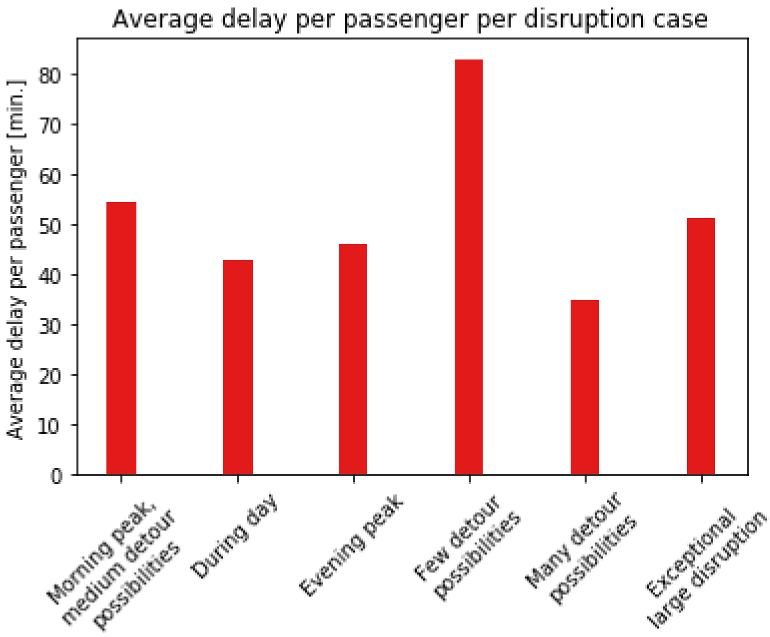
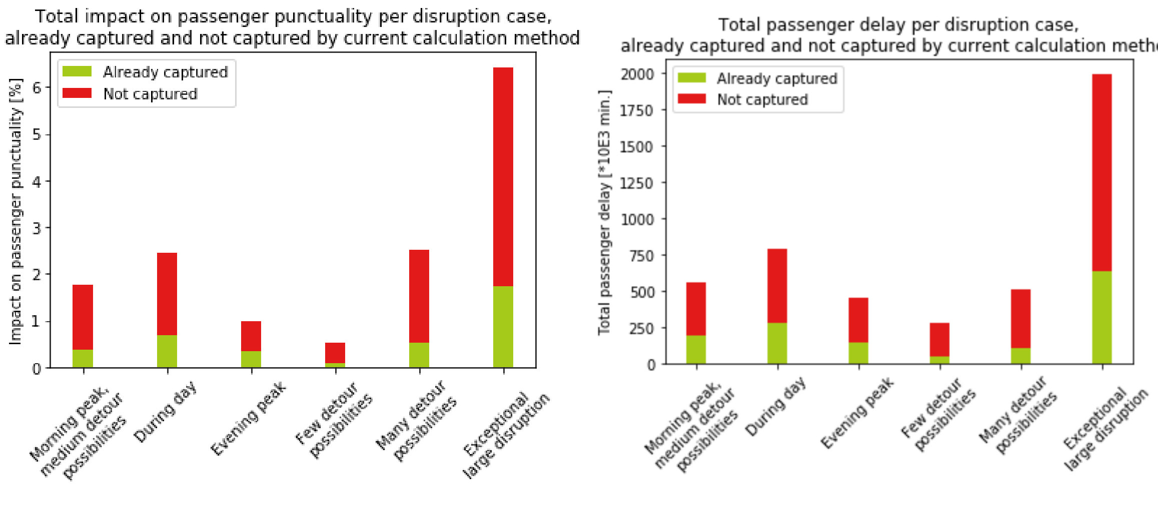


Figure 4.4: Average delay per passenger per disruption case

4.3.5. Total impact and impact already captured

Figure 4.5 divides the impact of disruptions into a part that is captured and a part that is not captured by the current calculation method. This is displayed for the impact on passenger punctuality and for the total delay. The total delay is slightly better captured by the current calculation method: on average, 28% of the delay is captured, while this is 25% for the impact on passenger punctuality. Furthermore, these numbers are relatively constant, so for the near future, it seems to be reasonable to multiply the measured impact on passenger punctuality by 4 to estimate the total impact.



(a) (b)

Figure 4.5: Total disruption impact on punctuality and delay divided in captured and uncaptured parts according to the current calculation method

4.3.6. Other findings

Besides the results that can be found when looking at one factor at a time, there are also other findings that do not specifically depend on one of the factors or that depend on other factors than the studied ones. For example, it appears that the decrease in passenger punctuality largely depends on the number of hindered passengers. This is a logical result, since most hindered passengers either appear not in the data or as punctual. Both these groups cause a decrease in passenger punctuality, the first by decreasing the nominator of the punctuality equation and the second by increasing the denominator of the equation. This effect is clearly visible in figure 4.6 where the decrease in passenger punctuality is plotted against the total number of hindered passengers. A straight line can be drawn through the observations with a relatively small deviation ($R^2 = 0.9837$), which also indicates that there may be a linear relation between the decrease in passenger punctuality and the number of hindered passengers. This is also an indication that the method developed yields plausible results.

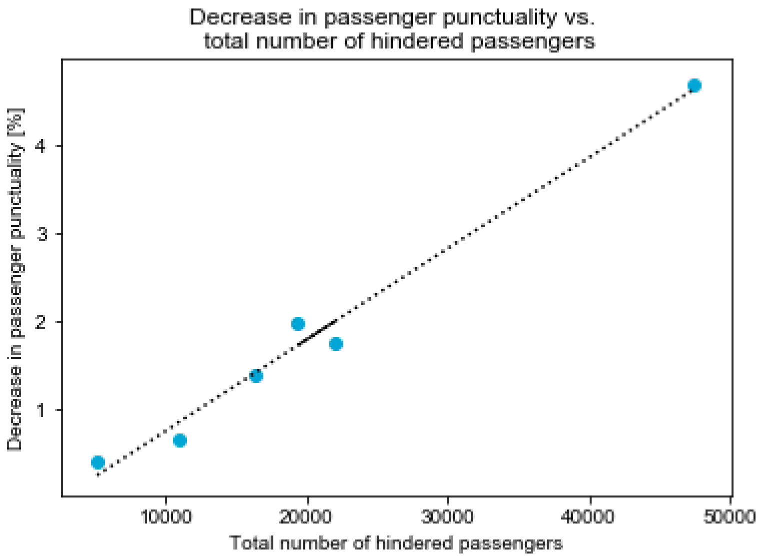


Figure 4.6: Decrease in passenger punctuality plotted against the total number of hindered passengers

A remarkable result is that postponing is the overall least popular option. This result may be caused by a lack of reliability of the reconstruction model at this point. For each request, the journey planner returns the three most evident routes. In some cases, the advise consists of three postponing options, but there are also cases where the planner only returns detour options. This is expected to have some influence on the percentage of passengers that postpones its trip. Another cause for the low postponing rate may be in the process of connecting the alternative journey advises to existing promised journeys. If an alternative journey traverses the disrupted link, it is concluded that the journey is postponed and the alternative journey is connected to the postponed promised journey. It is then assumed that a passenger checked in at the departure time of the postponed journey. This is, however, not necessarily the case, in particular when the disruption is almost solved. In that case, passengers may have checked in at their planned departure time and waited 15 or 30 minutes till they could make their journey. Also when passengers already made a journey by metro, bus, bike or other mode to reach the railway station, they will have a higher willingness to wait for the resumption of the rail traffic. Therefore, a journey may be postponed, but, since the passenger already checked in, the journey appears in the data as the original planned journey.

5 Conclusions

The problem addressed in the current research is the unmeasured part of the impact of disruptions on passenger punctuality. In dense transit networks with the availability of different modes, hindered passengers that take detours do not always show up in the data or as punctual. Therefore, the Journey Pattern Reconstruction (JPR) method was developed to reconstruct the observed journey pattern during and after a disruption in order to track down the behavior of passengers during disruptions. Based on these results, the size of the currently unmeasured part of the impact of disruptions on passenger punctuality could be estimated.

This chapter discusses the results from the case studies and draws conclusions from them. The goal is to reach the main research objective:

> **Objective**
> Assess the unknown part of the impact of disruptions on passenger punctuality and evaluate the current calculation method.

Finally, the conclusions lead to recommendations for NS and ProRail and possible directions for future research. First, the key findings will be reported in section 5.1. These findings will lead to policy implications in section 5.2. Section 5.3 will call the limitations of the current research, which will lead to directions for future research in section 5.4.

5.1. Key findings

The objective of this research is to assess the unknown part of the impact of disruptions on passenger punctuality and to evaluate the current calculation method. In order to reach this objective, subquestions have been formulated. The answers to these subquestions will be summarized.

1. **State of practice and research**
   - How is the passenger punctuality KPI currently defined, what is the reasoning behind it and what function does it fulfill?
   - How do the available methods for passenger punctuality take disruptions into account?

The reasoning behind the passenger punctuality KPI is that the journey that is offered to the customer must be made possible. If a journey can not be made as planned, the passenger arrives unpunctual. The punctuality is measured with thresholds of 5 and 15 minutes. In the current definition, the punctuality is the percentage of punctual passengers within a time interval. The KPI is used in the first place to supervise the railway operator and infrastructure manager. In the second place, it can be used as an instrument to steer improvement at all planning levels.

A review has been conducted of available methods for quantification of service reliability with the focus on handling disruptions. Re-assigning the demand of an undisrupted day to the realized timetable on a disrupted day is a method that is used often in different shapes. Assuming that a passenger arrives at the station at its planned departure time on a disrupted day seems to be a reasonable assumption.

Another finding is that definitions of passenger punctuality differ a lot across different researchers and public transport operators. This raises the question which of the definitions best reflects the experience of the passengers.

2. **Method**
   How can passenger hindrance be determined during disruptions, concerning detoured, postponed and cancelled trips?

A new method has been developed that can be used to determine passenger punctuality and delay during disruptions. This method is based on the concept of reconstructing the observed journey pattern of the disrupted day. The reconstruction is made from the expected demand in undisrupted conditions by generating alternative journey advises and assigning the demand to these new options. The result is a reconstruction of the journey pattern that can be used to recalculate the passenger punctuality. Besides, the results of the reconstruction give more insight into passenger behavior during disruptions, which could formerly only be obtained from predicting models. The method is called the Journey Pattern Reconstruction (JPR) method.

3. **Application**
   What is the impact of disruptions on passenger punctuality?

The impact of disruptions on passenger punctuality depends on the disruption case. In general, the impact of a case is determined by the amount of hindered passengers. It appears that, according to the model, the majority of the expected passengers is canceling its journey by train. This number decreases in the evening peak, when passengers need to get home. The unavailability of train detour possibilities for a disrupted track does not necessarily imply that less passengers take a detour. In a lot of cases, it is possible to take the train to the disrupted part and then take the bus to finish the journey. For the studied cases, the uncaptured part of the impact of disruptions on the daily value of passenger punctuality ranges from below 0.5% for a disruption that affects about 5000 passengers to more than 4.5% for a disruption that affects almost 50000 passengers.

5.2. Policy implications

Disruptions in railway traffic appear to have a significant impact on passenger punctuality that is not captured in the current calculation method of this metric. It appears that this method structurally overestimates punctuality in case of disruptions, which affects the reliability of the KPI. The part of the impact that is already captured is different per case, but lies around 25%. So, it is known what the total impact is of disruptions on passenger punctuality, what part is captured in the current calculation method and what part is not.

The following questions need to be asked while considering an improvement of the current method. What is the total impact of disruptions on the yearly value of passenger punctuality? Is it necessary for fulfilling the functions of the KPI to have the uncaptured part of the impact implemented?

This research only addressed six disruption cases. For these cases, it appeared that punctuality is overestimated. However, more cases need to be examined to find the impact on the yearly value of passenger punctuality. The first advise is, therefore, to further automate the developed method and to apply it to a larger set of cases.

Secondly, it is advised to consider the accuracy level of the KPI with regard to its function. For the supervision function, it may be sufficient to adjust the threshold value. Regarding the steering function, it likely that passenger punctuality plays an important role. Otherwise, it would not be called a *Key* Performance Indicator. This applies especially for NS, because transporting passengers from A to B in time is their core business. Reliability of the passenger punctuality KPI is therefore assumed to be vital for the well-functioning of both organizations. It is, consequently, advised to explore ways to improve the current calculation method with respect to the impact of disruptions. The method developed in this research may serve as a first step towards a more reliable KPI.

This advise assumes that the KPI already is an important steering instrument inside the organizations. If this is not the case, the advise is, instead, to (re)consider and evaluate the role of the KPI.

5.3. Limitations

Although the research yielded some very interesting results, there are some limitations that need to be mentioned. First of all, the research is based on rough estimations of undisrupted demand. Although these estimations were made while taking the day of the week and the fluctuation over some weeks into account, the reliability of them is debatable. This limitation has a direct effect on the reliability of the JPR method.

Another factor that probably had a negative influence on the reliability of the method is that real-time trip information has not been taken into account in the process of generating alternative journeys. Real-time trip information of at least the NS train network would have led to more realistic alternative journeys and a higher reliability of the applied method. For example, severe delays may have caused alternatives to fail and others to arise. These changes have not been taken into account in the current model development.

There are also some weaknesses in the method itself. For example, overcrowding is not taken into account. During a disruption, other modes like bus are often sensitive to overcrowding. With the JPR method, it is possible to make an estimation of the number of passengers on a bus alternative in case of disruptions, so if the capacity of the bus is known, overcrowding could be taken into account in the future.

As already indicated in section 4.3.6, the module that generates the alternatives only returns the three most evident routes. As a result, some affected promised journeys do not have an alternative to postpone the journey. This may have caused the low popularity of the postpone alternatives in the reconstruction. If there would be more postponing alternatives for each affected promised journey, it might appear that more passengers are assigned to a postponing alternative in the reconstruction. This limitation also has a possible effect on the passenger punctuality, since passengers may have postponed their trip to a later moment that is not taken into account in the current JPR method.

Another drawback is in the final phase of a disruption, where it is assumed that a passenger checks out and in again if it postpones its journey. This assumption needs to be made because of simplicity reasons, but may affect the quality of the model. In reality, a passenger that has to wait about 15 minutes is not expected to check out and in again in most cases.

Overall, the JPR method produces plausible results that are well explainable. However, the reliability of the reconstruction can be improved. As visible in the bottom part of table 4.1, the average deviation from the observed journey pattern per unique promised journey in the reconstruction of the journey pattern ranges from 0.67 to 2.08. It is expected that, with improvements at the points mentioned above, these numbers can be decreased, leading to a more accurate recalculation of the passenger punctuality.

5.4. Future research

The limitations of the current research can serve as input for future research. Future research can aim to develop a model for forecasting passenger demand on the level of promised journey. With such a model, it can be determined on beforehand how many passengers will be in a train and how many will be affected by a disruption. It will also make the analysis afterwards much more reliable. A possible model would be a machine learning model that takes the historic demand and several factors that may influence the demand (e.g. weather conditions, holidays, infrastructure maintenance etc.) into account.

Another enhancement to the method can be made by including real-time trip information in the process of generating alternative journeys. Doing so, alternatives that became feasible as a result of delays will be added and alternatives that became unfeasible will be removed from the sets of alternatives. This will make the reconstruction process more reliable. Future research should point out how this improvement can be achieved.

There are several minor improvements that can be made to the JPR method. The first of them is to correct for overcrowding. This is expected to be a problem especially at alternatives that don't use the national rail network, but, for example, the bus or light rail. If this correction is made, it can also be determined how large the overcrowding effect is in reality.

Future research may also go in the direction of check-in/check-out patterns. This can, in the first place, provide information about the slack time passengers are taking between check-in and departure. In the second place, it can be used to improve the JPR method in the final phase of a disruption. Currently, it is hard to assign passengers to the right promised journey in that phase. Such research may lead to improvements in this process. If it appears that passengers on average take a slack time of several minutes, this can also be implemented in the process of generating alternative journeys; passengers can possibly take earlier alternatives if they arrive early to the station.

The shortcomings of the JPR method where it comes to the unrealistic percentages of postponing passengers may be solved in a future study by manually adding postponing alternatives to the set of generated alternatives. Therefore, it should be analyzed to what extent passengers want to postpone their journey. Are extra passengers observed on the disrupted track until half an hour or until 2 hours after the disruption? Based on this analysis, extra postponing alternatives can be added.

The final suggestion for future research is based on the review of available definitions and methods for calculating passenger oriented reliability measures. The variety of these available definitions and methods raises the question what is a good passenger oriented definition of service reliability and which of the available definitions and methods performs the best in different situations. The focus in such research can be either on the quality of reflection of the experience of the passenger, on the best representation of reality or on a combination of both.

A
Stakeholder analysis

Several stakeholders are involved in this project. This appendix introduces them and places them in a power-interest grid in order to indicate their particular roles. The stakeholders that can be identified are ProRail and NS, the Dutch Ministry of Infrastructure and Water Management. Passengers are represented in consumers' associations like Rover in The Netherlands.

A.1. ProRail

ProRail is the infrastructure manager in The Netherlands and is in that function responsible for construction, maintenance, management and safety of the Dutch rail network. ProRail fulfills tasks in distributing the network capacity over transport agencies, rail traffic control and construction, management and maintenance of rail and stations [2]. These duties are fulfilled in commission of the Dutch Ministry of Infrastructure and Water Management, formerly known as the Ministry of Infrastructure and Environment. Together with NS, ProRail is responsible for carrying passengers over the main rail network (Hoofdrailnet, HRN). As part of this responsibility, ProRail has taken over the Key Performance Indicators (KPI's) that are also used by the NS. One of these KPI's is the passenger punctuality, which explains ProRails' interest into this topic.

A.2. Dutch Railways (Nederlandse Spoorwegen, NS)

In former times, NS has been responsible for the complete railway operation in The Netherlands. In the European program of unbundling the railway sector, the responsibility for infrastructure has been transferred to ProRail. NS is still the main railway operator in The Netherlands and responsible for the transport equipment that is needed to carry passengers over the HRN. NS is interested in the passenger punctuality for the same reason as ProRail.

A.3. Ministry of Infrastructure and Water Management (I&W)

The Ministry of I&W is working on livability and accessibility in The Netherlands. Part of its tasks is to guarantee reliable connections on the road, rail, through the water and through the air [1]. In order to accomplish that, I&W granted concessions to ProRail and NS respectively to manage and operate the HRN. In these concessions, agreements have been made on, among others, the passenger punctuality. Therefore, the Ministry is not only interested in the value of the KPI, but also in the right definition of it. Thus, caution is required in contact with the Ministry, because certain subjects may be sensitive.

A.4. Customers' associations

Customers' associations like Rover in The Netherlands act on behalf of the passengers to ensure the quality of public transport. In this function, they are a second watchdog besides the Ministry. Since punctuality is one of the core values in public transport, passenger punctuality can also count on considerable attention from these associations. Although their power is limited when compared to the other parties described, their influence should not be ignored.

A.5. Power-interest grid

Based on the descriptions of the parties involved, figure A.1 shows a power-interest grid in order to indicate their particular roles.

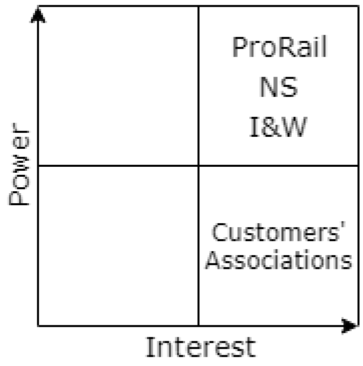


Figure A.1: Power-interest grid

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