EVELIEN VAN DER HURK

Passengers, Information and Disruptions

Passengers, Information, and Disruptions

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Reizigers, informatie, en verstoringen

Thesis

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Evelien van der Hurk
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ERASMUS UNIVERSITY ROTTERDAM

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Train between Rotterdam and Utrecht, March 2015
Evelien van der Hurk

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Chapter 1

Introduction

1.1 Motivation

Public transportation is important as a sustainable alternative for private transport. To be and remain competitive with other transport modes, it is important that it provides a high level of service to its passengers, and that this service is reliable. Unfortunately, disruptions occur frequently in public transport due to, for instance, malfunctioning infrastructure, malfunctioning rolling stock, extreme weather conditions or accidents. The field of *disruption management* is dedicated to the mitigation of the negative effects of a disruption. This thesis studies how new detailed data on passenger journeys can enable operators to improve service in the case of disruptions, given the limited flexibility in the logistic planning. Specifically, research in the thesis focuses on obtaining relevant information on passenger behavior from this new data, and on using this information to improve passenger service during disruptions in public transport systems. The objective is to assist passengers in making complex travel decisions during disruptions, as illustrated by the following example.

Imagine you are at the beautiful new station 'Rotterdam Central', and decide to travel to the city of Utrecht. You plan to take the direct Intercity from Rotterdam, stopping only at Rotterdam Alexander and Gouda before arriving 38 minutes later at Utrecht Central. However, upon your arrival at Rotterdam it turns out that there are no trains running between Rotterdam Central and Gouda because of infrastructure problems — your planned Intercity has been canceled. You therefore need a new travel plan.

Rescheduling your journey may be a bit overwhelming, especially if you are an inexperienced traveler. Will you reroute through the Hague, Leiden, or Schiphol? Are there replacement shuttle buses to Gouda? Would it be better then, if these buses are running, to follow your original geographical route and take a bus? Alternatively, you could postpone your journey — to explore the new Markthal, for example — and maybe upon your return the train service is back up and running so you could simply take the planned Intercity later. You are pressured to make this decision quickly, because while you are contemplating all these choices, time is ticking away, trains and buses on alternative routes are departing, and your delay is increasing.

Although the smartphone application of the operator may help you to plan your route, and may even give an indication of the crowding in the train, it is not able to predict whether or not you will be able obtain a seat on a certain train. Indeed, you might be inclined to choose the shortest route around the disruption. However, if this requires standing shoulder-to-shoulder with your fellow passengers for an hour, you might prefer a longer route which provides you with a seat. Even worse: the 'shorter' route could actually turn out to be *longer* when there is insufficient capacity for all the passengers who selected it. In this case passengers are competing to board the train, and passengers who are unable to board the train are left at the station to incur even more delay. Information about available capacity is therefore important to passengers, but is currently not always available to them in the case of disruptions.

Operators, on the other hand, could estimate available capacity as they schedule capacity *and* have information about the passenger demand thanks to new data generated by automated fare collection systems, such as the smart card (OV-chipcard) system in the Netherlands. These data contain information on the origin, destination and travel time of individual journeys of passengers. Moreover, other technological advances have lead to the wide adoption of smart phones and the availability of wireless communication which allow immediate and direct communication with passengers — a communication that can be personalized to the passenger's specific journey.

However, operators are also limited in that they cannot dictate which routes passengers take. The operator can only influence passenger route choice decisions by providing advice, and by using the limited flexibility in the logistic schedule to support passenger demand. Although new information on passenger journeys helps to anticipate the demand, passengers themselves must decide whether or not to follow the advice. This is an important limitation since the objective of the operator to provide the best overall service within a limited budget for operational costs may conflict with the desire of the passengers to follow paths that are in their personal best interest. Determining which path is best for an individual passenger is complicated, as the quality of a path is influenced, be it positively or negatively, by the route choice of other passengers because of the limited available capacity.

This thesis addresses the complex question of how operators can improve passenger service during disruptions, given the limited, yet substantial, influence they have on passenger flows through the provision of travel advice, and through adjusting the capacity planning to the demand within operating constraints.

1.2 Complexity in Public Transport

One of the objectives of this thesis is to investigate the practical value of Complexity Theory for disruption management in public transport. Boccara (2010) lists three common characteristics of complex systems, namely (*i*) that the system can be described as a large number of agents that interact, (*ii*) that certain properties emerge from this system, in other words that the behavior of the system is not easy to predict or extrapolate from the behavior of the agents individually, and (*iii*) that this behavior is not the result of a central controller. Indeed, when agents have simple behavior and a central controller orchestrates their actions and reactions, it does not, according to this definition, constitute a complex system. However, we could argue that a system can still be complex if there is a central controller who has only limited influence on the behavior of the agents, such as in the case of a public transport system where passengers have free route choice.

One of the best-known examples of a system with emerging behavior is John Conway's 'Game of Life' (Gardner, 1970). This game considers a grid where every rectangle represents an agent with simple behavioral rules on birth, life and death. Playing (or simulating) this game shows that these simple behavioral rules can give rise to intricate patterns in the behavior of the system as a whole, which emerge from the interaction among the individual agents. Later people found that such a model with few and simple rules for the interaction between agents can explain the behavior of natural phenomena, such as the flocking of birds or the behavior of fish schools. Indeed, Couzin (2007) shows how simple behavioral rules for individual fish can explain the emergent behavior of fish schools. The interaction between the components at the micro-level results in the emerging macro-behavior of the system.

The travelers' experienced service emerges from the interaction between the travelers and the provided logistic network or schedule in systems where passengers have free route choice. For example, the desire of passengers in traffic to take the same route may cause traffic jams and therefore delays. Within public transport, a demand higher than the available capacity causes delay for passengers who are unable to board their desired train. Adding capacity to such systems with free route choice may therefore even decrease the quality of service experienced by passengers, as shown by Braess (1968) in what later became famous as the Braess-paradox.

We distinguish between two streams within complexity research related to transport. The first uses approaches common in physics, where the aim of the research is to describe patterns and find common laws between different systems. For example, Barabási and Albert (1999) study many different networks that are present in our world, from the internet to social networks to transport networks, and find that many of them are similar in that they have scale free properties. Watts and Strogatz (1998) introduce the concept of *small worlds* in order to describe common structures across networks. These measures have been used to qualify various networks such as the internet, social networks, and biological networks. Within public transport, Derrible and Kennedy (2010) study the robustness of rail-based public transport networks around the world by investigating whether or not these networks are scale-free and have the property of small worlds. Thus they aim to give a general qualification of what constitutes a robust network. Tero et al. (2010) study the formation of networks in slime mould and compare this to the development of public transport networks.

Networks are also formed by human mobility patterns. Both Song et al. (2010) and González et al. (2008) use mobile phone location data to investigate the predictability of a person's location. Their objective is to determine whether this behavior could be predicted by a model by determining to what extent a person's behavior is either random or shows some regularity, rather than actually proposing a specific model that provides these forecasts. They indeed find that human behavior is highly "predictable". Wang et al. (2012) even go one step further in their study of human behavior for traffic patterns. In addition to the previous, they conduct a what-if analysis through which they are able to show that if a small portion of a select group of travelers postpone their journeys, a lot of time could be saved by many other travelers in the system.

The second stream of research concerns the mimicking of these complex systems by building large agent-based simulation models. Raney et al. (2002); Balmer et al. (2006) and Arentze and Timmermans (2009) are examples of researchers who developed such agent-based simulations to describe transport systems. These models often include activity programs of agents (travelers) that explain the travel decisions the agents make over time in different situations. The travelers interact with each other during the simulation, for instance when traffic jams form or when there is insufficient capacity available in a public transport system. The simulation results serve the analysis of passenger service. These models generally analyze transport systems in equilibrium. The inclusion of the motivation for traveling, such as the inclusion of activity lists for agents, makes the model suitable for strategic planning and what-if analysis. As a result, however, these models are commonly computationally expensive and large systems could easily need an hour (or more)of computation.

1.3 Research Question

The main research question of this thesis is as follows:

How can public transport operators use new sources of information on passenger behavior to improve service in the case of disruptions, given the limited flexibility in the logistic operations, and the limited influence on passenger's route choice?

The term "new sources of information" refers to data on passenger journeys and location that are generated (close to) real time for the entire (or a large part of) passenger population. Such data is, for instance, generated by mobile phones and automated fare collection systems such as smart card ticketing. These data are new in that they provide information on both the geographical journey of the passenger and the time at which the passenger is traveling, which did not exist in the detail scale until recently. Previous data on passenger journeys, such as origin-destination matrices or numbers of passengers per train, only contained information of one dimension, i.e. location or time. Although peak and off-peak demand matrices were previously available, they do not represent the per-second arrival times of passengers that are available with this new source of data. Other sources that include both, such as travel diaries and surveys, only store such information for a subset of passengers after which statistical models can be used to upscale the data to the full population. The combination of location and time, as well as the large scale, is what makes the new data different from that previously available.

The objective is to improve service quality for passengers during disruptions, thus reducing the inconvenience resulting from disruptions by, for example, decreasing delay or the number of additional transfers. To this end, the operator has limited means defined by monetary, but also physical, constraints: for example, a spare unit of rolling stock cannot immediately appear at the location where it is most needed, but will need to move there. Furthermore, we will consider systems with free route choice, where an operator may advise, but not dictate, a specific path in the network for an individual.

In answering the main research question, we want to draw upon the fields of both complexity and Operations Research. Disruption management requires concrete solutions such as alternative logistic schedules and travel advice to the passengers in real time. Descriptive models for network structures or general predictability of passenger flows cannot provide this. However, studying passenger service as emerging from the interaction between passengers and the logistic system may enable the modeling of the free route choice of passengers. Within this thesis the focus is therefore on using agent based simulation models within disruption management models.

We answer the main research question by studying three sub- questions. The first is the question of what information on past passenger behavior can be obtained from this new source of data. The second question is to what extent past information can be used to make predictions in order for this information to be useful in decision support tools for disruption management. Finally the third question is how this information can be used in decision support models for disruption management in order to improve passenger service. This last question is answered by considering two specific applications and developing decision support models for each. The approach is further illustrated in the description of the research framework below.

Framework

Figure 1.1 presents the three-step framework used in this thesis to answer the research question. First of all, past passenger behavior is analyzed based on the available data on passenger journeys and information on the logistic system. This was done by deducing passenger's route choice from smart card data as presented in Chapter 2. The outcome of this model allows analysis of passenger service and passenger route preferences retrospectively.

To use the data in real-time applications, forecasts of passenger demand and behavior are required. In Chapter 3 a framework for forecasting passenger flows in the case of a disruption is presented.

Finally, in step 3, models that measure passenger inconvenience given realistic passenger behavior are developed to support operators in minimizing passenger inconvenience during a disruption. Two models for different applications are developed. The first (Chapter 4) considers a planned closure of one (or more)link(s) in an urban public transport network. Bus shuttle services are planned to mitigate the effect of this closure. Rather than aiming to restore the previous network structure, this model aims to redesign the network using the shuttle services so as to minimize the passenger inconvenience resulting from the closure, given the expected travel demand.

The second application (Chapter 5) considers a real- time disruption with uncertain duration in a passenger railway transport system. The model aims to reduce passenger inconvenience resulting from the disruption by providing individual travel advice to passengers in combination with an alternative rolling stock circulation. The objective is to

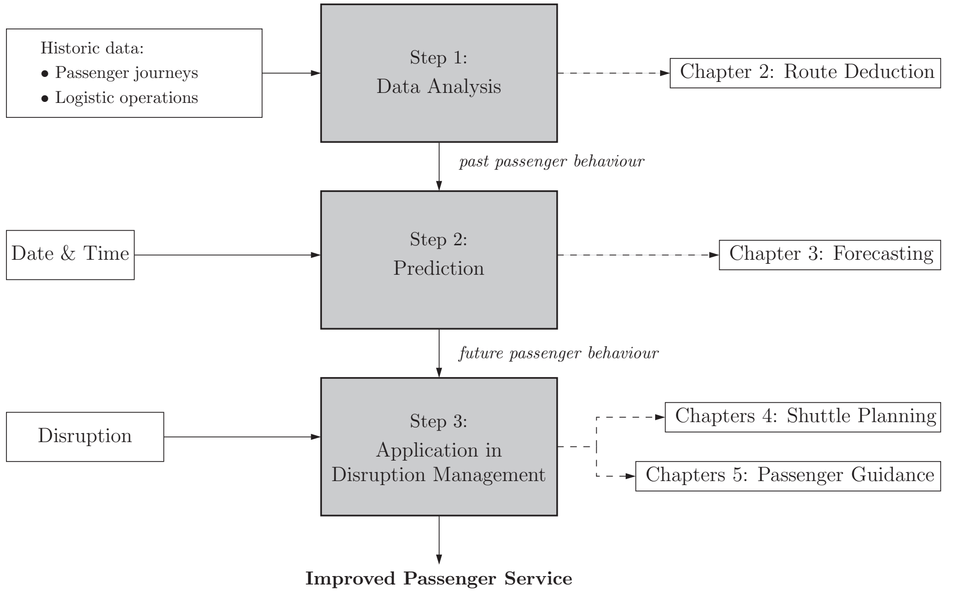


Figure 1.1: Analytical framework

improve service by advising passengers on their route, given the uncertain duration and limited available capacity, and to accommodate demand through the new rolling stock circulation.

Both models evaluate solutions given realistic assumptions about passenger behavior using agent-based models. Indeed, we found that passenger service can be significantly improved in comparison to standard practice (Chapter 4), and in comparison to not providing individual route advice to passengers (Chapter 5).

Behavior

One of the objectives is to include realistic models of passenger behavior within disruption management models. In systems with seat reservation, such as in the airline industry, operators can assign passengers to new paths and thereby minimize overall inconvenience resulting from a disruption. However, when passengers are free to select their own route, such socially optimal solutions may not be feasible in practice. For example, passengers are unlikely to disembark from a direct train to their destination in the interests of other passengers if this is not in their own best interest. Thus, when aiming to minimize passenger inconvenience, it is important to consider realistic behavior.

This thesis draws upon new available data on passenger journeys for the analysis of passenger behavior, and upon the field of complexity to model this behavior and thereby evaluate the service as experienced by passengers as emerging from the interaction between passengers and the logistic system. Solutions are evaluated under realistic passenger behavior assumptions and, wherever possible, realistic passenger behavior constraints are included in the disruption management models.

1.4 Contributions of this Thesis

This section summarizes the contributions of the individual chapters that together comprise the framework presented in Figure 1.1. The computational experiments in the chapters were conducted for cases based on the networks of Netherlands Railways and the Massachusetts Bay Transportation Authority (MBTA), USA.

Chapter 2: E. van der Hurk, G. Maróti, L.G. Kroon and P.H.M Vervest. Deduction of passengers' route choice from smart card data. IEEE Transactions on ITS, vol.16, p430-440, 2015.

Chapter 2 analyzes if and how passenger route choice can be deduced from passenger journey data. Deducing passenger route choice from smart card data provides public transport operators with the opportunity to evaluate passenger service. This is an advantage especially in the case of disruptions, when traditional route choice models may not be valid. This chapter proposes a method for deducing the route chosen by passengers by analyzing smart card data, and validates this method on a real life data set that includes days with high punctuality as well as days with a modified service that were also prone to minor and major disruptions. In our validation sample the method achieves an accuracy of about 90 percent even on days with disruptions. Moreover, it is shown that the data resulting from the passenger route deduction method allows retrospective evaluation of passenger service.

Chapter 3: adaptation of E. van der Hurk, L.G. Kroon and G. Maróti, and P.H.M Vervest. Network Reduction and Dynamic Forecasting of Passenger Flows for Disruption Management. In the Proceedings of the 5th International Seminar on Railway Operations Modeling and Analysis - 2013, Copenhagen, Denmark, 2013.

Automatic Ticketing Systems such as smart card systems provide detailed data on passenger behavior that was not previously available at this detailed level. Such information may assist operators in obtaining insight on the demand for travel. In the case of disruptions, information on the current location of passengers, and their destination, is of great value in order to provide good service during, for instance, (planned) disruptions.

This chapter proposes a three-step framework for forecasting passenger flows consisting of (i) a data analysis to deduce the planned path of passengers, (ii) a statistical forecasting model to predict the current number of passengers per planned path, and (iii) a simulation model that calculates how passenger flows change from the planned situation due to the disruption under realistic assumptions on passenger behavior. Furthermore, a preprocessing step provides insight into when and where passengers need to reroute due to the disruption. A computational experiment is conducted comparing four different forecasting models using a 10-month smart card data set from Netherlands Railways generated during the introduction of the smart card system. Although no definitive conclusions can be drawn from the analysis, given the limitations of the data sample, results suggest that accurate passenger forecasts may indeed be derived from smart card data.

Chapter 4: E. van der Hurk, H. Koutsopoulos, N.H.M Wilson, L.G. Kroon and G. Maróti. Shuttle Planning for Link Closures in Urban Public Transport Networks. ERIM Technical Report, Submitted to Transportation Science, 2014.

In Chapter 4 a new optimization model is proposed for shuttle planning during link closures in urban public transport networks. These transport networks must periodically close certain links for maintenance, which can have significant effects on the service provided to passengers. In practice, the effects of closures are often mitigated by replacing the link with a simple shuttle service. However, alternative shuttle services could reduce passenger inconvenience without increasing operating cost. This paper proposes a model to select shuttle lines and frequencies subject to budget constraints. A new formulation is proposed that allows a minimum frequency restriction on any line that is operated and which minimizes passenger inconvenience cost, including transfers and frequency-dependent waiting time. This model is applied to a real world shuttle network design problem of the MBTA network of Boston (USA). The results show that additional shuttle routes can reduce passenger delay in comparison to the standard practice at the same operating budget, while also distributing delay more equally over passengers. Moreover, changing frequencies on existing lines could further reduce passenger inconvenience within the same budget constraint. The results are robust under different assumptions about passenger route choice behavior. Computational experiments show that the proposed formulation, coupled with a preprocessing step, may be fast enough for real time applications.

Chapter 5: E. van der Hurk, L.G. Kroon, G. Maróti and P.H.M Vervest. Passenger Guidance and Rolling Stock Rescheduling under Uncertainty for Disruption Management. ERIM Technical Report, to be submitted for peer review.

In Chapter 5 we investigate the potential benefits of providing individual travel advice to passengers in the case of major disruptions of uncertain duration. The operator may help the passengers through travel advice to avoid the overcrowded part of the network and anticipate the uncertain duration, using the operator's knowledge of capacity bottlenecks and possible lengths of the disruption. By combining the travel advice with appropriate decisions on the rolling stock circulation, one can expect to decrease the overall passenger delays. We propose a new optimization-based approach to simultaneously provide individual travel advice and an updated rolling stock schedule. The approach consists of mathematical programming models and a simulation module with realistic assumptions on passenger behavior. We deal with the uncertain length of the disruption by modeling it as a two-stage decision process. In the first stage, at the start of the disruption, initial advice and a rolling stock schedule are developed. In the second stage, the actual length of the disruption is revealed. Then passengers may change their path and the operator may adjust the rolling stock schedule. Decisions in the first stage are selected such that the expected inconvenience, given all possible disruption deviations and the allowed recovery actions, is minimal. The model aims to provide travel advice that is in the best interest of the passengers, and evaluates the solution under the assumption that not all passengers may follow the advice. Our computational tests on realistic instances of Netherlands Railways indicate that the addition of the travel advice effectively improves the service quality to the passengers.

1.5 Contributions to this Thesis

The contributions of the various organizations and people involved in the research of this thesis are summarized in this section.

Data

- Netherlands Railways provided the data for Chapters 2, 3, 5. These data consisted of information on passenger demand, schedules, and rolling stock availability. Test cases for Chapter 5 are based on test cases used in Kroon et al. (2014), which resulted from discussion with, and data provided by, Netherlands Railways. Ownership of these data has remained with Netherlands Railways.

- The Massachusetts Bay Transportation Authority provided the data for Chapter 4, consisting of information on passenger demand, schedules, and operational cost. Ownership of these data has remained with the Massachusetts Bay Transportation Authority.

Research The majority of the work in this thesis has been done independently by the author. The author has been responsible for formulating the research question, studying relevant literature, conducting the data analysis, formulating and implementing the models, analyzing the results, and writing the chapters and belonging papers. While doing so, the quality of the research has benefited significantly from the discussions with the co-authors:

- Leo Kroon and Gábor Maróti on Chapters 2, 3, 4 and 5 on problem framing, methodology, results, and writing phase.
- Peter Vervest on Chapters 2 and 3, specifically on problem framing and writing. Furthermore, Peter contributed on the strategic level of this thesis. Most importantly, Peter's perseverance to include research on the topic of informing passengers is the foremost reason Chapter 5 exists and is part of this thesis.
- Nigel Wilson and Harilaos Koutsopoulos on Chapter 4 on problem framing, methodology, results, and writing phase.
- The rolling stock model of Kroon et al. (2014) has been used in Chapter 5. The passenger simulation in this chapter has been based on the passenger simulation of Kroon et al. (2014).

Furthermore, the comments and suggestions of Leo Kroon and Peter Vervest have improved Chapters 1 and 6.

1.6 Outline

The remainder of this thesis is organized as follows. Chapters 2 and 3 represent our work on analyzing passenger behavior. Chapters 4 and 5 present new optimization based models for minimizing passenger inconvenience in the case of major disruptions in systems with free route choice for passengers. Finally, Chapter 6 summarizes results, presents conclusions, and contains recommendations for future research. We have chosen to use exact copies of the papers as Chapters 2, 4 and 5, in order to allow easy independent reading of these chapters. Chapter 3 is an adaptation of a conference paper. As a result, there might be some overlap in terms of introductions and definitions in the different chapters.

Chapter 2

Deduction of Passengers' Route Choices from Smart Card Data

This chapter has been published in IEEE Transactions on Intelligent Transportation Systems (Van der Hurk et al., 2015b). A preliminary version of the paper was nominated for the Best Paper Award at the 2013 IEEE Conference on Intelligent Transportation Systems in The Hague, The Netherlands.

Co-authors: L.G. Kroon, G. Maróti and P.H.M. Vervest

2.1 Introduction

Passenger route choice information is important for public transport operators. Indeed, based on this information train utilizations can be calculated. Moreover, the experienced journey of the passengers can be analyzed in detail in terms of waiting time, in-vehicle time, and number of transfers, together resulting in a measure of passenger service.

Most passenger route choice models are based on utility maximization (Ben-Akiva, 1974) or regret minimization (Chorus et al., 2008). However, in case of sudden changes in the timetable or disruptions in a public transport system, these models may not be valid. For one, passengers may not travel as predicted by the existing models due to the lack of up-to-date information. Secondly, the urgency to make quick decisions may result in unexpected travel routes. Thus route choices based on the traditional models may be incorrect in these specific situations. Therefore a different method is required to analyze passenger route choice and passenger service in case of disruptions.

New data sources generated by automated fare collection systems allow for a data driven study of passenger route choice. In contrast to classical data collection methods such as travel diaries and surveys, these recently introduced systems store all passengers' journeys every day while they do not suffer from recall error.

An excellent overview of research on smart card data is provided by Pelletier et al. (2011). We focus on those smart card systems that register the start and end of each full journey. However, some smart card systems do not register the destination of the journey, or may register different legs of a journey as separately, thus requiring the estimation of destinations or the linking of journeys. In these cases, methods proposed by Zhao (2004), Gordillo (2006), Trépanier et al. (2007) and Seaborn et al. (2009) could be used to enrich these data.

Previous studies on *passenger route choice deduction*, that is the problem of deducing the chosen route of passengers from smart card data, include the research of Sun et al. (2012) who estimate the location of a passenger over time based on smart card data containing origin and destination in the Singapore MRT system. They consider a single metro line and estimate the location of passengers and the waiting time on the platform directly from the smart card data, as timetable information is not available. This is possible as consecutive trains will follow the same route and there are no transfers. Based on data from the Oyster smart card of the London Overground, Frumin and Zhao (2012) analyze arrival behavior, and Zhao et al. (2013) estimate excess journey time based on the registered origin and destination stations. Routes are based on the planned timetable and departure waiting time is estimated on the first reasonable departing route, while excess time is estimated on the first arriving route. Also Kusakabe et al. (2010) consider the problem of linking routes through the usage of a timetable for a rapid transit system. However, they choose the route with the longest in-vehicle time rather than the earliest departing route or the earliest arriving route. Routes are generated based on shortest path computations, as by Frumin and Zhao (2012).

The contribution of this paper is that it proposes a new method for Route Deduction and validates this method through additional data resulting from conductor checks for one of the most complex public transport networks studied so far in this context: the complete network of Netherlands Railways. This network contains stations connected to multiple lines and contains different geographical routes for several origin-destination pairs, and, as a result, is more complex than networks studied by, for instance, Sun et al. (2012) and Kusakabe et al. (2010). Validation of the method is possible as conductor checks provide partial information on route choice for a significant subset of all journeys made by smart card. The results of our case study show that commonly made assumptions on route choice behaviour, that is, that passengers either take the first departing route or the first arriving route, do not hold true in our case study.

We distinguish a Route Generation and a Route Selection step, following the traditional split of route choice models as proposed by Nguyen and Pallottino (1988) and Spiess and Florian (1989). Our results show that both are equally important for successful Route Deduction. Our best method for Route Generation contains a correct route for at least 90 % of the journeys in our validation sample. Of this sample, the most successful Route Selection rule selects the correct route for 95% of the journeys in our sample. For our case study, we show how passenger service, defined in terms of added travel time due to increased in-vehicle time, transfer time, or waiting time, can be compared between normal and special days with reduced frequencies of trains.

The route data resulting from our Route Deduction method can be used to evaluate and calibrate statistical route choice models, for instance similar to Schmöcker et al. (2013), or to analyze passenger service, for example the effectiveness of different disruption management methods such as proposed by Carrel et al. (2013).

The rest of this paper is organized as follows. In Section 2.2 the problem of passenger route choice deduction is described. Section 2.3 provides an overview of the links between the available data and of our three step method: (*i*) Route Generation, (*ii*) Route Selection, and (*iii*) Validation. The methods for these steps are described in Sections 2.4, 2.5 and 2.6, respectively. The data of our case study is described in Section 2.7. The results for the case study based on the data of Netherlands Railways are presented in Section 2.8, which includes the results of the validation of the method as well as an analysis of passenger service. Finally, Section 2.9 provides conclusions and discussions.

2.2 Problem Description

This paper describes methods for deducing passenger route choices based on smart card and timetable data. This means that, for each journey that is made by a smart card, the aim is to reconstruct the detailed route through space and time in the timetable that is made by the corresponding passenger. Here a journey is defined as a registered check-in and check-out time at respectively an origin and destination station. A route is defined as an ordered set of train trips connecting the origin and destination through space and time. A train trip is a train driving from one station to the next for which both a planned and a realized timetable are available.

The data of a journey does not contain detailed information on the route the passenger took, but contains only information about its origin (location and time) and destination (location and time). Due to the high frequencies and the density of the Dutch railway network, several routes can exist in the timetable leading from origin to destination within the time frame of the journey. In this paper we determine how to find a route in the timetable that has a high probability of being the route that was actually used by the corresponding passenger.

To that end, we need (*i*) methods for generating a set of potential routes in the timetable that fit with a certain journey (Route Generation), and (*ii*) rules for selecting the correct route from the set of potential routes (Route Selection). We propose several methods for Route Generation and several rules for Route Selection, since it is not a priori clear which method or rule will perform best. These methods and rules are discussed in Sections 2.3.1 and 2.3.2, respectively.

A combination of a Route Generation method and a Route Selection rule is called a Route Deduction method. Each Route Deduction method requires the coupling of two data sets (the smart card journeys and the timetable) that are related, but that are not linked directly. Thus a third data set that provides a link between journeys and routes is needed to validate the Route Deduction method. Section 2.3.3 discusses this validation based on conductor check data that does provide the required link between smart card data and timetable.

2.3 Methodology

Figure 2.1 provides an overview of the process of Route Deduction for a specific day d of data. The input data is listed on the left: the timetable, smart card data, and conductor checks for this day, as well as data of conductor checks of earlier days. Moreover, we use a set of Route Generation methods $m \in M$, which will be defined in Section 2.4, and a set of Route Selection rules $s \in S$, which are defined in Section 2.5, thereby following the common split between route generation and route choice in route choice models as proposed by Nguyen and Pallottino (1988) and Spiess and Florian (1989).

- In the first step, Route Generation, a set of routes $\mathcal{R}^m$ is generated by each Route Generation method m, based on the smart card data, the realized timetable, and possibly conductor checks of earlier days. Routes are generated for all OD-pairs and all possible departure times.

- In the second step, the route set $\mathcal{R}^m$ and the smart card data serve as input for each of the Route Selection rules s selecting a single route r_j^{ms} for each journey j in the smart card data. This is the route that, according to the used rule, has a high probability of being the one that was actually used by the journey.

- Finally, for the subset of journeys j with at least one conductor check, the performance of the Route Generation method m together with Route Selection Rule s is measured by determining per journey j in this set if the selected route r_j^{ms} is a likely route given the conductor check. The performance p^{ms} is calculated as the average performance over all journeys j with a conductor check. The validation is described in detail in Section 2.6.

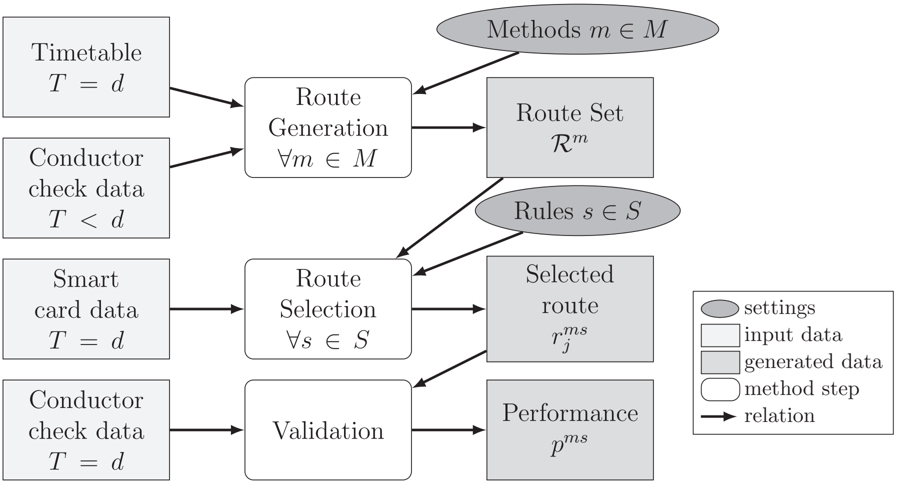


Figure 2.1: Overview of Route Deduction method for a single day d of data

2.3.1 Route Generation

In a system without seat reservation, like the Dutch railway system of our case study and many urban transportation systems around the world, the journey information does not contain information about the chosen route. In these systems passengers are free to choose their own routes, within certain bounds. As a result, the set of routes chosen by passengers is unknown and needs to be constructed.

Routes can be constructed based on timetable information of the operator containing information on train trips, preferably the realized rather than the planned timetable. By translating the timetable into an event-activity network, shortest paths algorithms like Dijkstra's (Dijkstra, 1959) or Bellman-Ford's (Bellman, 1958; Ford Jr. and Fulkerson, 1962) algorithm are able to find minimum cost routes quickly.

However, passengers are known to not always travel along a unique minimum cost path. Other routes may be more attractive because they contain fewer transfers, are carried out by different train types, have lower fares, or have a departure or arrival time that is more convenient for the passenger. Moreover, two equally attractive routes could exist in the network with different geographical routes associated to them. Thus the Route Generation methods should find a diverse set of routes. We define a set of different methods $m \in M$ for the Route Generation step in Section 2.4.

2.3.2 Route Selection

Given a set of generated routes, each Route Selection rule selects one of these routes for the registered journey. Based on the registered time and space dimensions of the journey, routes are selected from the generated set of routes. There may be multiple routes that fit this requirement in a dense network. Moreover, multiple routes may fit within the time frame of check-in and check-out when passengers undertake other activities than traveling between the registered time of departure and arrival, like for instance shopping. Therefore, additional rules are required to select a single route for a journey.

A Selection Rule defines how to select a single route from a set of candidate routes that fit within the registered time interval of the journey and connect its origin to its destination. We define and compare different Selection Rules, and investigate if there is a single rule that selects the correct route for the majority of all journeys. By making these rules dependent on the check-in time, check out time, and in some occasions the number of transfers, we aim to make very few a priori assumptions on the preference of passengers for different routes. As a result, the resulting route data could be used for analyzing passengers' preferences for different routes.

A set of rules $s \in S$ is defined in Section 2.5. Among the tested rules of this nature, we find one that reconstructs a correct route for over 95% of the journeys in our validation set by assigning the correct route to a journey.

2.3.3 Validation

Data used for validation is generated by conductors checking the smart cards of passengers by using a Mobile Chipcard Reader (MCL, "Mobiele Chipkaart Lezer"). The resulting data, internally known as MCL data, contains conductor checks that are centrally stored and contain a time, train number, and smart card number per conductor check. Fig. 2.2 shows how MCL data forms the bridge between smart card data and timetable information: the smart card number and time allow finding the specific journey corresponding to the conductor check. The time and the train number of the conductor check enable the selection of the specific train in the timetable the passenger was on. Because only a subset of all journeys is checked by a conductor, this data cannot be used for the Route Deduction of all journeys.

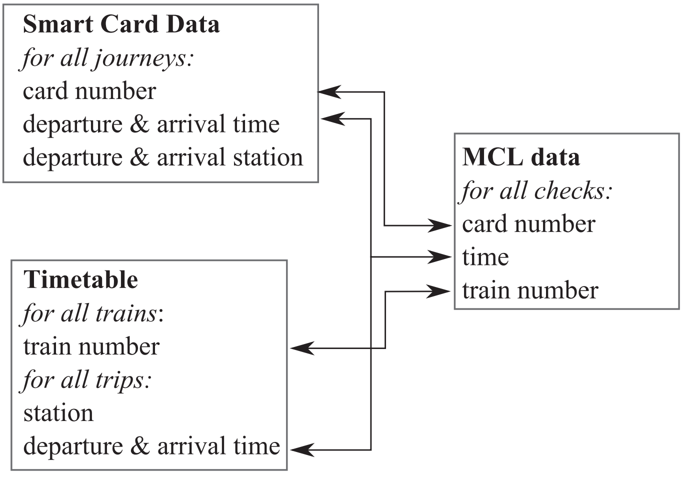


Figure 2.2: Conductor check data (MCL) link the timetable and the smart card data.

We therefore use these data to validate both Route Generation methods and Route Selection rules using the MCL data. A Route Generation method is validated by determining the percentage of the checked journeys where there *exists* a matching route in the generated route set that links the origin and destination of the journey within the registered check-in and check-out time. Secondly, we define the performance of a Route Selection rule as the percentage of the checked journeys where the assigned route matches with the conductor check(s) of this journey. They match when the train number(s) and time(s) of the conductor check(s) of a journey are the same as those of the train trip(s) in the route assigned to this journey. A performance of 100% would mean that for all checked journeys, all routes match with the registered conductor checks' train numbers and times.

Note that in this procedure three data sets are linked based on time. However, each of these data sets have their own registration of time, and sometimes even multiple base clocks exist within one data set, e.g. the clocks of the check-in and check-out devices. Therefore, the assumption that there exists a true route in the timetable that matches the MCL data, the route in the timetable, and the journey, may not be true. As part of the validation, we pay specific attention to the possible errors due to unsynchronized clocks and possible other registration errors in the data, in order to not confuse them with the errors that may be due to the method.

2.4 Route Generation

The objective of the Route Generation step is to find all time-dependent routes that passengers use to travel from an origin to a destination. A route set $\mathcal{R}_{OD}$ is constructed per origin-destination pair (OD) containing a set of time dependent routes connecting the origin with the destination. The routes are generated based on the translation of the timetable into an event-activity network, as described in Section 2.4.1. We define two translations of a timetable into an event-activity network and discuss their advantages and disadvantages. Next, three different algorithms for route construction are defined in Section 2.4.2.

The network definition together with the route construction algorithm define a Route Generation method. We will compare the following 5 combinations in our case study:

1. Basic Network, Minimum Cost: *BN-MC*

2. Basic Network, Extended Search: *BN-ES*

3. Extended Network, Minimum Cost: *EN-MC*

4. Extended Network, Learn Links: *EN-LL*

5. Extended Network, Learn Links and Minimum Cost: *EN-LL-MC*

2.4.1 Definition of the Event-Activity Network

The timetable is translated into an event-activity-network $\mathcal{N} := (\mathcal{E}, \mathcal{A})$. This network is a directed network, where $\mathcal{E}$ denotes the set of events (nodes) in the network, and $\mathcal{A}$ represents the set of activities (arcs) in this network. A timetable consists of a list of train trips. A *trip* is a train ride between two consecutive stations with a departure time and an arrival time. This information is used in two ways to construct an event-activity network: the Basic network (BN) and the Extended Network (EN).

Basic Network

In the Basic Network, each node $e \in \mathcal{E}$ represents a departure or an arrival of a train. Thus each node is characterized by a time instant and a station. The time instant of event e is denoted by $t(e)$, and the station of event e is denoted by $s(e)$.

The set of arcs $\mathcal{A}$ consists of a set of train arcs $\mathcal{A}^{\text{train}}$ and a set of station arcs $\mathcal{A}^{\text{station}}$. Each train trip in the timetable is represented by a train arc $(u, v) \in \mathcal{A}^{\text{train}}$ from node u

to node v. These nodes are such that $s(u)$ and $t(u)$ are the departure station and time of the train trip, and $s(v)$ and $t(v)$ are the arrival station and time of the train trip.

Each station arc $\mathcal{A}^{\text{station}}$ connects two nodes representing consecutive time instants at the same station. Thus each arc $(u, v) \in \mathcal{A}^{\text{station}}$ connects nodes u and v, which are such that $s(u) = s(v)$ and $t(u) < t(v)$, and for each other node w with $s(w) = s(u) = s(v)$ we have $t(w) < t(u)$ or $t(w) > t(v)$. Passengers can use the station arcs to board a train, to leave a train, or to transfer from one train to another. The lengths of the arcs are described in Section 2.4.2.

An example of a Basic Network is shown in Fig. 2.3a. A Basic Network is a compact translation of the timetable into a network, which benefits the speed of the shortest path computations. However, as we will describe below, the inability to distinguish transfers of passengers from one train to another is a major disadvantage.

Extended Network

In contrast with the Basic Network, the Extended Network allows to distinguish the transfers of the passengers. Therefore, the set of nodes consists of train nodes $\mathcal{E}^{\text{train}}$ and station nodes $\mathcal{E}^{\text{station}}$.

In the Extended Graph the complete path of a train consisting of train trips and dwellings in stations are modeled. Therefore, train nodes $v \in \mathcal{E}^{\text{train}}$, again representing arrivals and departures of trains, are characterized by a time instant, a station, and a *train number*. Station nodes $v \in \mathcal{E}^{\text{station}}$ represent time instants at which passengers board a train departing from a station, or alight from a train arriving in a station. The boarding time is earlier than the departure time of the train. The alighting time is later than the arrival time of the train. Station nodes are characterized by a time instant and a station.

The set of arcs consists of train arcs $\mathcal{A}^{\text{train}}$, station arcs $\mathcal{A}^{\text{station}}$, and transfer arcs $\mathcal{A}^{\text{transfer}}$. Each train arc $(u, v) \in \mathcal{A}^{\text{train}}$ connects consecutive departures and arrivals of trains at stations, not only connecting a departure with the next arrival of the train (a train trip), but also connecting an arrival with the next departure (a dwelling in a station). As before, each station arc $\mathcal{A}^{\text{station}}$ connects two nodes representing consecutive time instants at the same station.

Finally, each transfer arc $\mathcal{A}^{\text{transfer}}$ represents the process of passengers boarding a train or alighting from a train. A transfer arc $(u, v) \in \mathcal{A}^{\text{transfer}}$ representing boarding a train connects a station node $u \in \mathcal{E}^{\text{station}}$ with a train node $v \in \mathcal{E}^{\text{train}}$. The nodes u and v are such that node v corresponds with a train departure, $s(u) = s(v)$, and $t(v)$ is the time the passengers departing with the train have to board the train. A transfer arc $(u, v) \in \mathcal{A}^{\text{transfer}}$ for alighting from a train is defined similarly.

An example of an Extended Network is shown in Fig. 2.3b. The benefit of the Extended Network is that, because transfers can be distinguished and penalized, important routes can be found that cannot always be found in the Basic Network. This leads to a better performance of the Route Deduction method. The disadvantage is that the numbers of nodes and arcs are much larger, thereby increasing the computation time.

Example

We compare the two networks based on an example network with 4 stations and 3 trains, for which the corresponding time-space diagram of the Basic Network is given in Fig. 2.3a and the Extended Network is given in Fig. 2.3b. Consider a passenger traveling from station A to station D and the routes that exist connecting these two stations in the two networks.

The Basic Network contains the fastest route that contains a transfer from Train 1 to Train 2. However, the transfer time is very short - in fact zero minutes in our example - not allowing for enough time to transfer.

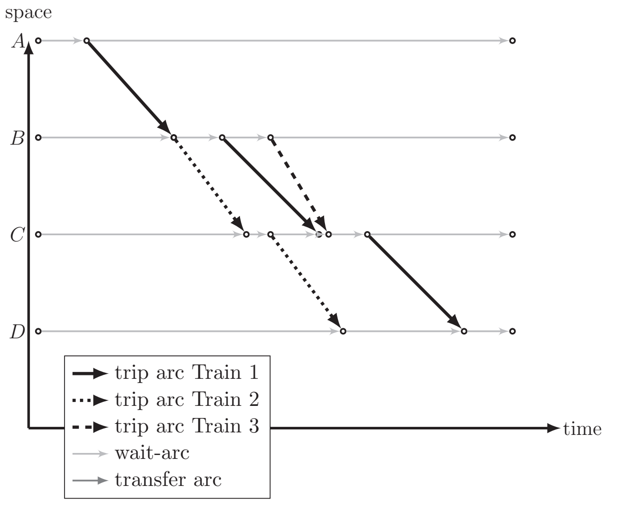
Therefore in the Extended Network, the arrival of passengers from Train 1 in station B is later than the departure of passengers from station B to Train 2. Thus this infeasible transfer from Train 1 to Train 2 in station B does not exist in the Extended Network. The direct route with Train 1 from station A to station D exists in both networks.

Finally a third route exists in both networks: Train 1 from A to B, Train 3 from B to C, and finally again Train 1 from C to D. Such a route with two transfers and no gain in time is inferior to the direct route with Train 1. However, in the Basic Network the difference between these routes cannot be seen. Even worse, when preferring station arcs over trip arcs in case of equal cost, the shortest path algorithm will find this inferior route with a transfer and will not find the direct route.

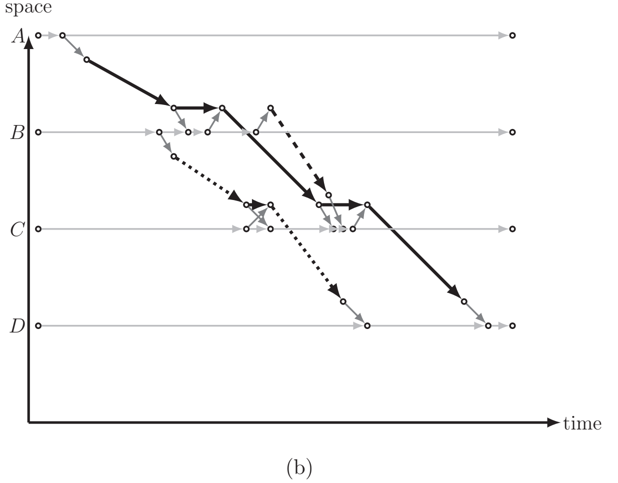
Although preferring trip arcs over station arcs would solve this problem for this specific case, it may lead to routes with unnecessary detours in case the actual route contains a long transfer. In the Extended Network, even a very limited penalty on transfer arcs would ensure that the direct route is found in this example.

2.4.2 Algorithm for Route Generation

The objective of Route Generation is to find all routes used by passengers to travel from their origin to their destination. As these routes are unknown, we define a set of algorithms



(a)



(b)

Figure 2.3: The Basic Network Formulation (a) and the Extended Network formulation (b) of a 4 station network with 3 different trains.

aimed at finding a diverse set of paths. These algorithms are all based on the minimum cost or shortest path problem: Given a directed network $\mathcal{N} := (\mathcal{E}, \mathcal{A})$ with node set $\mathcal{E}$ and arc set $\mathcal{A}$, source and sink nodes s and t, and cost c_a for each arc $a \in \mathcal{A}$, find the shortest (or cheapest) route from node s to node t.

For all shortest path computations we use the well-known Bellman-Ford algorithm (Bellman, 1958; Ford Jr. and Fulkerson, 1962). By using a topological ordering of the nodes in the event-activity network based on time, a single round of the Bellman-Ford algorithm is sufficient to build a shortest path tree. The running time of Bellman-Ford's Algorithm is known to be $O(|V| \times |E|)$, and, because of the topological ordering, in our case only $O(|E|)$.

A shortest path tree contains information on shortest paths from the source node to *any* node in the network (forward computation) or from any node in the network to the sink (backward computation). A shortest path tree can be built from a *set* of sources or to a *set* of sinks. As a result, it is computationally more efficient to pre-generate the set of candidate routes for all OD-pairs, by computing shortest paths for the full time period per OD-pair from a single shortest path tree, and ordering the OD-pairs by origin such that shortest path trees can be re-used between OD-pairs with the same origin. Finally, parallel computation of routes for different OD-pairs is used to increase the computation speed further. A full set of shortest path routes for a full day for a single OD pair is computed in 0.2 seconds on a standard server within NS for the Basic Network. Although one could further speed up the algorithm by using more advanced shortest path algorithms or an intricate ordering of OD-pairs and possible storage of popular shortest path trees, our implementation was fast enough for the purpose of Route Deduction.

The 5 Route Generation methods defined at the beginning of this section differ in the selection of sinks and sources used as a starting point for finding routes, and in the network formulation used (Section 2.4.1). The results depend on the arc cost settings, which we will discuss first.

Arc Cost The arc costs for station and train arcs are set equal to the time length of the arc. This fully defines the costs of arcs in the Basic Network. The transfer arcs in the Extended Network still require a specification of both a length and a cost, as these do not follow directly from the timetable.

In the example of Fig. 2.3 we showed that at least a small penalty for the transfer arcs is needed to assure that, in the case of equal length routes, a route with the least transfers is found. The best settings of these parameters will depend on the network. To generate all routes with a single setting of these parameters would require a deep knowledge of the network and passenger behavior, which is not available for our case study. Therefore we must be careful in making any assumptions here that influence the set of generated routes - and thus the results of the Route Deduction method.

We choose to run the Route Generation methods for multiple settings of the length of the transfer arcs in the Extended Network. One setting allows passengers to make a one-second transfer, the other setting requires at least a 4 minute transfer time, by defining the length of each transfer arc as 2 minutes. The 4 minutes are sufficient to make a transfer in any station in the Netherlands. Alternatively, one could use minimum transfer times based on the walking time between platforms at stations and the arrival platform of the specific trains in future research. Such a specification of train-to-train transfer times is possible in this formulation. Moreover we penalize each transfer by 1 additional minute. The arrivals and departures of trains are given in minutes - thus 1 minute is the minimum gain in time a transfer should provide.

The settings for these parameters, as well as the number of instances one should run to find a broad set of routes, depend on the network. For example, take a transfer station with trains from two different lines arriving at 1 minute intervals. With a 2 minute margin there are already three trains departing from the first line and three trains departing from the second line, leading to 6 different possible routes: $\{(1,1)(1,2)(1,3)(2,2)(2,3)(3,3)\}$. The usage of several settings of the transfer time in the Extended Network will allow to find these different routes. Moreover, one might be able to find good values for these settings through research on minimal transfer times. Our data set of 5 days was unfortunately too limited to fine tune these settings based on the data.

Route Generation methods In the following, we describe the Route Generation methods that are used for generating routes in the Basic Network and in the Extended Network.

- *Minimum Cost (MC):* The MC method runs the Bellman-Ford algorithm forward and backward. In a forward search, shortest paths are generated starting at any time a train leaves the origin. In a backward search, shortest paths are generated ending at any time a train arrives at the destination. Though both methods will find minimum cost routes, one will find the earliest arriving routes, while the other will find the latest departing routes.

- *Extended Routes Search (ES):* In an attempt to quickly find more diverse routes, we use the ES method in the Basic Network. Given a source node for a route starting in an origin station, we construct a new route based on *every* train arc that leaves this source node: for each such train arc we find a shortest path from the arrival station of this train arc to the destination station, while forbidding this route to return to the origin station. Similarly we construct routes for all train arcs ending in a sink node of a route arriving in a destination station. The disadvantage of this approach is that many initially selected train arcs are leading into the wrong direction, thus resulting in unlikely routes or in routes that do not fit within the ticket requirements. In an attempt to delete the most unlikely routes while keeping a diverse set of routes, we delete all *dominated* routes. Domination is determined based on the length and the number of transfers.

- *Learn Links (LL):* The LL method constructs routes based on conductor checks from earlier days. A set of train trips is constructed per OD-pair: for every conductor check the corresponding train trip is found in the timetable. Next, for each of these train trips we find the shortest route from the origin to the destination of the OD-pair including this train trip. The conductor check, and thus the trip, is time dependent. Netherlands Railways has a cyclic timetable. Therefore we can translate all initially found time dependent routes into time independent routes, using the cyclicity of the timetable. Note that there is no dependency between this Route Generation method and the validation of the methods, because only conductor checks from earlier days are used.

2.5 Route Selection

In this step for each journey a single route is selected from the pre-generated route set resulting from the Route Generation step. For each journey, first all routes in the generated route set are selected that lead from origin to destination of the journey within the registered time horizon. In case multiple routes are contained in this set, we consider the following Selection Rules:

1. First Departure (FD)
2. Earliest Arrival (EA)
3. Last Arrival (LA)
4. Least Transfers (LT)
5. Maximum Route Length (MRL)
6. Selected Least Transfers Last Arrival (STA)

We explain these rules by the example shown as a time-space diagram in Fig. 2.4. Given is a journey from station A to station D. Within the time of check-in (ci) and check-out (co) there are 5 routes from the candidate route set $\mathcal{R}_{OD}$ that fit with the journey. Note that there are many more routes in the network, but not all routes are in the generated route set. The routes are denoted by $R_i, i = 1, \ldots, 5$. All train trips are represented by arrows. Trips $B_1 - C_1, C_1 - D_1$ are carried out by a different vehicle than trip $A_1 - B_1$. Therefore they are dotted.

- The rule *FD* selects the route that departs closest to the time of check-in, R_1, minimizing the waiting time at the departure station.
- The rule *EA* selects the earliest arriving route, R_1 thereby choosing the quickest option.
- The rule *LA* selects the route arriving closest to the time of check-out, R_5. This route minimizes the waiting time at the arrival station.
- The rule *LT* selects the route with the smallest number of transfers. As there are two direct routes, R_3 and R_4, a tie breaking rule is needed. These generic tie breaking rules will be ordered, best performing first, as: *LT, LA, FD*. Thus *LT* selects R_4.
- The rule *MRL* selects the route with the maximum length (time duration) that fits within the check-in and check-out time of the journey, which is R_2. This rule is similar to the Route Selection rule proposed by Kusakabe et al. (2010) and therefore included in our comparison.
- Finally, the rule *STA* selects R_3. STA first selects routes where the sum of the difference between the check-out and the route's arrival, together with the check-in and the route's departure, is less than x minutes. If multiple routes remain, it applies the generic tie-breaking rules: *LT, LA and FD*. If no routes remain after the first selection, the tie breaking rules are applied to all routes within check-in and check-out. Therefore *STA* is a combination between the *MRL* and *LT* rule. The most suitable value of x depends on the frequency in the public transport network, and on common entrance and egress times of passengers. By evaluating several values, we found that $x = 10$ minutes works well in our case study.

2.6 Validation and Calibration

We discussed several Route Generation methods (Section 2.4) and Route Selection rules (Section 2.5), together leading to 30 different settings for the Route Deduction: 5 Route

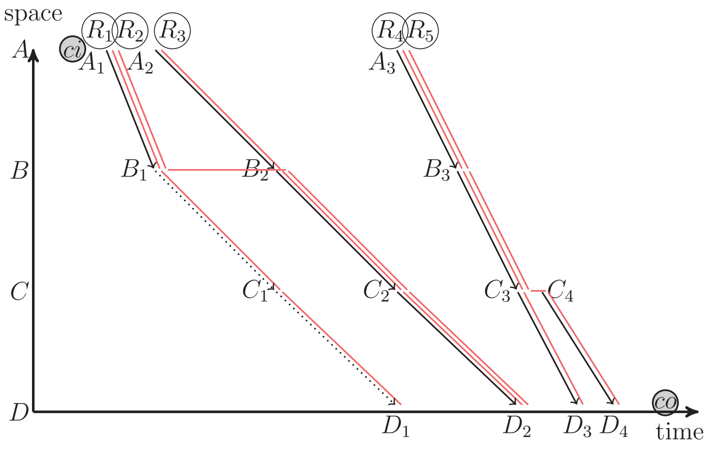


Figure 2.4: Time-Space diagram of five candidate routes for a journey with a check-in (ci) at station A and a check-out (co) at station D.

Generation methods together with 6 Route Selection rules. Thanks to the availability of conductor checks, we are able to evaluate the performance of each of these settings.

These conductor checks provide a ground-truth data set for the subset of journeys that were at least checked once. Based on the train number and the registered time of the conductor check, we can find a train trip in the timetable. Based on the smart card number and the time of the conductor check, a journey can be selected from the smart card data that belongs to this conductor check.

If the train number of the conductor check is contained in the route assigned to the journey around the time interval of the check, we conclude that the assignment of route to journey was correct: the conductor check *matches* the assigned route. In case of multiple conductor checks for one journey, an assignment is only considered correct if all conductor checks match the assigned route. We define the *performance* as the number of journeys with a conductor check that were assigned to the correct route.

Whether a route matches a conductor check depends on both the Route Generation and the Route Selection step, which we will evaluate separately. The procedures for each are discussed in respectively Section 2.6.1 and Section 2.6.2.

2.6.1 Validation of Route Generation

A successful Route Generation method generates a route set that contains for each checked journey j a matching route that leads from the origin to the destination of journey j and is within the time between check-in and check-out registered for journey j.

In the following, we denote the set of *all* generated routes by $\mathcal{R}^{RG}$ and define $\mathcal{R}_j^{RG}$ as the set of routes in $\mathcal{R}^{RG}$ that connect the OD-pair of journey j within the time frame of the journey. Furthermore, we use the term $\mathcal{R}_j$ for the set of all routes *in the timetable* that connect the OD-pair of journey j within its time frame. The term $\mathcal{R}_{OD}^{RG}$ is used for the set of all routes *in the generated route set* that connect the OD-pair of journey j, irrespective of time.

To evaluate the performance of the Route Generation methods we distinguish the following 4 cases:

1. A matching route exists in the generated route set $\mathcal{R}_j^{RG}$.

2. A matching route exists in the set $\mathcal{R}_j$ of all routes in the timetable, but not in $\mathcal{R}_j^{RG}$: there exists a route in the timetable that connects the OD-pair of journey j and within its time frame, but this route is not generated.

3. A matching route does not exist in the set $\mathcal{R}_j$ of all routes in the timetable.

4. A matching route exists in the generated route set $\mathcal{R}_{OD}^{RG}$ but not in $\mathcal{R}_j^{RG}$: there is a route connecting the OD-pair of journey j, but not within its time frame.

For all Route Generation methods, and for all journeys with a conductor check on our sample days, we determine which case applies for the generated routes. The more matching routes are found in the set $\mathcal{R}_j^{RG}$ (Case 1), the better the Route Generation method. Case 2 gives an indication for possible improvements of the Route Generation method. In principle, Cases 3 and 4 should not occur. However, in our data set they *do* occur. This is mainly due to the fact that the clocks of the three data sets are not synchronized and the fact that e.g. replacing bus services are not contained in the timetable.

For over 10% of the smart card journeys in our data set there does not exist a route in the timetable that connects the origin and destination of the journey within the registered time frame. However, a global correction of the smart card data, extending the check-out time with three minutes, reduces the time-error in our case study from 10% to less than 1.5%. A global check-in time correction did not improve the results.

2.6.2 Validation of Route Selection

To separate the data errors from the errors that result from the Route Selection rules, we evaluate these rules based on the subset of journeys for which there exists a journey in the generated route set $\mathcal{R}^{RG}$ that falls within the registered check-in and check-out time of the journey. The performance of a Route Selection rule is denoted as the percentage of routes for which the rule selects a correct route: a route that matches with the conductor checks.

2.7 Data

This section describes the data used in our case study: smart card data (Section 2.7.1), timetable information (Section 2.7.2), and data from conductor checks (Section 2.7.3). The comparison of passenger service for special and normal days is based on a larger data set containing *all* journeys made by smart card on these days. We use a 5 day sample of real life data of Netherlands Railways, who provides on average 1.2 million journeys per day.

The selected 5 days contain two regular days and three special days with reduced train frequencies due to expected extreme bad weather. On the special days, the changes in the timetable were communicated to the passengers at 17:00h of the previous day. Due to the relatively late communication, not all passengers were aware of the change in service at their time of departure on those days. A changed timetable contains approximately 20% less trains, and reduces the frequency of the trains by 50% on the main corridors. The timetable is reduced in order to prevent major disruptions and add-on effects due to the bad weather. Though it is clear that this reduced service decreases the probability of an out-of-control situation during bad weather, the punctuality of the trains on these days is significantly below average, and smaller and larger disruptions will likely have occurred at a higher rate than on the normal days due to the bad weather. Therefore it provides a good case study for testing the performance of the passenger route choice deduction and analyzing passenger service in case of disruptions.

2.7.1 Smart Card Data

Netherlands Railways' smart card system requires passengers to tap their smart card to a device positioned at the station at the beginning and end of each journey, referred to as checking-in and checking-out. This system is similar to such systems implemented for metro, train and subway in respectively London, Tokyo, and Seoul. A journey contains a smart card number, a check-in time, a check-in station, a check-out time and a check-out station.

Our data set contains all journeys paid for by smart card for the 5 selected days. Not all passengers of Netherlands Railways were using the smart card system at this time, as the smart card is still in its introduction phase. Specifically, most annual subscriptions were excluded from this system, therefore regular travelers are less represented in our data set. Still a significant portion of all journeys is made by smart card, and a significant number of these journeys is checked by a conductor. Because of the sensitivity of this information, we can only state that each of our data sets contains hundreds of thousands of records. We cannot report more exact numbers.

From the data set, we select journeys that have both a check-in and a check-out, and that do not have more than 5 routes fitting within the registered time interval. Finally, we select only those 7000 origin-destination pairs that occurred at least once on each of these days accounting for 95% of all journeys. The first two rules aim to eliminate passengers who forgot to check-in or check-out. The second rule reduces the computation time while allowing to compare the performance per OD-pair for each day.

Neither seat reservation nor reservation for a specific train is available in the Dutch railway system, thus smart card data is the only source of rather exact time-dependent journey information.

2.7.2 Timetable Information

The timetable contains the set of all train trips with arrival and departure times per station and per train number. Here a train trip refers to a train connecting two consecutive stops on its route. For our case study we use the realized timetable that contains the arrival and departure times as realized on the 5 selected days. There are between 30,000 and 40,000 train trips connecting about 360 stations per day. Moreover, for the Learn Links method we also used a planned timetable to generate a set of train trips per OD-pair as described in Section 2.4, as realized timetables were not available to us for these specific days. Emergency replacement busses are not contained in either the planned or realized timetable.

2.7.3 Conductor Checks

Netherlands Railways employs conductors who, as part of their duty, check the validity of tickets of passengers between stops of a train. The validity of a smart card ticket is checked using a Mobile Chip smart card Reader (MCL). The device then stores the smart card number, the current time, and the train number of the current train. The conductor checks the validity of only a sample of the passengers in a train, and only for a sample of the trips of this train. Apart from the 5 selected days our method was evaluated on, the Learn Links method was used over 30 earlier days of conductor checks to generate the set of additional routes.

2.8 Results

In Section 2.8.1 we compare the performance of different Route Generation methods (Section 2.4) and different Route Selection rules (Section 2.5) based on the realized timetable. Next in Section 2.8.2 the Route Deduction data is used to compare passenger service on normal and special days in terms of on-route time and departure waiting time of passengers.

2.8.1 Evaluation of Route Deduction

We separately discuss results on Route Generation and Route Selection, which together define the Route Deduction method. The Basic Network of the transportation network has on average 50,000 nodes and 86,000 arcs. The Extended Graph is two to three times larger than the Basic Network and has on average 144,000 nodes and 211,000 arcs.

Evaluation of Route Generation

Table 2.1 contains the percentage of journeys with a conductor check having a matching route in the route set $\mathcal{R}_j^{RG}$, that is, a route that contains the train trips matching with the conductor check associated with the journey. A 100% score would mean that the Route Generation method finds a correct route for all journeys with a conductor check. Because of the clock synchronization errors we observed in our data, we allow a time interval of 10 minutes around the time of the conductor check to find the correct train number in the route.

Our tested Route Generation rules score between 75.5% to 93.3%. Route Generation methods based on the Extended Network (EN) have the best performance. The method that allows for penalizing transfers combined with the Learn Links method finds correct routes for 93.3% of the all journeys with a conductor check. This is a great deal better than the methods based on the Basic Network. The performance of the Learn Links method alone is less than that of the minimum cost based methods. A possible explanation is that conductor checks are not a random sample of train trips nor of journeys, so some Origin-Destination pairs may be not or under represented in this sample.

To examine whether it is possible to construct an even better Route Generation method, we focus on the best performing method *EN-LL-MC* (top row of Table 2.1). For 93.3% of the journeys with a check a matching route is contained in the data set. Thus for 6.7% of these journeys no such route is found. For the majority of the 6.7%, at least 4% of all journeys with a conductor check, no route can be found in the timetable. For 2.3% a route exists in the set of OD-pairs, but this route does not fit within the registered check-in and check-out time. For only 0.4% of all journeys with a conductor check a matching route *can* be found in the timetable, but was not contained in the generated route set $\mathcal{R}^{RG}$. Thus we estimate the maximum gain of a new route generation method to find matching routes for 0.4% more journeys. However, both in the construction of the new routes and in the conclusion that there is no correct route, clock synchronization errors influence the results. Therefore one must be careful in concluding that the 0.4% journeys are actually missing. In any case, we conclude that only a marginal improvement could be expected from different Route Generation methods.

One may notice that the percentage of journeys with no route in the timetable varies over the generation methods in Table 2.1. The conclusion that there exists a route in the generated route set is based on a *time interval* around the conductor check. However, when no such route is contained in the generated set, the conclusion that there exists a route in the timetable is based on finding a train trip at the *exact time* of the conductor check. Due to clock synchronization errors this may be the wrong train trip, or a train trip is not found at the time of the conductor check. As a result, the number of journeys without a route in the timetable can only be estimated, and thus varies over the different Route Generation methods.

Given the significant error due to time synchronization errors, one might wonder whether the Learn Links method is actually better than the minimum cost method. Although the *EN-LL-MC* method finds 1% more journeys with a route, no guarantee can be given on the quality of these routes. The advantage of the Route Generation methods based on minimum cost, together with the Extended Network, is that they find a broad set of routes that can easily be considered as reasonable routes, as they are minimum cost routes given some definition of cost.

Table 2.1: Performance of the Route Generation methods.

Generation Method	Journeys with Route	No Route in Timetable	Route in OD set-Not in Journey Set	Route in Timetable-Not in Generated Set
EN-LL-MC	93.3%	4.0%	2.3%	0.4%
EN-MC	92.3%	5.0%	1.2%	1.5%
EN-LL	88.4%	4.1%	5.9%	1.3%
BN-ES	89.0%	5.3%	1.0%	4.7%
BN-MC	75.5%	5.3%	10.3%	8.9%

Evaluation of Route Selection

In case there are multiple candidate routes for a journey in the generated route set, a route is selected based on one of the 6 selection rules discussed in Section 2.5. Table 2.2 gives the number of correctly linked routes for the different selection rules (rows) and different generation rules (columns). The presented percentages are the percentages of the journeys deducted correctly based on the subset of journeys with a known existing route. These are the 93.3% of the journeys with a route in the *EN-LL-MC* method, as this is our best estimate of the actual number of journeys for which there exists a route matching the conductor check.

We find that, independently of the Route Generation method, the selection rule *STA* consistently performs best by comparing the performances *within* the columns in Table 2.2. Although there is no guarantee that a global selection rule will work well for all journeys, *STA* reaches a performance of on average 95% in combination with the *EN-MC* and *EN-LL-MC* generation methods, at least 3% better than any other selection rule. Selection rules minimizing egress time and travel time, like *FD* and *EA* have generally a poor performance.

The addition of routes does not necessarily result in a better performance: there is hardly any difference between the *EN-MC* and *EN-LL-MC* generation methods. In fact the difference is only in the second decimal (not given in the table). Thus generating more routes does not necessarily increase the performance: if the generated route set is larger, then also the probability of selecting the wrong route increases. Moreover, given our previous discussion on the quality of the routes generated through Learn Links, one might say that *EN-MC* is the better Route Generation method.

Note that Table 2.2 is based on the 93.3% of the journeys for which a correct route was found by the *EN-LL-MC* generation method. The performance of the *STA* rule for the full sample of all journeys with a conductor check is 88%. The analysis of the missing journeys in the Route Generation step, discussed above, suggests that the majority of the

Table 2.2: Performance of the Route Selection rules, average over days, best performing in bold.

Selection Method	BN-MC	BN-ES	EN-LL	EN-MC	EN-LL-MC
FD	65%	84%	54%	86%	53%
EA	67%	84%	82%	86%	86%
LA	65%	84%	82%	86%	86%
LT	68%	87%	86%	90%	90%
MRL	70%	88%	84%	92%	89%
STA	73%	91%	90%	**95%**	**95%**

Table 2.3: Performance per day based on the Route Generation method *EN-LL-MC*.

Date	FD	EA	LA	LT	MRL	STA
Regular day 1	46%	83%	83%	88%	86%	93%
Regular day 2	49%	88%	88%	93%	91%	99%
Special day 1	64%	85%	85%	89%	89%	94%
Special day 2	52%	86%	86%	89%	89%	94%
Special day 3	53%	86%	86%	90%	88%	94%

12% journeys with an error are to be blamed on the synchronization errors in the data and *not* on errors in the Route Deduction method. However, it would be good to confirm this based on additional data, for example data on train utilization data.

Table 2.2 gives the average performance over all 5 days. Table 2.3 zooms in on the scores per day. We present results for the selection rules in combination with *EN-LL-MC*, the best performing Route Generation method. Results in Table 2.3 show that the *STA* selection rule performs well for all days. The relatively good performance on special days may be partly explained by the fact that, due to the reduction in train frequencies, the choice set per journey is smaller, and hence the probability to choose the correct route is higher. Regular day number 2, the latest date in our sample, has a remarkably high score of 99%. Possibly the Learn Link method finds more interesting routes as the number of earlier days with conductor checks increases. This issue is left for future research.

To analyze whether the accuracy depends on the OD-pair, we assigned a performance score for each OD-pair defined as the percentage of correctly selected routes. This score is weighed by the number of journeys corresponding to the OD-pair. We found that less than 2% of all journeys have an OD-pair performance below 50%. Moreover, almost one third of all journeys have an OD-pair with a perfect score of 100%, while over two thirds of the journeys have an OD-pair performance of 90% or more.

Note that, as these scores are calculated per OD-pair, they cannot directly be compared to the number of options per journey. Fig. 2.5 shows the cumulative performance score per OD-pair on the horizontal axis, and the percentage of journeys with this minimal score on the vertical axes. The overall good performance is indicated by the slow decline of the line. The perfect score for over 30% of the journeys is indicated by the end of the graph at (1, 0.33), indicating that 33% of the journeys has an OD-pair with a performance of 100%.

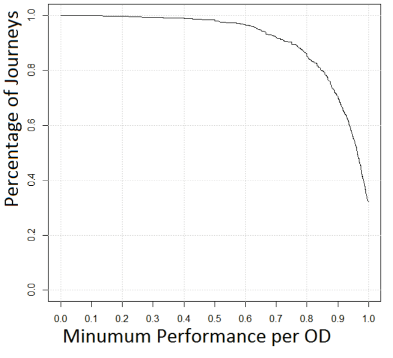


Figure 2.5: Performance per OD-pair, weighted by the number of journeys.

2.8.2 Analyzing Changes in Passenger Service

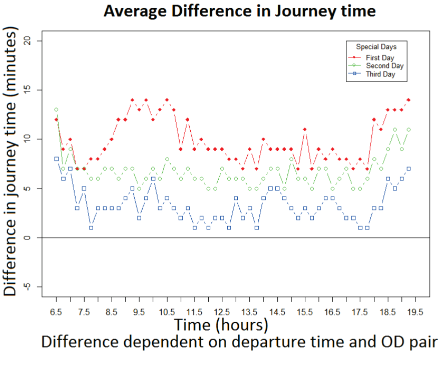
Based on the passenger route choice deduction, we compare differences in travel time between normal and special days. This comparison is based on *all* fully registered smart card journeys on these days, and we consider weekdays only (no weekends). Still 5 days are a very limited sample. Also, current results are likely not representable for weekends where the majority of trips are known to be motivated by leisure activities, while during the week the majority of jobs results from people commuting for work. Therefore the results in this section are more an illustration of the possibilities of this data set than aimed at drawing definitive conclusions.

We evaluate the passenger service as the difference in durations of identical journeys (*journey-time*) between special days and normal days, and the difference in route-time duration of identical routes (*route-time*) between special days and normal days. Differences in *route-time* reflect delays due to disruptions, disturbances, and additional transfers.

Differences in *journey-time* reflect the possible added waiting time of passengers in addition to increased on-route time. The journey-time can be calculated from the smart card data directly, but the route-time can only be computed after the Route Deduction. By comparing differences in route-time and journey-time, we can evaluate the change in logistic service and the change in service experienced by passengers separately. Especially with a reduction in frequency, this is important.

Differences are calculated per OD-pair, to prevent a change in the OD-matrix to cause a change between special and normal days. Differences per OD-pair are weighed by the number of journeys on the special days, to obtain the average change in service for all journeys on the special days. To compare differences in passenger service between peak and off-peak hours, the difference in route-time uses the departure time of the journey. The journeys are distributed in 15 minute blocks per OD-pair based on the departure time, in order to have large enough numbers of passengers per time-unit for comparison.

We find that, indeed, special days have both longer journey-times and a longer route-times than regular days. The two regular days are not significantly different in this respect. Fig. 2.6 contains graphs of the average difference in journey-time (left) and route-time (right) for each of the three special days. Further analysis based on Route Deduction shows that the longer journey times mostly result from longer waiting times at the departure station, while the waiting time at the arrival station is statistically similar for all days. Moreover, it seems that passengers learn over time to adjust their departure time to the reduced timetable, while at the same time punctuality increased a bit, both leading to better passenger service on later special days.



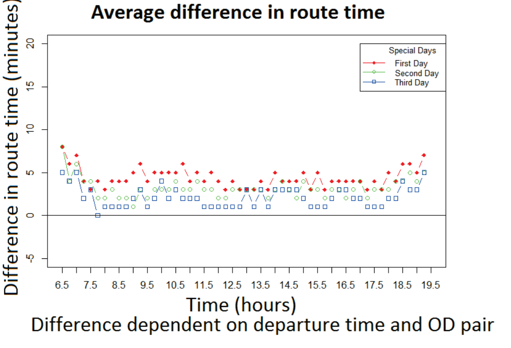


Figure 2.6: Difference in mean journey-time (left) and mean route-time (right) between normal and special days.

2.9 Conclusions and Discussion

This chapter proposes a method for passenger route choice deduction from smart card data. The passenger route choice deduction is important for analyzing passenger service in terms of travel time, which is dependent on route choice. Thanks to the unique data set resulting from conductor checks, the passenger route choice deduction can be validated at the journey specific level. The journey validation is of a higher accuracy than previous validation methods based on train capacity utilization proposed by Kusakabe et al. (2010). Especially when not all passengers travel by smart card, validation on a per journey level is more accurate than validation on an aggregate level over all passengers. To our knowledge, this is the first paper to include validation of this method, and to specifically evaluate different methods for Route Generation and Route Selection. Evaluations are based on a real life data set from Netherlands Railways.

We compared several Route Generation methods based on different network formulations of the public transport network. We showed that the network formulation strongly influences the ability of finding all reasonable routes. Although no Route Generation method is known to find all reasonable routes (Fiorenzo-Caralano, 2007), our best method finds routes for 93 % of the journeys in our validation sample. Route Generation methods based on minimum cost searches in the Extended Network that allow penalizing transfers perform significantly better than minimum cost searches in the Basic Network formulation. Moreover, although the set of routes is increased by using data from earlier days to learn routes from the conductor checks, a minimum cost based generation method performs almost as well as this learning algorithm.

Through the implementation of 5 route Selection Rules we compare previously made assumptions on passenger route choice including first departure by Frumin and Zhao (2012), longest route by Kusakabe et al. (2010) and latest arrival by Sun et al. (2012), with two additional rules of least transfers and a balancing rule between longest journey and least transfers. We measure performance based on the subset of journeys that were checked by a conductor during their journey. We find that previously assumed selection rules perform poorly in a complex network such as that of Netherlands Railways. Especially the first departure rule performs badly, as was also concluded by Schmöcker et al. (2013).

However, a single Route Selection Rule weighing travel time and transfers, STA, is able to assign 95% of the journeys in our sample correctly. We find that this method works well on both regular days and in case of disruptions. The resulting data is suitable for analyzing passenger service, as illustrated by our case study, but could also be used for, for instance, calibrating route choice models as done by Schmöcker et al. (2013).

Currently conductor checks are used to broaden the route set. Alternatively, a learning algorithm could be used to *reduce* the set of routes. Future research could develop statistical arguments that define when to eliminate a route, or where to gather additional data to validate the elimination of a route. Moreover, results of the Route Deduction method could be used to fine-tune the parameter settings of the Extended Network, possibly aiming to set them in such a way that, based on a single setting, all possible routes can be found. This would increase the computational speed, reduce the number of candidate routes, and possibly increase the performance of the method.

Chapter 3

Forecasting Passenger Flows during Disruptions based on Smart Card Data

This Chapter is an adaptation of Van der Hurk et al. (2013), which was presented at the IAROR Conference in Copenhagen, 2013.
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3.1 Introduction

Although timeliness of operations is one of the key performance indicators of public transport operators, disruptions causing delays unfortunately do occur in these systems. When they do occur passengers expect quick solutions that minimize their inconvenience. Detailed data on passenger demand is required to minimize passenger inconvenience. Recently introduced automated fare collection systems, such as smart card ticketing, generate data on passenger journeys. These data are often not available in real-time, and therefore forecasts of passenger demand are needed to anticipate passenger demand in disruption management practices. This chapter presents a framework for forecasting passenger flows in case of disruptions using these new data.

Traditionally, demand forecasts in (public) transport are split into two phases: in the first phase, the origin-destination matrix (OD matrix) is estimated for a specific time period, for instance for a day or a (peak) hour. In the second phase, the OD matrix demand is assigned to paths through the public transport network. The assignment to paths aims to estimate the choices of passengers according to a behavioral model. Nguyen and Pallottino (1988) and Spiess and Florian (1989) introduced the concepts of hyperpaths and travel strategies to describe different observed path choices of passengers. Trozzi et al. (2013) propose a model for assigning passengers to paths in networks with congestion. Anderson et al. (2014) estimate a model for multi-modal route choice using survey data. Schmöcker et al. (2013) formulate and calibrate a route choice model for bus passengers based on smart card data. Generally these models are aimed at estimating passenger route choices in undisrupted situations.

Newly available smart card data contains information on the OD matrix, and is suitable to deduce information on the routes chosen by passengers (Chapter 3. Unlike OD-matrices, it does not aggregate journeys over time but rather contains information about both the departure and arrival time of individual passengers. It is available for all passengers using smart cards, which is generally a much larger number of passengers than the number of participants in a survey. Moreover, smart card data does not suffer from inaccuracies due to errors made by survey participants in their recollection of past journeys. Passenger counts per trip, either estimated by conductors, resulting from samplers specifically counting the number of passengers on a specific trip, or from automatic sensors in the vehicle, provide information on the crowdedness and overall demand per trip, but not on the origin and destination of passengers. This information is especially important when aiming to estimate a change in passenger flows due to a disruption. Consequently smart card data provides a unique combination of detailed data per journey for a large set of passengers.

The objective of this chapter is to propose a framework for forecasting demand during disruptions. Specifically, the paper proposes a model to forecast the number of passengers per planned path using smart card data, rather than to separate the estimation of OD-matrix and path choice models. These forecasts could be more accurate than traditional methods, as they use the combined information of origin, destination and route choice which can all be derived from smart card data. These forecasts for the number of passengers per planned path will provide the likely location and destination of passengers at the start of a disruption. Thereby these forecasts can assist in estimating the change in passengers' routes from the start of the disruption without changing route choices of passengers before the start of this disruption. The derived estimates are also aimed at supporting dispatchers in their decision making process during a disruption by providing insight into the passenger inconvenience resulting from the disruption.

The framework consists of three steps (i) analyze the smart card data to derive the combined OD matrix and path assignment over time, (ii) generate forecasts on the number of passengers per planned path, and (iii) use a simulation model to evaluate the passenger inconvenience using the forecasts. Forecasts are intended to be detailed enough to evaluate both individual passenger delay over time and the number of passengers per vehicle in order to, for instance, signal crowding. Additionally, a preprocessing step is proposed that provides insight to dispatchers on when and where passengers are affected by the disruption, and could possibly provide computational benefits.

The forecast model is tested on a real-life smart card data set of Netherlands Railways (NS), the largest passenger railway operator in the Netherlands. The forecasts can be used both by computer-aided disruption management tools and by the dispatchers themselves in order to improve the service level during and after the disruption. Moreover, they can be used to obtain insight into how passengers are affected by a disruption. Our future work on disruption management applications builds upon these detailed demand forecasts. In particular, we are interested in using the forecasts in capacity rescheduling and in providing travel advice to passengers with the objective of improving the overall service quality.

The remainder of this chapter is organized as follows. Section 3.2 contains a literature overview of related research on forecasting, smart card data and disruption management. The three-step framework and the preprocessing step are described in Sections 3.3 and 3.4, respectively. Data and computational experiments are discussed in Section 3.5, and results based on smart card data of NS are presented in Section 3.6. We conclude this chapter with a discussion and comments on future research in Section 3.7.

3.2 Literature Review

In this section we give an overview of research related to short term forecasts of passenger flows for disruption management. We start with literature on demand forecasting for transport, followed by a short overview of research on the application of smart card data.

3.2.1 Forecasting OD flows and demand for transport

Before the existence of smart card data, demand forecasting models for public transport usually relied on panel data or aggregate data, and focused on long term predictions of demand and elasticities.

Some research focuses on long term predictions of demand, for example Gaudry (1975) uses aggregated data on the demand for public transport in a specific urban area to forecast future demand given the price of public transport, the price of alternatives to public transport and the demographics of the population, such as the income distribution of its inhabitants. Wardman (2006) specifically focuses on forecasting railway demand in the long run, using similar variables as Gaudry (1975).

Others focus on the elasticity of demand. Hsiao and Hansen (2011), for instance, focus on predicting demand for air passengers, combining predictions for demand generation and assignment in their model. They base their model on panel data, and they focus on predicting the sensitivity of demand to both time and price of the journey. Rolle (1997) also forecasts the elasticity of demand to price, specifically of railway demand, accounting for the different kinds of services offered. Batley et al. (2011) focus explicitly on the long term effects of lateness of trains on railway demand. He compares a market level model with an individual level model given panel data, and comes to the conclusion that the effects on the aggregate level in terms of elasticity is less severe than the individual level models based on panel data suggest.

From the area of complexity research, González et al. (2008) show that human mobility patterns are quite predictable, by analyzing US cell phone location data. The AURORA [1] project within NS focuses on predicting numbers of passengers per train, and combines several data sources, including quite recently, smart card data.

The success of previous research in developing accurate prediction models suggests that in general data on passenger journeys is regular enough to enable forecasting. The focus of this chapter on short term forecasts is however slightly different from the focus of the above literature aimed at medium and long term forecasts and the estimation of elasticities.

3.2.2 Research on smart card data

Literature on smart card data and applications of smart card data mostly stem from the start of the current millennium. Blythe (2004) was one of the first to give a functional overview of smart card systems for ticketing in public transport. The recent paper by Pelletier et al. (2011) provides a review of literature focused on analyzing smart card data. They divide the literature into the categories of strategic level, tactical level, operational level and commercialization. We use a different categorization of papers on smart card data, and divide them into those on passenger behavior, on route choice and OD. We refer the interested reader to Pelletier et al. (2011) for a broader review of smart card data.

[1] AURORA is the name of a series of projects at Netherlands Railways focused on medium term predictions of the number of passengers per train, (Hoogenraad et al., 2013).

Analysis of passenger behavior

One of the uses of smart card data is analyzing passenger travel behavior. Bagchi and White (2005) are one of the first to use smart card data for this purpose. They use smart card data of a UK bus company, where they analyze the passenger population of that company. Similar is the work of Park and Kim (2008), who analyze the usage and mode choice of passengers, using smart card data of the Seoul public transport system.

Morency and Trépanier (2007) and Agard et al. (2006) extend these analyses by using data mining techniques to deduce travel behavior for different groups of passengers. They show that clustering techniques can reveal patterns of groups of passengers that are valuable for the analysis of transport usage for a public transport operator. They focus on the analysis of past performance and behavior of passengers. Moreover, in their data sets the destination of the journey is not included.

Zureiqat (2008) focuses on the prediction of passenger travel behavior for revenue management. He focuses on the prediction of product type choice together with the number of journeys per passenger, and develops a model for forecasting the effect of product and price changes of a public transport operator.

Route choice and ODs

A second stream of research exists on estimating route choice and ODs from historical smart card data. These estimations are in general focused on constructing route choices and ODs of passengers retrospectively, since the destination is not registered all smart card system data. Seaborn et al. (2009) analyze smart card data of the London public transport system, investigating transfer times between different legs and modes of transportation. Kusakabe et al. (2010) focus on linking check-ins and check-outs to trains for the Tokyo public transport system. In this system they focus on one line having different services. Analyzing the check-ins and check-outs of passenger journeys, they deduce the route choice as the (combination of) services the passenger has chosen for his journey. The algorithm they propose is very similar to the algorithm used in practice by NS for linking journeys to routes.

We also mention here the work of Zhao (2004) and Gordillo (2006) since they focus on OD matrix estimation, although their problem setting is different from the one studied in this chapter. In their papers, they do not aim to forecast the OD flows, but instead they focus on deducing these from historical data, since the end destinations of trips are not registered. From the estimated OD matrix, the routes of the passengers are then inferred.

The article focuses on the London bus system in which, as opposed to the London subway system, just check-in is required.

3.3 Framework

The framework presented here generates passenger flow forecasts that allow estimation of both the number of passengers per trip as well as the inconvenience experienced by individual passengers due to a disruption. Forecasts are calculated given the timetable , a disruption, and a set of smart card data.

A timetable is defined as a set of trips. A *trip* is a train ride between two consecutive stops. The timetable graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is an acyclic time-space graph. It contains a node $v \in \mathcal{V}$ for the departure and arrival of each trip. The arc set $\mathcal{E}$ contains an arc for each trip, together with arcs connecting the nodes at the same station to a time-line, where the latter arcs represent the option of waiting at a station. A straightforward modification of this intuitive graph allows us to account for transfers , for example using the definition proposed in Chapter 2. A *path* refers to a path in the timetable graph consisting of a sequence of time dependent arcs, that is equivalent to a sequence of timetable services that can be taken by a passenger.

A disruption δ defines a set of arcs $e \in \mathcal{E}$ that are canceled in the graph $\mathcal{G}$, thereby defining the disrupted timetable graph $\mathcal{G}_\delta$. The disruption represents a cancellation of service for a fixed time period on a limited part of the network. A *journey* j, characterized by (u, v, t, p), represents a single passenger traveling from an origin station u, to a destination station v, at a specific departure time t, following a specific path in the timetable p. Furthermore, a *passenger group* q defines a number of passengers w making a specific journey j on a specific date d, and is thus characterized by (u, v, t, p, d, w).

The framework consists of three steps, as presented in Figure 3.1. In Step (1) passengers' route choices are deduced from historical data defining a set of passenger groups $\mathcal{Q}$, as described in Section 3.3.1. Step (2) forecasts the number of passengers per planned path using statistical forecasting models resulting in a set of forecast passenger groups $\mathcal{Q}'$, as presented in Section 3.3.2. Finally, Step (3) uses a simulation model to calculate the change in passenger flows due to the disruption resulting in the set of passenger groups $\tilde{\mathcal{Q}}$ with paths adjusted based on the disruption, as discussed in Section 3.3.3. A preprocessing step, intended to provide insight to dispatchers on how to support passengers during a disruption, and possibly decrease computation time of future applications, is proposed in Section 3.4.

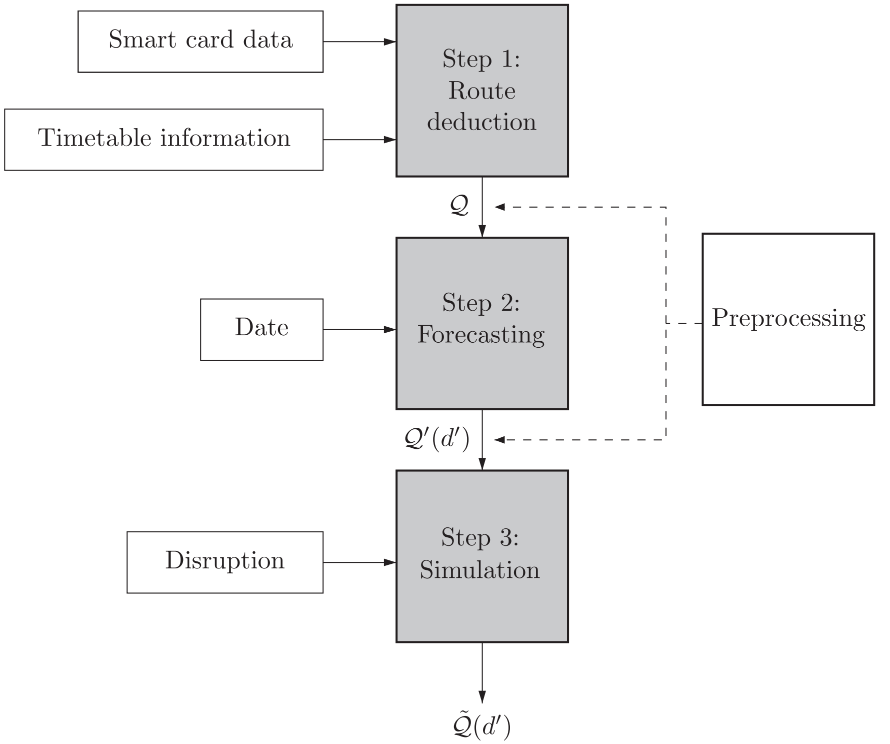

Figure 3.1: Framework for forecasting.

3.3.1 Step 1: Route deduction

In the first step of the framework, passenger groups q are derived from the smart card data. Thus, both the OD matrix and the route assignment are derived simultaneously from this historical data and lead to the definition of the set of passenger groups $\mathcal{Q}$. A passenger group $q \in \mathcal{Q}$ represents a group of passengers that have a planned journey j on date d. The smart card data contains the origin, destination, departure and arrival time of each passenger on a specific date, but not the planned path. In the first step these planned paths are derived from the smart card data, and timetable information.

Chapter 2 propose a method for deriving passenger route choices from smart card data. Although others, like Kusakabe et al. (2010), propose similar methods. The research in Chapter 2 is the first and, to the best of our knowledge so far the only, that have validated their results. They are able to correctly deduce the routes for over 90% of the journeys in their validation sample. One could therefore use their method to construct the set of passenger groups $\mathcal{Q}$.

An important remark is that in Chapter 2 the objective is to deduce the *realized* path. However, for the forecasting of passenger flows in case of a disruption, we need the *planned* path – or more specifically, the planned path the passenger would choose given the planned timetable on the date of interest d'. Although for the majority of the passengers the planned and realized paths will be the same, small disturbances and larger disruptions will cause changes in some passengers' realized paths. The realized paths deduced from the smart card data may in these cases be different from the planned path of the passenger. Moreover, due to events and planned maintenance there may be small changes between the planned timetables on different dates. As a result, a passenger's planned path on date d' may differ from that on an other date d''.

Several path deduction strategies could help in finding the planned routes during disruptions. For example, within Netherlands Railways some applications estimate the planned path to be the first departing path as recommended by the journey planner application of the operator. Polman (2013) used a planned timetable to link a path to a registered journey in the smart card data, which he translated next to a realized path using the realized timetable to estimate passenger delay. The difficulty with deducing the planned path is that it is an unobserved path, and therefore the smart card data provides insufficient information for the validation of the planned path.

Alternatively, one could try to translate the realized path – which can be both deduced and validated as proposed in Chapter 2 – to a planned path in any timetable. The advantage of such an approach is that, unlike the planned path that is unobserved, the correct selection of a realized path can be validated using the smart card data, timetable information, and conductor checks. However, the realized path is influenced by disturbances and disruptions, and depends on the information available to passengers on alternative paths during their journey. Such an approach should therefore take the uncertainty about the disruption length into account. Records on communication to passengers, such as for example publicly available at rijdendetreinen.nl, could assists in such a reconstruction. Furthermore, this question closely tied to the question of which paths in general passengers consider to travel from their origin to their destination – which choice set is unobserved.

Developing such methods would require an extensive data analysis and validation for which the data available to us, at the time of conducting this research, was insufficient. Therefore developing such a method is left for future research.

3.3.2 Step 2: Forecasting

The hypothesis is that passengers who chose journey j in the past are a good representation of the number of passengers who will choose this journey on the forecast day d'. Input for the forecasting step is the set of passenger groups $\mathcal{Q}$ obtained in Step (1). We denote q_{jd} as the number of passengers that make journey j on date d. Output consists of the forecast q_{jd}'s given normal operations, together defining the set $\mathcal{Q}'$. In Step (3) the change in flows due to the disruption is estimated based on these forecasts.

Time series $\mathbf{q}_j$ are constructed for all journeys j by aggregating and ordering all passenger groups over time that have the same planned journey on a specific day in the data set. Because of the large differences between weekdays, and high similarity on the same weekday (e.g. Tuesdays), separate time series are formulated for each weekday. Econometric forecasting models are used to predict the number of passengers planning to make a specific journey on a specific day based on the time series.

The following notation is used in discussing the forecasting models: q_{jd} and q'_{jd} represent the actual and forecast number of passengers for journey j on date d, respectively. Furthermore, $d-1$ represents the previous period to date d. That is, in the case of forecasting demand for a Tuesday, $d-1$ refers to the Tuesday the week before d. Finally, ε denotes an error term, or the variation not captured by the forecasting model, where $q_{jd} = q'_{jd} + \varepsilon$. An accurate forecasting model has small, or zero, ε. In the computational experiment the size of the error terms are used to compare the performance of the forecasting models.

One could select any time series forecasting model for this task within the framework. We selected a few models that are widely used in practice, as an intial test on predictability. Future research could use more advanced models.

Average: As a simple base case, one could select the average over all previous periods as the forecast for the date of interest d. Define $\mathcal{D}_d$ as the set of periods before d. The average model can be written as:

$$q_{jd} = \frac{1}{|\mathcal{D}_d|} \sum_{d \in \mathcal{D}_d} q_{jd} + \varepsilon \tag{3.1}$$

An advantage of this model is that it is easy to understand and implement, and it is also very fast. It is, however, not a very sophisticated model, and might not use all information that is available in the data for forecasting.

Exponential smoothing: This method is slightly more advanced than averaging, as it assigns a weight α to the most recent observation. It is thus a weighted average between the forecast of the previous weekday, and the current observation:

$$q_{jd} = \alpha q_{j(d-1)} + (1-\alpha)\alpha q'_{j(d-1)} + \varepsilon \tag{3.2}$$

The value of α lies between 0 and 1. It assigns an exponentially decreasing weight to previous observations over time. The higher the weight α, the stronger the influence of the most recent observation $q_{j(d-1)}$. To initialize the model a value must be selected for the forecast of the first period, q'_{j0}. Generally, either q'_{j0} is set equal to the first observation q_{j0}, or is calculated as the average over the first few observations. In any case, the performance of the model generally increases after the first few values. Advantages of the model are that it is intuitively easy to understand and computationally efficient, and allows for slightly more customization to the time series than simply taking the average. However, it is not a sophisticated statistical model, and there could still be information in the data that could improve the accuracy of the forecasts, but which is not used by this model.

AR(1) The AR(1) model, an auto regressive model with explanatory variables dating one period back, is a model often used in financial and economic time series forecasting. The model is defined as:

$$q_{jd} = c + \beta q_{j(d-1)} + \varepsilon \tag{3.3}$$

The auto regressive models allow more historical information to be included by adding more terms. For example, an AR(3) model forecasts based on a linear combination of the last three periods (e.g. 3 previous Tuesdays to date d). Moreover, cross terms can be added, for example representing the number of passengers for journey j on previous weekdays, or the total number of passengers for all journeys on day $d-1$. However, the required number of observations to estimate these models increases with the number of terms included.

AR(1)T This model differs from the AR(1) model in that it allows estimating a trend by including a dummy variable k_d. This variable can represent a change in demand – e.g. to model less demand in the holiday seasons. Moreover, k_d can represent a linearly increasing or decreasing trend over time. Therefore k_d can be binary (in the first case) or linearly increasing over time (in the second case). The value of the trend is represented by the value of γ, estimated in the model. The AR(1)T model is defined as:

$$q_{jd} = c + \beta q_{j(d-1)} + \gamma k_d + \varepsilon \tag{3.4}$$

One could include multiple trend variables to represent different trends or differently sized trends. However, the number of variables needed to forecast the demand will increase.

There exist many other forecasting models one could evaluate. We have selected these four since they represent models often used in practice. Moreover, the comparison of basic models, such as the average and exponential smoothing, with more advanced statistical models like the AR(1) and AR(1)T models, can suggest whether such more advanced statistical models produce better results, or whether relatively simple models provide sufficiently accurate forecasts already.

3.3.3 Step 3: Simulation

The simulation translates the number of passengers per planned path forecast in Step (2), forming the set of passenger groups $\mathcal{Q}'$, to the number of passengers per *realized* path given the disruption, represented by the new passenger group set $\tilde{\mathcal{Q}}$. The realized paths result from the disruption, the location of passengers at the time of the disruption (based on their planned path), and the behavioral model of how passengers react to a disruption. This behavior could be obtained from other analyses or expert opinion, and could be validated using the available smart card data.

Agent-based simulation models allow one to model the reactions of passengers to a disruption in detail, and also define how passengers interact in case of a disruption. Raney et al. (2002); Balmer et al. (2006), and Arentze and Timmermans (2009) have developed large detailed agent-based simulation models for transportation systems, that e.g. include activity plans for travelers and microscopic interactions between agents. So far these models have been developed to study transportation systems in equilibrium. For instance the simulation model of Raney et al. (2002) models the microscopic interactions between passengers. A consequence of microscopic modeling is that these models are generally computationally expensive.

Kroon et al. (2014), Cadarso et al. (2013) and Chapter 5 use simulation of passenger flows in combination with combinatorial optimization models to support the logistic scheduling of operators. These models are intended for use in real time, and therefore computational efficiency is of great importance. The models adopted in these papers strongly depend on minimum cost path computations (e.g. earliest arrival), model only the essential passenger behavior such as the desire to follow the minimum cost path (e.g. earliest arriving path) and competition for seats, and are as a result more computationally efficient than the above mentioned microscopic models.

The best choice between microscopic or macroscopic modeling of behavior of passengers will depend on the application, and the available information on passenger behavior that can serve as input for these models.

3.4 Preprocessing: Network Reduction

Network Reduction reduces the set of passenger groups by selecting only those passenger groups that are affected by the disruption, and secondly by aggregating passenger groups with similar rerouting options. The advantages of using this preprocessing step include:

- A reduction in the number of passenger groups resulting in less cluttered data and facilitating manual validation and verification.
- The origin stations and times of the new passenger groups indicate where, and when, passengers need to reroute:
  - This allows practitioners to see when and where to support passengers with route advice.
  - This allows manual dispatchers to see if and when a few minutes difference in announcing the end of the disruption can prevent passengers from starting an unnecessary detour.
- The reduction in the number of passenger groups may increase the computational speed of other applications, such as rolling stock rescheduling.
- Forecasts based on the aggregate passenger groups could be more accurate than forecasts calculated for the initial groups.

Although we cannot prove that the last statement is always true, the results of computational experiments indicate that forecasts on aggregate passenger groups are generally (slightly) better than forecasts for the initial passenger groups. For all the reasons staded above, the preprocessing step may provide deeper insight into passenger flows and the changes in passenger flows, in addition to perhaps having some computational advantages.

The Network Reduction algorithm consists of two phases: an initialization phase described in Section 3.4.2 followed by a phase in which similar passenger groups are aggregated as described in Section 3.4.3. This method is intended for time-dependent aggregation, and could easily be extended to take transfers into account. For ease of explanation, the example of Section 3.4.1 explains Network Reduction based on a time independent example without transfers.

3.4.1 Example

Consider the public transport network presented in Figure 3.2, where the segment between stations C and E is disrupted with no service for the foreseeable future. Passengers traveling to E from stations A, B or C therefore need to reroute through station D or F. The proposed preprocessing step aggregates passenger groups (A to E), (B to E) and (C to E) as they all have similar rerouting options.

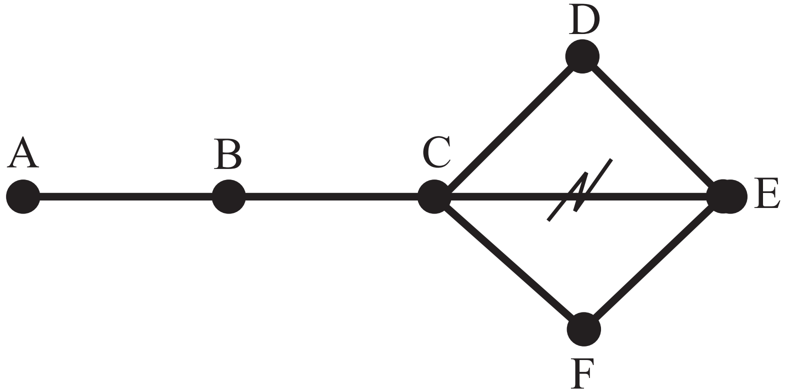

Figure 3.2: Example public transport network with 6 stations.

Passengers starting at E and traveling to C, B or A also have the same rerouting options: to reroute through station D or through station F. Therefore these groups are aggregated into one new passenger group.

In total there are 30 different passenger groups that (time-independently) can be defined for the example network in Figure 3.2. Of these, only 6 are affected by the disruption, that is, they need to change their path due to the disruption. These groups can be aggregated into 2 groups, again, independent of time. Moreover, the origin and destination stations of these groups are stations C or E; these are the stations where passengers need to decide on how to reroute. The preprocessing step thus reduces the number of passenger groups, and provides insight into where passengers are affected by the disruption.

3.4.2 Initialization

The initialization defines a set $\mathcal{P}_q$ of rerouting options for all passenger groups q in $\mathcal{Q}$ affected by a disruption δ. Each rerouting option is a path for a passenger group that starts no earlier than their planned departure time t, and connects their origin u^* to the destination v^* in the timetable graph $\mathcal{G}_\delta$, which is a timetable adjusted to the disruption δ. A condition for the presented approach is therefore that there exist rerouting options for passengers, although this may include the option to wait until the disruption is over. Passengers unaffected by the disruption are not required to reroute, and therefore not included in the algorithm.

Passengers are affected by a disruption when they need to change their originally planned path due to the disruption. Passengers are directly affected when their planned path contains one of the trips canceled due to the disruption. Passengers are indirectly affected by the disruption in case of capacity shortages resulting from the disruption. In this case, passengers fail to board a train on their planned path because there is insufficient capacity for them to board this train. Although the description of the algorithm focuses on passengers directly affected by the disruption, it can be extended to include indirectly affected passengers as well.

In the initialization step, we collect all rerouting options for each of the affected passenger groups. We use a set of passenger behavioral assumptions, intending to generate all paths that could be attractive to passengers. For example, the generated rerouting options may include the shortest path, the path with minimum transfers, and the earliest arrival path. One could construct a rerouting set based on a set of criteria (e.g. containing both the shortest path, and the path with minimum transfers). Moreover, one can define the rerouting options by setting a budget value α: a path is declared to be a rerouting option if its costs exceed the costs of the cheapest path by no more than α. Here the inconvenience, or cost, of a path is defined by the weighted sum of the arcs in the path.

3.4.3 Constructing the reduced set of passenger groups

For all passenger groups affected by the disruption, this phase defines a new origin station u^*, a new destination station v^*, and a new departure time t^*, and a set of sub-paths $\mathcal{P}_q^*$ of the rerouting paths $\mathcal{P}_q$. The sub-paths represent the part of the journey where passengers deviate from their original planned path. These sub-paths are defined as time-dependent.

Next, we aggregate passenger groups with similar rerouting options, represented by the same set of time-dependent rerouting sub-paths. The procedure is described below.

Input consists of a set of forecast passenger groups $\mathcal{Q}'$ for a specific date d, where each passenger group has a weight w. Specifically, input consists of the passenger groups affected by the disruption selected in the initialization, together with the generated set of rerouting options $\mathcal{P}_q$ per passenger group.

For each of these passenger groups q characterized by (u, v, t, p, d, w), we define a new origin station u^* and a new departure time t^*. We follow the nodes along path p as well as along the paths $\mathcal{P}_q$ from their common departure station u. We compare the paths node and arc based, where a node represents a station at a specific time. The last common *node* among the rerouting paths $\mathcal{P}_q$ and the planned path p before a change in the stop sequence or arc sequence defines the new station u^* and the new departure time t^*. All arcs between u and u^* are therefore contained in all paths in $\mathcal{P}_q$, as well as in p. In other words, between u and u^* the passengers use the very same services in the disrupted situation as they would do in the undisrupted situation.

The new destination station is defined according to a different rule. The disruption will likely delay the passengers, and therefore it is unlikely that they can return to their planned path after following the rerouting path in the disrupted situation. The tail of the rerouting paths will therefore almost always contain different nodes than the tail of the planned path, offering no opportunity for consolidation according to the rule used for defining the origin. However, from some point on, the rerouting path may be very similar to that of the planned path, e.g. by using the same train service lines and passing the same stops. During this last part of the trip, a passenger is likely not in need of further support and route advice. Therefore, we compare the rerouting paths and the planned paths *geographically*.

Starting at the destination and moving back on the path, we define the new destination station v^* as the station of the last node that is geographically in all paths in $\mathcal{P}_q$ and in p after a geographically identical set of arcs, and which is in p before the disrupted trip arc in this planned path. Two nodes are geographically the same when they represent the same physical station, possibly at different points in time. The arcs are geographically the same if they represent a similar service with equal costs to connect two nodes representing the same geographical stations. The last common node is obtained by geographically comparing nodes and arcs between all paths in $\mathcal{P}_q$ and p starting from the destination node and moving backwards. Node v^* is found when either the next node or arc is not geographically in all paths, or the next trip in p that ends in v^* is the disrupted trip. By construction, all paths in $\mathcal{P}_q$ and in p are geographically similar between v^* and v, thus following a similar service, although not necessarily at the same time.

We define the new planned path p^* as all arcs in the sub-path of p between u^* and v^*. The new set of rerouting paths $\mathcal{P}_q^*$ is constructed similarly from $\mathcal{P}_q$ by selecting all arcs in the sub-path between u^* and v^* for every path $p \in \mathcal{P}_q$. By construction, all paths $p \in \mathcal{P}_q$ contain u^* and v^* and therefore all these paths contain sub-paths that connect the two nodes. Moreover, by the definition of u^*, we have $u^* \neq v^*$, and therefore p^* and the paths in $\mathcal{P}_q^*$ are non-empty. That is, they contain at least one trip.

A new type of passenger group q^* is defined for each q, where q^* is characterized by $(u^*, v^*, t^*, p^*, d, w^*)$ together with the set of detour options $\mathcal{P}_q^*$. All passenger groups in the preprocessing have the same date d, as the input consists of a forecast of passenger groups for one specific date d. Next, passenger groups q^* are aggregated whenever they have the same u^*, v^*, t^*, p^*, d and $\mathcal{P}_q^*$. That is, the aggregate passenger groups are identical in all properties apart from, possibly, the weight w. The weight w^* of the aggregate passenger group is defined by the sum of the weights of the initial passenger groups to be aggregate.

3.5 Data and Computational Exploration

In order to illustrate the practical value of the framework, we conduct an exploratory computational study. The focus is on illustrating whether the passenger demand is predictable, and how successful is the proposed preprocessing step in reducing the number of passenger groups.

At the time of analysis, the smart card system was still in its introduction phase in the Netherlands and not all passenger journeys were therefore represented in our data sample, since not all passengers were using this system. The introduction of the system is currently close to complete, and as part of future research more thorough experiments can be performed. Such a future study would preferably compare forecasts derived from smart card data with forecasts calculated using alternative data sources, such as surveys and passenger counts.

The presented study is intended as a proof of concept of the framework, rather than a ready-to-use decision support tool. Full development of such a decision support tool would require significant additional research and extensive calibration of all three steps, as already discussed in Section 3.3 and further discussed in this section.

In this section we discuss the input data, specifically smart card data in Section 3.5.1 and timetable information in Section 3.5.2.

3.5.1 Smart card data

We obtained 10 months of smart card data of Netherlands Railways, from January to October 2012. These data were generated during the introduction of smart card ticketing in the Netherlands. Although our data set contains tens of thousands of journeys, it is far from being a complete representation of passengers traveling on Netherlands Railways. Because ticketing through smart cards was introduced by ticket type, the sample is not a good representation of the full passenger population – specifically, regular travelers are not well represented in this data set. Moreover, during this 10-month period an increasing number of passengers started using the smart card for ticketing. Thus there is likely thus a trend in the data that can be explained by this introduction phase, which will disappear when the introduction has been completed. We can therefore only conduct a computational exploration of the performance of this forecasting framework, without being able to derive any definitive conclusions. Once the introduction of the smart card system has been completed, one could thoroughly test and validate the proposed framework.

3.5.2 Timetable and disruptions

We use a single planned timetable for this period obtained from Netherlands Railways for the route deduction. A disruption cancels a set of trips in the graph defined by the timetable for the entire duration of the disruption, which we assume to be known.

Three disruption scenarios are included in the experimental study of Network Reduction, two of which are used for evaluating the performance of the forecasting model. The scenarios are specifically chosen to be on busy and central parts of the network where one would expect a high number of journeys to be affected by a disruption. These scenarios consist of a disruption between Utrecht (Ut) and Breukelen (Bkl), a disruption between Gouda(Gd) and Rotterdam(Rtd), and a disruption between Eindhoven (Ehv) and 's Hertogenbosch (Ht). Figure 3.3 provides an overview of the network of Netherlands Railways, in which the above stations are marked. All scenarios consider a complete blocking of the tracks, and are chosen such that passengers can divert to another route to get to their destination. The fact that passengers can divert requires forecasts of passenger flows for capacity rescheduling, and since it is beneficial for passengers to reschedule their routes, it provides the opportunity for improved service by providing them with travel advice.

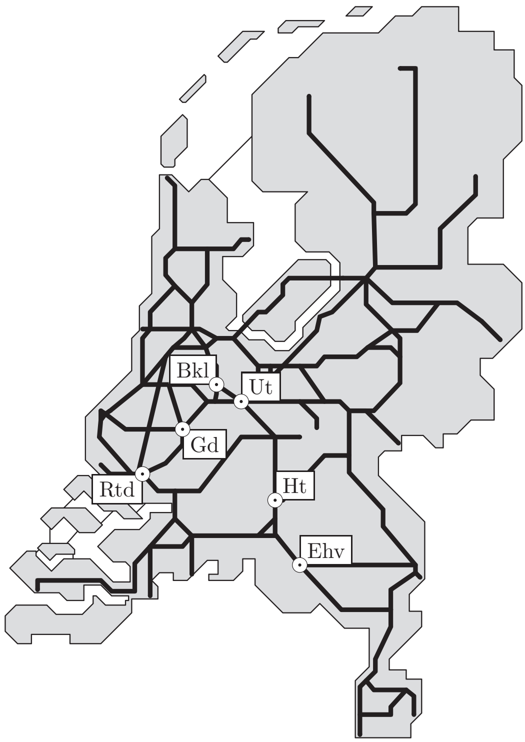

Figure 3.3: Netherlands Railways network.

3.6 Computational Results

In this section we present results for a "proof of concept" implementation of the framework.

Step (1) uses the proposed method of Chapter 2, and therefore we refer to this chapter for a further discussion of this method. For the presented implementation a single planned timetable was used for the route deduction. This adjustment guarantees that journeys between dates are to a high extent comparable. For a practical implementation a more detailed method that takes into account previous delays and uncertainty about the disruption duration may be required. The data available at the time this research was conducted was not sufficient yet to develop such a method, and therefore this is left for future research.

First results of the preprocessing step are presented in Section 3.6.1. Next results for Step (2) Forecasting are presented in Section 3.6.2, that compares all discussed forecasting models based on estimates derived from available smart card data. Section 3.6.3 discusses some preliminary results for a simulation model of Step (3).

3.6.1 Preprocessing: Network Reduction

During the preprocessing step journeys affected by the disruption are selected and aggregated given the available alternative routes, as described in Section 3.4. A general measure of success is hard to define, since the result depends on the specific disruption and on the network.

For the purpose of a proof of concept, we have chosen to perform the preprocessing step on time-independent paths and passenger groups. Thus passenger groups are defined as OD pairs, for which the planned path is defined as the shortest path in the timetable graph $\mathcal{G}$, and the detour set is defined as the shortest path in the disrupted timetable graph $\mathcal{G}_\delta$, where a disruption δ cancels trips on the disrupted segment for the entire day. The new departure and arrival stations u^* and v^* are defined by geographically comparing the detour path and the planned path. For this proof of concept implementation, passenger groups with the same u^* and v^* are aggregated into one group. However, for application in practice the preprocessing step is intended to be executed time dependently and take transfers into account, thus requiring a more detailed process for aggregation of passenger groups.

We have limited the total set of passenger groups to those groups that had on average at least 3 journeys a day in 2012. These 6500 groups are responsible for at least 95 percent of all journeys in the network. Although the algorithm is capable of analyzing all 160,000 possible groups, the given comparison seems more fair in light of the practical application. Moreover, we show that the preprocessing step on its own reduces the number of journeys in a way that cannot be directly derived from data analysis.

Disruption	Network Reduction	$\mathcal{Q}$	Stations	Reduction Percentage	
				$\mathcal{Q}$	Stations
Utrecht, Breukelen	yes	190	52	23%	35%;
	no	821	146		
Gouda, Rotterdam	yes	123	41	39%	47%
	no	318	89		
Eindhoven, 's Hertogenbosch	yes	12	7	4.3%	4.6%
	no	276	151		

Table 3.1: Summary of results of preprocessing step.

Table 3.1 contains the results of the preprocessing step in the three scenarios. For the experiments we defined the groups to be time-independent. Consequently, the number of groups here is equal to the total number of different origin-destination pairs in the original set of passenger groups. The table reports the number of affected (time independent) passenger groups with and without preprocessing. Furthermore, it reports the number of unique stations represented as either origin or destination in these groups. Finally, it expresses the reduction in passenger groups and stations as a percentage of the group size before preprocessing. For the example of Utrecht - Breukelen, the 23% reduction percentage of passenger groups is calculated as the number of passenger groups after reduction (190) divided by the number of affected passenger groups (821), times 100%. Simlarly, the station reduction percentage (35%) is calculated as the number of stations contained in either the origin or destination of the Network Reduction groups (52), divided by the number of stations contained in the origin-destinations of all affected pasenger groups before aggregation (146) times 100%. The lower the percentage, the fewer stations or groups are left, thus signaling a better performance of the network reduction.

The first scenario is a blockage between Utrecht and Breukelen, blocking the connection Utrecht-Amsterdam, which is one of the busiest routes in the Dutch railway network. The highest number of stations and journeys are affected by the disruption in this scenario. The preprocessing step reduces the 821 groups to 190, which is less than one fourth (23%) of the original set. In the second scenario the tracks between Gouda and Rotterdam Alexander are blocked, blocking the route to the east of Rotterdam. Due to the introduction of a high speed line, there are numerous ways for rerouting, and the best one depends on the specific origin and destination. This is probably why the reduction factor is least for this scenario, 39%, although it still reduces the number of journeys by a factor two. The third scenario considers a blockage between 's Hertogenbosch and Eindhoven. Both passenger groups and stations are reduced to less than 5% of the original sizes of these sets, namely 4.3% and 4.6% respectively, which shows a reduction factor of over 20. This is first of all because less passenger groups are affected by the disruption (276 versus 318 and 821 in the previous scenarios), but mostly because there only exist a very limited set of options for rerouting, which makes the network reduction very effective in this situation. The reduction from 276 to 12 passenger groups shows that the preprocessing step can greatly simplify the problem of rerouting passengers.

3.6.2 Step 2: Forecasting

We forecast the number of passengers that plan to make a specific journey using the time series constructed per passenger group per weekday in Step (1). We found that the correlation between weekdays over the weeks is typically much stronger than the correlation between consecutive days. As previously mentioned, we therefore decided to construct separate time series for each passenger group q for each weekday. Thus, in the computational exploration $d-1$ refers to the previous similar weekday stored in the data (i.e. 7 days earlier), and not to the previous day to date d. As a result, the time series are significantly shortened, and a longer period of time is required to estimate the model. Seasonal trends may therefore affect the forecasts relatively strongly.

The performance of the different statistical models are compared based on their fit to the data. Unfortunately, the data set was too limited for a meaningful out-of-sample forecast evaluation, specifically due to the constant increase in the part of the population that used a smart card.

The forecasts are derived for both the original set of passenger groups (Full), and for the reduced set of passenger groups (NR) after the preprocessing step. Moreover, forecasts are presented for all models discussed in Section 3.3.2: Mean, Exponential Smoothing (ES), AR(1) and AR(1)T. We compare the forecast performance on the aggregated level as a result of the preprocessing step. In other words, in-sample forecasts for the full set of passenger groups are aggregated to form the same groups as after the preprocessing step, before statistics on performance are calculated. The difference between the two approaches is that during the preprocessing step we first aggregate the separate series, and thereafter we use this aggregate data to estimate the forecast model. The full-network model forecasts the number for each initial planned path separately. To compare forecast accuracy, after forecasting the full-network estimates are aggregated before calculating the performance statistics, to allow comparison across models. Results depend on the specific disruption location. Forecasts are evaluated on two of the scenarios presented in Section 3.6.1.

We compare the in-sample forecasting errors of the two models, calculated as the difference between the true and the forecast numbers of passengers, that follow a path on a specific day. For each group and for each weekday, we calculate the Relative Root Mean Squared Error, the Absolute Relative Error and the (Root) Mean Squared Error. These measures are commonly used for the evaluation of forecast models and differ in the weight they assign to large errors versus small errors. Table 3.2 represents the average error over all time series for one disruption scenario. The smaller the error, the smaller the value of these statistics, and the better the model.

	Disruption Scenario 1 Utrecht - Breukelen							
Model Type	Relative Root Mean Squared Error		Absolute Relative Error		Mean Squared Error		Root Mean Squared Error	
	NR	Full	NR	Full	NR	Full	NR	Full
AR(1)	2.85	2.86	1.19	1.20	6.67	8.17	1.40	1.50
AR(1)T	2.87	2.88	1.02	1.01	8.47	8.83	1.51	1.53
Mean		2.87		1.22		14.78		1.77
ES		3.51		1.25		14.86		1.93
	Disruption Scenario 3 Eindhoven - 's Hertogenbosch							
Model Type	Relative Root Mean Squared Error		Absolute Relative Error		Mean Squared Error		Root Mean Squared Error	
	NR	Full	NR	Full	NR	Full	NR	Full
AR(1)	1.76	1.79	0.89	0.92	18.80	28.61	4.34	5.35
AR(1)T	1.79	1.80	0.81	0.79	27.22	29.73	5.22	5.45
Mean		1.82		0.95		53.88		7.34
ES		2.20		0.97		48.96		7.00

Table 3.2: Different performance measures of forecast quality comparing full passenger groups with Network Reduction (NR). Exponential Smoothing (ES) model with $\alpha = 0.7$

Comparing results between forecasts with and without preprocessing in Table 3.2, we find that the differences are small, but mostly in favor of the forecasts calculated after the preprocessing step. This comparison is not made for the Exponential Smoothing and Mean model since these forecasts are, by definition, the same for the preprocessing step and for the full set of time series. By reducing the set of passenger groups in the preprocessing step, we reduce the number of forecasting models that need to be estimated. Given the time pressure in a disruption management situation, this could be beneficial. However, our experience is that the estimation of the here proposed forecasting models is very fast.

Comparing results of different forecasting methods in Table 3.2 the AR(1) and AR(1)T models generally outperform the other models. Changing the α value for the ES model did not change this finding, and only results for a single value for α in the ES model are therefore reported in Table 3.2. This is an indication that more sophisticated models may be able to further improve these forecasts. The modest size of the errors is an indication that the forecasting quality of these models may be sufficient for the purpose of estimating the demand per train.

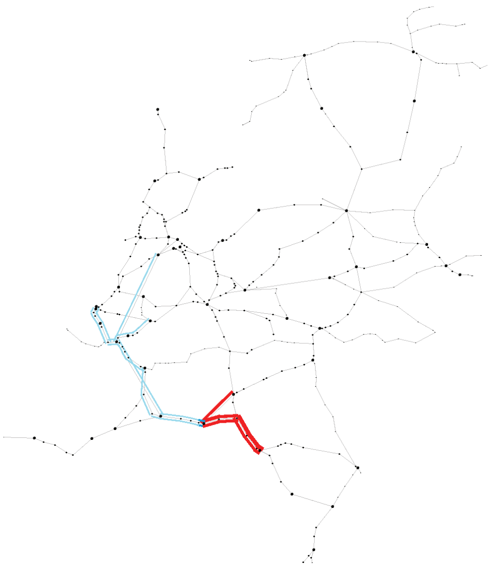

Figure 3.4: Change in passenger flows due to disruption. The thicker the line, the more passengers are rerouting.

3.6.3 Step 3: Simulation

The forecasts of Step (2) define the expected number of passengers per planned path. In Step (3) a simulation model is used to calculate how passengers react to the disruption, i.e. how they reroute. This route choice has been modeled by a shortest path algorithm that passengers call at the start time of the disruption given their current location, time, and destination, to plan their new route. It thus assumes there will be sufficient capacity available. Capacity constraints are not included in the current analysis, because no reliable estimates of the true demand versus capacity could be obtained from the available data, and errors in these estimates could significantly influence the results. The simulation in Step (3) could however be easily adjusted to deal with capacity shortages. Later research presented in this thesis aims to reduce the delay of passengers resulting from a disruption, such as for instance through including shuttle services (Chapter 4) and through providing individual route advice (Chapter 5). Both will include capacity constraints, which are not included in this proof of concept.

We performed this simulation for the scenario where there is a disruption between 's Hertogenbosch and Eindhoven. Input is the set of planned paths, the timetable, and the definition of the disruption. Output consists of the set of realized paths resulting from the disruption, recognizing that passengers cannot anticipate the occurrence of the disruption.

The passenger delay or inconvenience is calculated based on the difference between the planned path and the realized path. Moreover, the change in demand per train is also calculated based on this comparison. Figure 3.4 shows the additional demand in the network due to a disruption between 's Hertogenbosch and Eindhoven calculated using the simulation results. The thin black lines with dots give an outline of the Dutch railway network. The thicker lines represent additional demand, a thicker line and darker color represent a larger volume of passengers. Although the majority of passengers selects a detour that is the shortest path between 's Hertogenbosch and Eindhoven, other passengers choose different detour options. This shows that indeed the change in flows depends on the Origin-Destination matrix, thus showing the value of this framework.

We find that the experienced delay in this example depends on the origin and destination of the passenger. Although almost half of the passenger groups experience delays of 30 minutes or less, over 20 percent of the passenger groups experience over an hour delay. The delay can even differ depending on the departure time of the passenger. This indicates that not only the path choice, but also the effect of a disruption strongly depends on the journey of a passenger. Passenger group information is therefore important for the purpose of estimating passenger service levels. These models can provide the essential information as input for disruption management models in order to maximize this service.

3.7 Conclusion

Forecasts of passenger flows are required for disruption management policies which focus on maximizing passenger service level. To this end, quick, comprehensible forecasts are needed that provide sufficient information for the purpose of estimating passenger service quality, forecasting additional demand per vehicle, and allowing the incorporation of passenger behavior such as their preferred rerouting options.

In this chapter we presented a three step framework for forecasting these passenger flows from smart card data. Within the framework (1) passenger groups are constructed from smart card data, which represent the number of passengers intending to travel on a specific path; (2) forecasts are made for the number of passengers per planned path on the disrupted day; and (3) a simulation is used to calculate the change in flows due to the disruption. Moreover, a preprocessing step is proposed, which can be called before either Step (2) or (3). By aggregating passenger groups with similar rerouting options, this Network Reduction preprocessing step, greatly reduces the number of passenger groups. This could lead to a reduction in computation time of the framework. Moreover, the reduction in the set of passenger groups due to Network Reduction enables manual validation, and provides insight to dispatchers when and where passengers need to make rerouting decisions.

We conducted computational experiments based on a real life data set of Netherlands Railways. We used our experience of passenger route deduction of Chapter 2 for the first step in the framework when passenger groups are constructed. For Step (2) we evaluated a set of forecasting models commonly used in practice. Results indicated that we can successfully forecast the number of passengers per group. However, these results are based on a very limited sample of data that is incomplete and contains a trend as a result of an increase in the number of passengers using the smart card. Due to the nature of this data, results are only indicative (and not conclusive) of the possible benefits of using such a framework, and specifically of using smart card data for forecasting, once the smart card system has been fully introduced.

We found that the preprocessing step has great potential for reducing the number of passenger groups. Applying the preprocessing before forecasting did not seem to reduce forecast quality, and may even slightly improve it. Our experience is that the forecasting models can be executed quickly. The need to apply the preprocessing step in the framework is therefore not great: differences in passenger flows may also be computed by comparing a full assignment in the non-disrupted and disrupted situations, which takes only slightly more computation time. A benefit of the preprocessing step is, however, that it provides insight to practitioners into when and where passengers need to make rerouting decisions.

The preprocessing step may be beneficial in future research where more advanced models are used during Step (3), and where the aim is to minimize passenger inconvenience. Indeed we applied a customized version of the preprocessing step to the shuttle planning problem in Chapter 4 and obtained a significant reduction in computation time. This suggests that there may also be other applications that involve flow assignment which may benefit from the proposed preprocessing step.

Chapters 4 and 5 extend this chapter, using the concept of forecasts as input. Chapter 4 proposes a new optimization-based method for shuttle planning based on estimated passenger, where a customized version of the preprocessing step is able to significantly reduce computation times. Chapter 5 considers minimizing passenger inconvenience for major disruptions through the provision of individual route advice to passengers, based on demand forecasts, and rolling stock rescheduling. It is thus an optimization-based replacement of Step (3) in the framework.

Chapter 4

Shuttle Planning for Link Closures in Urban Public Transport Networks

This chapter is the result of a 3 month research visit to the Department of Civil Engineering and the Engineering Systems Division at Massachusetts Institute of Technology, Cambridge, USA. This chapter has appeared as ERIM technical report Van der Hurk et al. (2014), and is currently under review for Transportation Science.

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4.1 Introduction

Rail systems such as Boston's subway and surface rail system, London's underground, and Netherlands' passenger rail network must periodically deal with link closures and capacity limitations due to maintenance. Such link closures can cause significant delays for passengers which in turn can have long-term effects on their perceptions of the service. Passengers' appreciation of the public transport system is often an important performance measure in granting licenses to operate the network. Therefore limiting the negative effects of these disruptions is extremely important for public transport operators.

Operators' standard procedure when facing these major disruptions is to replace the closed link with a shuttle service. However, additional shuttle services in the vicinity of the disrupted area may reduce passenger inconvenience, determined by additional travel time, additional wait time, and additional transfers, at similar operating cost.

This chapter studies the Shuttle Planning for Link Closures ($SPLC$) problem that concerns the location and service frequency of shuttle lines for link closures. The research is meant to support operators in minimizing passenger inconvenience under budget constraints when facing link closures. The aim is to develop a model that can solve realistic cases comprising a large number of Origin Destination pairs (OD-pairs) fast.

We propose a new mixed integer programming formulation for the *SPLC*. Key features of the model are that it includes a minimum operating frequency restriction for all candidate shuttle lines, and frequency-dependent passenger inconvenience costs such as transfers and waiting time costs, and it allows for changes in frequencies for both the existing network and the shuttle lines. A path reduction process is proposed that reduces the problem size significantly. Computational experiments indicate that the new formulation, together with the path reduction process, is able to solve realistic problems with large numbers of OD-pairs quickly.

The practical relevance of the proposed model is demonstrated based on a real world case study. The results indicate that (1) solutions for realistic sized problems with a large number of OD pairs can be generated fast, (2) allowing the selection of shuttles beyond the disrupted area, and allowing changes of frequency in the full network, can reduce both passenger inconvenience and operating cost, (3) inconvenience of the closure is distributed more evenly over passengers, and worst case delays are reduced, and (4) solutions are relatively robust with respect to different assumptions on passenger behavior.

The three key contributions of this chapter are summarized as:

- a novel mixed-integer formulation for the *SPLC* that a) allows specifying a minimum operating frequency for lines and b) includes frequency dependent passenger inconvenience costs.
- a proposed path reduction process that a) reduces problem size and therefore b) allows including large numbers of OD-pairs in the model.
- demonstration that the proposed methodology proposes practically relevant solutions quickly for realistic problem sizes based on a real world case study.

The proposed model and path reduction step may also be applicable for more general line planning problems. Moreover, computational experiments indicate that the solution speed may also be high enough for use in the case of real time occurrence of link closures due to disruptions.

The remainder of this chapter is organized as follows. Section 4.2 provides a problem description, Section 4.3 presents related work, and the problem formulation is described in Section 4.4, together with the proposed model. Two important preprocessing steps, to reduce problem size and increase speed, are presented in Section 4.5. Section 4.6 discusses the results of the application of the proposed model to a real world case study. Finally, Section 4.7 summarizes the paper and draws conclusions.

4.2 Problem Description

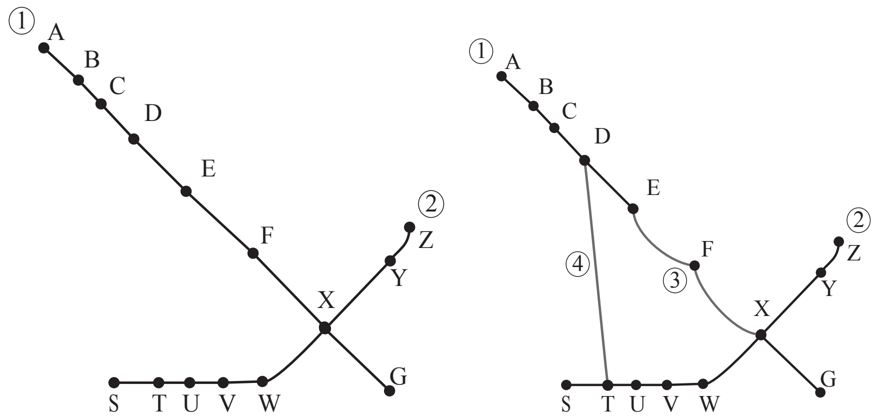
Consider the public transport network in Figure 4.1 which consists of two lines: line 1 connecting stations A to G and line 2 connecting stations S to Z. A link closure between stations E and X disconnects the northern branch of line 1 from the rest of the network. Replacement shuttles are needed to restore the network connectivity while providing sufficient capacity and minimizing the inconvenience experienced by passengers due to the closure.

Standard practice introduces a single new shuttle line reconnecting stations affected by the closure (line 3 in Figure 4.1). This default route is easy to implement as the required capacity of the shuttle can be estimated from the expected demand on the closed link, and passengers can easily find the replacement shuttle by following their standard route. However, when the majority of trips originates beyond the disrupted area, this introduces two additional transfers for most passengers: from the regular line to the shuttle bus, and from the shuttle bus to continue on the regular line. The additional travel time depends on the frequency of both the shuttle line and the regular line in addition to the extra running time of the shuttle.

Other shuttle lines could be more convenient for passengers and have similar operating cost. For example, if stations D and T are major demand generators, the opening of an additional shuttle line (line 4 in Figure 4.1b) could significantly reduce passenger inconvenience by providing a faster connection and reducing the number of transfers. The attractiveness of such a line will depend on the shuttle frequency which determines the waiting time of passengers boarding the line, and on the number of transfers of passengers using this line. The proposed model specifically includes frequency-dependent transfer and waiting time cost.

The *SPLC* model determines the optimal set of shuttle lines and their frequencies to minimize passenger inconvenience within a budget constraint given passenger demand, a transportation network, a set of candidate shuttle lines with minimum and maximum frequencies, and a link closure. Alternatively the operating cost could be weighted against the passenger inconvenience. The budget is defined as a maximum number of vehicles, equal to the number of vehicles needed for the standard solution. Passenger inconvenience is measured by the route assignment of passenger demand to paths, including transfers, in the public transport network.

The *SPLC* model simultaneously assigns passengers to paths and selects frequencies for the lines, as these are interdependent. The attractiveness of a path depends on the service frequency, while the required frequency depends on the demand for that line.



(a) Existing network

(b) Network with closure and two candidate shuttle lines

Figure 4.1: Example of a public transport network

However, including passenger assignment in the optimization model would lead to minimizing inconvenience for all passengers, instead of for each individual. In a system with free route choice and capacity constraints, the model's passenger assignment may therefore differ from the actual passenger flows. Consequently, the assignment of passengers to paths is restricted to a set of *reasonable* paths in the optimization model. A path is reasonable if its cost is within a small increment of the shortest path in the network defined by the regular lines, the closure, and the standard shuttle bus solution replacing the closed link. Moreover, the solution's quality is evaluated under several different assumptions about passenger behavior.

4.3 Related Work

Link closures can cause significant disturbances in public transport networks. The different models proposed to increase the robustness of public transport networks and timetables to relatively small delays (Cicerone et al., 2009; Fischetti and Monaci, 2009; Liebchen et al., 2010) are aimed at the planning phase. Link closures however, are not, and cannot, be taken into account in this planning of standard operations, as they occur infrequently and require significant alterations from normal operations. Therefore, they are considered within the broader category of real-time disruption management, even if they are planned. At the same time, the problem of minimizing passenger inconvenience under planned closures through the introduction of shuttles also has a strong link to the strategic problem of line planning.

Disruption Management: Disruption management aiming at minimizing passenger delay was first studied in the context of airlines. Lan et al. (2006) examined the problem of reducing passenger delay through the rerouting and re-timing of flights. Jespersen-Groth et al. (2009) discuss disruption management in rail transport focusing on the three subproblems of adjusting the timetable, rescheduling crews, and rescheduling rolling stock. Initially research in the area of disruption management in high frequency public transport focused on the complex questions of how to reschedule resources. For instance, Nielsen et al. (2012) and Cacchiani et al. (2012) focus on rolling stock rescheduling in the case of disruptions. Potthoff et al. (2010) and Veelenturf et al. (2014) present research on crew rescheduling.

Recent focus is shifting to using passenger service quality explicitly as the objective. Both Kroon et al. (2014) and Cadarso et al. (2013) incorporate passenger rerouting in the optimization of capacity rescheduling. Kroon et al. (2014) present a model for rolling stock rescheduling. Cadarso et al. (2013) also include timetabling decisions. Both studies use minimization of passenger delay as the objective. Both papers assume that arrival times of passengers are based on the schedule and thus delay is defined by the deviation from the planned timetable. Veelenturf et al. (2013) extend the passenger-oriented disruption management approach for resource rescheduling by studying the benefit of altering the stop sequence of a line. They allow adding or removing a stop on a line. Cacchiani et al. (2014) provide an extensive overview of real time rescheduling in passenger rail transport, noting that most research is focused on small delays with little attention given to major disruptions, such as link closures.

Line Planning: The introduction of shuttle services to minimize the negative effects of a link closure is essentially a network re-design problem. Therefore, it is strongly linked to the line planning problem. Ceder and Wilson (1986) present a framework that divides the problem into two parts: the generation of a line pool, and the selection of lines from this pool. This approach is followed by most research in this area. An excellent overview can be found in Schöbel (2011).

Claessens et al. (1998) solve the line planning problem for the Dutch passenger railway network. They assume the line pool is given and the demand per link is fixed. They propose a branch- and -price method for selecting lines. Their formulation is unique in introducing separate, binary decision variables that not only represent the decision on which line to include, but also at what capacity to operate it.

In contrast to Claessens et al. (1998), both Schöbel and Scholl (2006) and Borndörfer et al. (2007) include continuous frequency variables, and include the dynamic routing of passengers. Both suggest a column generation approach to solve the model, replacing the multi-commodity flow model for the routing of passengers by a path formulation. This greatly reduces the number of decision variables needed to solve the problem, as instead of one decision variable per OD-group per edge in the network, a decision variable per path is included. Column generation requires solving the LP relaxation of the main model. However, this may result in operating some lines at a very low frequency, which makes them unattractive to passengers. These models do not include a relation between the frequency of a line and the cost of passengers traveling on the line, nor do they include a minimum frequency restriction conditional on whether the line is operated. Both are part of the proposed model in this chapter.

Finally Kaspi and Raviv (2012) present an alternative heuristic approach aiming at overcoming the rounding problem while including the dynamic routing of passengers. The heuristic solves the line planning problem simultaneously with the timetabling problem, thereby minimizing passenger travel time including waiting time and transfers, as well as operating cost.

Shuttle planning for link closures and link failures: Pender et al. (2013), in their survey of disruption management practices, note that bus bridging is the most common approach to link closure or failure in rail networks. Pender et al. (2009) evaluated crossovers in the context of bus bridging and link closures, but did not look at the optimal selection of shuttle routes, which is the focus of this work. Kepaptsoglou and Karlaftis (2009) present a methodological framework for what they call 'the bus bridging problem', which is similar to the problem of shuttle planning for link closures. As is customary in planning, they split the problem into two parts: the generation of possible bus bridging routes and the capacity assignment to those routes. Their heuristic approach changes possible routes found through a shortest path method.

The work of Jin et al. (2013) is closest to this work, presenting a three-step procedure: (a) generating routes using column generation; (b) selecting the feasible routes; and (c) assigning capacity to the selected routes. They show that adding 'non-intuitive' routes can significantly reduce passenger delay. They focus on routes starting and ending at the edges of the disruption, although the approach can be extended to include other stations. In their most recent work, Jin et al. (2014), steps (b) and (c) are integrated into a single optimization model that includes a modest time-tabling component for shuttle buses, and includes transfer-to-shuttle bus times in the calculation of passenger delay. The method was applied in a network of around a 100 nodes, and a limited set of OD pairs (26).

The contribution of the current paper is the development of a method for link closures with dynamic passenger routing that can solve real life problem instances with a *large number of OD-pairs* (1397) thanks to a *path reduction* pre-processing step. The proposed formulation combines the path-formulation of Schöbel and Scholl (2006) and Borndörfer et al. (2007) with the capacity formulation of Claessens et al. (1998), and adds flexible capacity assignment. The formulation allows specifying a frequency-dependent path cost, thus including frequency-dependent passenger waiting time and transfer times. Furthermore, a minimum frequency restriction can be included on the condition that a line is operated, preventing lines being included at very low frequencies. Finally, the concept of *reasonable paths* is used to prevent the assignment of passengers to overly altruistic paths, and indeed, solutions prove relatively robust under different passenger behavior assumptions. Complex cases can be solved in one minute, making the model a candidate for real-time application.

4.4 Problem Formulation

The *SPLC* problem is static, with the link closure lasting for the full planning horizon. Full information about the location and duration of the closure, as well as the substitute shuttle services is available to passengers in advance, which is a natural assumption in the context of planned closures. The pool of candidate shuttle lines is given. Moreover, a set of candidate frequencies is given for both shuttle lines and existing lines. The number and type of vehicles assigned to a line define the passenger capacity per segment. The minimal number of vehicles depends on the frequency and the length of the geographical route of the line. The *SPLC* model solution selects those frequencies for existing lines and shuttle lines that minimize passenger inconvenience at reasonable operating cost. The operating cost depend on the number of assigned vehicles to a line.

The demand matrix is given and fixed, and passengers are assumed to arrive randomly over time. The assumption of random arrivals is consistent with high-frequency networks that do not operate according to a published timetable, for which Frumin and Zhao (2012) find empirical support. A valid solution to the *SPLC* problem should provide sufficient capacity for all passengers.

To define the *SPLC* problem formally, we use the Public Transport Network graph, PTN, defined in Section 4.4.1. Section 4.4.2 defines the operating cost OC and Section

4.4.3 defines passenger inconvenience, *PI*. Finally the model formulation is presented in Section 4.4.4. An overview of notation and terminology is provided in Table 4.1.

Table 4.1: Notation and terminology

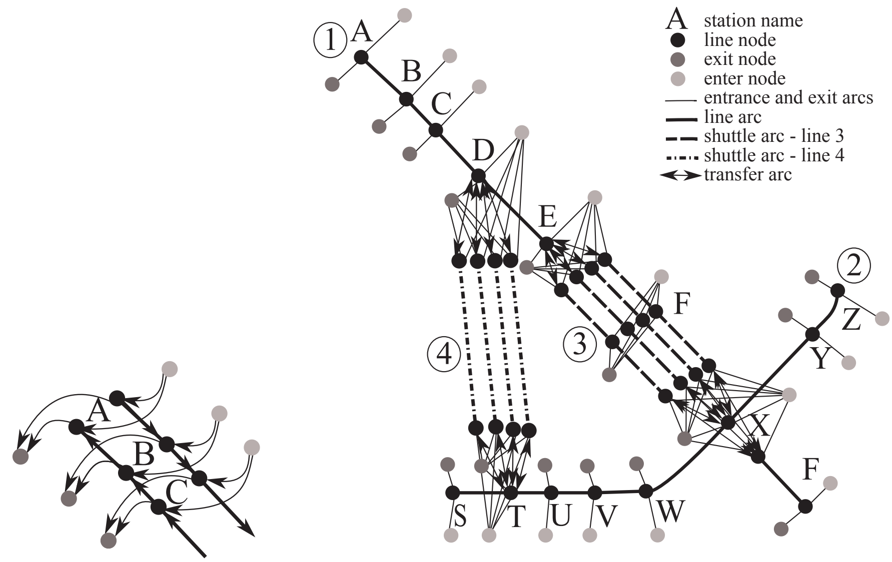
Symbol	explanation	Symbol	explanation
PTN	public transport graph with frequency set $\mathcal{F}$	$\mathrm{PTN_f}$	public transport graph with a single frequency per geoline
$\mathcal{E}$	set of arcs of PTN	$\mathcal{V}$	set of nodes of PTN
$\mathcal{G}$	set of geolines	S_g	ordered list of stops of geoline $g \in \mathcal{G}$
$\mathcal{F}$	set of frequencies	δ_{lg}	arc capacity for geoline $g \in \mathcal{G}$ provided by single vehicle $l \in \mathcal{L}$
$\mathcal{Q}$	set of OD-groups	w_q	passengers in OD-group $q \in \mathcal{Q}$
s_q	origin station OD-group q	t_q	destination station OD-group q
$\mathcal{P}$	set of paths in the PTN-graph	$\mathcal{P}_q$	path set for OD-group $q \in \mathcal{Q}$
c_p	cost of path p	k_{lg}	cost per vehicle of type l for geoline g
$\mathcal{P}_q(e)$	paths traversing arc e for OD-group q, $\mathcal{P}(e) \subseteq \mathcal{P}_q$	$\mathcal{E}_{gf}$	arcs associated with geoline g at frequency f
M_g	maximum passenger capacity geoline g	ϕ_{gf}	minimum number of vehicles for geoline g at frequency f
$\mathcal{L}$	set of vehicle types	$\mathcal{L}_g$	set of vehicle types accepted for geoline g
β	maximum number of shuttles		
x_{pq}	number of passengers of OD-group q on path p	y_{gf}	decision to open (1) or close (0) geoline g at frequency f
v_{lg}	number of vehicles of type l assigned to geoline g		

4.4.1 The Public Transport Network

Consider a set of geographical transit lines, *geolines* $\mathcal{G}$, containing *both* candidate shuttle lines and existing lines, and the set of all frequencies $\mathcal{F}$. For each geoline $g \in \mathcal{G}$ an ordered list of stops S_g, and a set of potential frequencies $\mathcal{F}_g \subseteq \mathcal{F}$ are defined. We extend the concept of geoline to include the option of walking from one station to the next. Walk arcs have infinite capacity, infinite frequency, and zero operating cost. Based on the set of geolines $\mathcal{G}$ and the set of frequencies $\mathcal{F}$ the directed *Public Transport Network Graph* (PTN), $G(\mathcal{V}, \mathcal{E})$, is defined as follows.

The node set $\mathcal{V}_{line}$ contains a node for each direction of a geoline $g \in \mathcal{G}$, each stop of this geoline $s \in S_g$ and each frequency $f \in \mathcal{F}_g$. The node set $\mathcal{V}_{OD}$ contains an entry node and an exit node for each unique geographical stop $s \in S_g, g \in \mathcal{G}$. Thus we define the node set of the graph as $\mathcal{V} := \mathcal{V}_{OD} \cup \mathcal{V}_{line}$.

The set of directed arcs $\mathcal{E}$ is composed of $\mathcal{E} := \mathcal{E}_{line} \cup \mathcal{E}_{transfer} \cup \mathcal{E}_{OD}$. The arc set $\mathcal{E}_{line}$ contains an arc for each consecutive pair of stops in S_g, for each direction of each geoline $g \in \mathcal{G}$, and each frequency $f \in \mathcal{F}$. A separate arc for each direction of the geoline is needed as capacity constraints are direction specific. The set of entry and exit arcs $\mathcal{E}_{OD}$ contains an arc connecting every entry node in $\mathcal{V}_{OD}$ to any node in $\mathcal{V}_{line}$ serving the same geographical station, and an arc from any node in $\mathcal{V}_{line}$ to the exit node in $\mathcal{V}_{OD}$ in the same geographical station. The set of transfer arcs $\mathcal{E}_{transfer}$ contains an arc for any pair of geolines with a stop at the same geographical station. Note that because the nodes $\mathcal{V}_{line}$ are frequency and geoline specific, the transfer arcs in $\mathcal{E}_{transfer}$ are also frequency and geoline specific.



(a) Directed network excerpt (b) Public transport network - undirected representation

Figure 4.2: Example of a public transport network graph

Figure 4.2 illustrates the public transport graph PTN for the public transport network in Figure 4.1(b). Figure 4.2(a) is the directed public transport graph for stations A, B and C. It corresponds with one geoline at one frequency stopping at stations A, B and C. Each physical station has an entrance and exit node. These nodes, together defining $\mathcal{V}_{OD}$, form the sources and sinks in the passenger-flow model. Furthermore, each station has nodes for each frequency and direction of a geoline that stops at this station. These nodes together represent $\mathcal{V}_{line}$. There are arcs leading from the entrance nodes to the line nodes and from the line nodes to the exit nodes that together form $\mathcal{E}_{OD}$. Arcs in $\mathcal{E}_{line}$ are introduced between line nodes of stations that are consecutive stops of a geoline at a specific frequency.

Figure 4.2(b) displays the full public transport graph for the network of Figure 4.1(b). To prevent clutter, it displays geolines undirected: the two directions of one geoline at a specific frequency are represented by one set of arcs and nodes. The network contains four geolines: two metro lines and two shuttle lines, as indicated by numbers in Figure 4.2(b). The PTN in Figure 4.2(b) has a single frequency for the regular lines 1 and 2, and four different frequencies for shuttle lines 3 and 4. Transfer arcs are introduced between all black line nodes of the same physical station that represent different geolines, together forming the set $\mathcal{E}_{transfer}$.

Throughout this chapter PTN refers to the public transport network graph defined by the full set of frequency options: PTN_f refers to a graph with a single selected frequency for each geoline, which may be 0. The solution of the *SPLC* defines a PTN_f.

4.4.2 Operating Cost

The operating cost (OC) is equal to the sum of the operating costs of all geolines $g \in \mathcal{G}$. The operating cost of a geoline g at a specific frequency is equal to the sum of the costs of all vehicles assigned to the line. Since geolines include existing lines, a change in frequencies on existing lines contributes to the *OC*. The objective of the *SPLC* is to minimize Passenger Inconvenience using no more than the available operating budget.

Define $\mathcal{L}$ as the set of vehicle types, and $\mathcal{L}_g$ as the subset of vehicle types that can be assigned to geoline g. Vehicle types distinguish between vehicles of different modes, vehicles with different seat capacities, and vehicles with different operating cost. Furthermore, define k_{lg} as the operating cost per vehicle of type $l \in \mathcal{L}$ assigned to geoline g. These costs may be vehicle type- and geoline-specific.

Operating geoline g at frequency f requires a minimum number of vehicles per hour ϕ_{gf}, which depends on the run time of the geoline g, the turn around times for vehicles assigned to this geoline, and the frequency f. Therefore the operating cost of a geoline g at frequency f, defined as the sum of the cost over all assigned vehicles to this geoline, depends on the route, the frequency, and the type of vehicle assigned to it.

4.4.3 Passenger Inconvenience

The *SPLC* model aims at reducing delay of passengers affected by the closure while providing sufficient capacity for all demand. Shuttle lines may attract passengers *not* affected by the closure if they provide a shorter route. The *SPLC* model minimizes Passenger Inconvenience (*PI*) defined as the sum of the differences in costs of paths with and without the closure. As the costs of paths in the planned network are fixed, minimizing the costs of assigned paths in the network with the closure minimizes the *sum* of the differences in cost.

If the PI is minimized over all passengers, PI can be reduced by improving service for passengers *not* affected by the disruption. Therefore, in the *SPLC* model 1) all passengers need to be assigned to a path, 2) this path needs to be *reasonable*, that is, the cost of the path is within a small increment of the standard solution's path cost, and 3) all candidate shuttle lines should benefit affected passengers. Consequently, passengers affected by the disruption are neither ignored nor significantly worse off than in the standard solution, and geolines that only benefit passengers not affected by the disruption are excluded. The solutions for the case study reduce delay of affected passengers. In the case where solutions benefit passengers *not* affected by the disruption, the costs of paths could be adjusted to reflect delay instead of absolute costs. This could however, fail to capture all the demand attracted by shuttle lines in systems with free route choice.

The cost c_p of a path in the public transport network is equal to the sum of the costs of the arcs in the path representing waiting time, in-vehicle time, and transfers. Entry arcs in $\mathcal{E}_{OD}$ represent frequency-dependent waiting time for the first vehicle given random arrivals of passengers. Costs of arcs in $\mathcal{E}_{line}$ are equal to the in-vehicle time between the two stops connected by the arcs. Arcs in $\mathcal{E}_{transfer}$ represent transfer costs, which are calculated as the expected waiting time to the transfer-to geoline as dependent on its frequency, plus a fixed transfer penalty.

Costs of arcs in a path can be mode, geoline, frequency, and station-specific. For instance, transfers at large stations can be penalized more than transfers at small stations, transfers to shuttles can be more costly than transfers to the same mode, and in-vehicle time cost can be geoline specific. Thus, the problem formulation allows for a realistic cost representation without additional complexity.

Passengers are in the model assigned to a single path, as also common in the previously discussed line planning models. A limitation of this model is that when two different geolines travel between the same pair of stations, the model would likely overestimate the expected waiting time of the passengers. Further research would be needed to deal with this specific issue.

4.4.4 Model

Required input for the *SPLC* model is a set of geolines $\mathcal{G}$, a set of allowed frequencies $\mathcal{F}$, and a set of OD-groups Q. A single OD-group $q : (s_q, t_q, w_q, \mathcal{P}_q)$ is defined by an origin node s_q, a destination node t_q, a (demand) weight w_q, and a set of paths $\mathcal{P}_q$ connecting s_q to t_q in PTN. The PTN is defined by $\mathcal{G}$ and $\mathcal{F}$. The set of paths $\mathcal{P}_q$ is obtained through the path generation method described in Section 4.5.1 and the path reduction method described in Section 4.5.2.

Continuous decision variables x_{pq} define the flow from OD-group q traveling on path p in the PTN, with x_{pq} defined only for paths $p \in \mathcal{P}_q$, $q \in \mathcal{Q}$. Binary decision variables y_{gf} represent the decision of opening geoline g at frequency f. Decision variables v_{lg} define the number of vehicles of type l assigned to geoline g, alongside which we define $\mathcal{L}_g$ as the subset of vehicle types that can be assigned to geoline g. The choice of continuous or integer vehicle variables did not significantly affect computation time in our case study.

Some further notation: δ_{lg} is the maximum number of passengers that can be transported by a single vehicle of type l assigned to geoline g, dependent on the vehicle capacity of type l and the length of geoline g. M_g is the maximum number of passengers that can be transported on geoline g over all selections of frequency $f \in \mathcal{F}$ and assignment of vehicle types $l \in \mathcal{L}_g$, and β_l is the number of available vehicles of type l. Let $\mathcal{P}_q(e)$ denote the set of paths in $\mathcal{P}_q$ traversing arc e, and $\mathcal{E}_{gf}$ denote the set of arcs representing geoline g at frequency f in PTN.

The formulation of the *SPLC* problem is:

$$\min \sum_{q \in \mathcal{Q}} \sum_{p \in \mathcal{P}_q} c_p x_{pq} + \sum_{g \in \mathcal{G}} \sum_{l \in \mathcal{L}_g} k_{lg} v_{lg}$$

subject to:

$$\sum_{p \in \mathcal{P}_q} x_{pq} = w_q \qquad \forall q \in \mathcal{Q} \tag{4.1}$$

$$\sum_{q \in \mathcal{Q}} \sum_{p \in \mathcal{P}_q(e)} x_{pq} \leq \sum_{l \in \mathcal{L}_g} \delta_{lg} v_{lg} \qquad \forall g \in \mathcal{G}, \forall e \in \mathcal{E}_g \tag{4.2}$$

$$\sum_{q \in \mathcal{Q}} \sum_{p \in \mathcal{P}_q(e)} x_{pq} \leq M_g y_{gf} \qquad \forall g \in \mathcal{G}, \forall f \in \mathcal{F}_g, \forall e \in \mathcal{E}_{gf} \tag{4.3}$$

$$\sum_{f \in \mathcal{F}_g} y_{gf} \leq 1 \qquad \forall g \in \mathcal{G} \tag{4.4}$$

$$\sum_{l \in \mathcal{L}_g} v_{lg} \geq y_{gf} \phi_{gf} \qquad \forall g \in \mathcal{G}, \forall f \in \mathcal{F}_g \tag{4.5}$$

$$\sum_{g \in \mathcal{G}} v_{lg} \leq \beta_l \qquad \forall l \in \mathcal{L} \tag{4.6}$$

$$x_{pq} \geq 0 \qquad \forall q \in \mathcal{Q}, \forall p \in \mathcal{P}_q \tag{4.7}$$

$$v_{lg} \geq 0 \qquad \forall l \in \mathcal{L}, \forall g \in \mathcal{G} \tag{4.8}$$

$$y_{gf} \in \{0, 1\} \qquad \forall y_{gf} \in \mathcal{L} \tag{4.9}$$

Objective: The objective function minimizes expected passenger inconvenience and operating cost. By setting k_{lg} to zero, one can optimize passenger inconvenience, in which case the model selects for each geoline the frequency $f \in \mathcal{F}$ such that the route assignment in $\mathrm{PTN_f}$ has minimal passenger inconvenience over all possible $f \in \mathcal{F}$ under fleet size constraints.

Capacitated multi-commodity flow component: Constraint (4.1) requires that all passengers are assigned to a path. Constraint (4.2) restricts the number of passengers assigned to a geoline not to exceed the capacity of vehicles assigned to geoline g. The constraint specifies that the sum of the number of passengers assigned to all frequency-specific arcs representing the same connection between two consecutive stops must be no larger than the capacity of the vehicles assigned to geoline g. Note that this constraint is not frequency specific. Therefore constraint (4.3) restricts passengers to only use geolines at their operated frequency f. This restriction is frequency dependent but not dependent on the number of vehicles assigned to the geoline, thus, both constraints (4.2) and (4.3) are needed to fully specify the capacity constraints.

Together constraints (4.1), (4.2) and (4.3) form the capacitated multi-commodity flow component of the model. A path formulation is chosen even though there exists an exponential number of paths in the graph and an arc-based formulation contains the large (but linear) number of $|\mathcal{E}| \times |\mathcal{Q}|$ decision variables. As the majority of existing paths will never be included in an optimal solution, for most practical applications the path-based formulation often leads to a significant reduction in the number of variables in comparison to the arc-based formulation. This however, requires the identification of the set of candidate paths, which we discuss in Section 4.5. The *SPLC* model could be solved through column generation, however, for the case study here presented this was not needed to obtain optimal solutions fast.

Geoline and frequency selection component: Constraints (4.4) to (4.6) define restrictions on the selection of geolines. Constraint (4.4) restricts the choice to at most one frequency f per geoline $g \in \mathcal{G}$. Thus, if a geoline is operated, it has to be at least at the minimum frequency in $\mathcal{F}$. Constraint (4.5) forces the number of vehicles assigned to geoline g to be at least equal to the minimum number of required vehicles to operate the geoline at frequency f, ϕ_{gf}, which depends on the run time of geoline g. Lastly, equation (4.6) captures vehicle type dependent fleet size constraints.

The *SPLC* problem formulation contains two decision variables for the geoline and frequency selection: y_{gf} for the opening of geoline g at frequency f, and v_{lg} for the number of vehicles of type l assigned to geoline g. A single decision variable y_{gf} combines the choice of opening a geoline g with the selection of a frequency f, as proposed for railway line planning in Claessens et al. (1998). This enables the formulation of an MIP that 1) allows specifying a minimum frequency conditional on the opening of a geoline, and 2) can include frequency-dependent passenger inconvenience costs, such as waiting and transfer costs. The usage of y_{gf} requires a discrete set of options, but there exists a continuous set of frequencies. Moreover, included paths p are frequency-dependent. Therefore the problem size grows rapidly with the number of frequency options included.

The choice of the set of frequencies $\mathcal{F}$ can change the model solution in the formulation of the *SPLC* inspired by Claessens et al. (1998). Let us assume that the true optimal solution given a continuous set of frequencies includes geoline and frequency selection $y_{g'f'}$. However, $\mathcal{F}$ includes only $y_{g'(f'-\varepsilon)}$ and $y_{g'(f'+\varepsilon)}$. Suppose $y_{g'(f'-\varepsilon)}$ provides insufficient capacity for all passenger demand, making it infeasible, and $y_{g'(f'+\varepsilon)}$ requires more vehicles than are available, making this solution also infeasible. In this case the model will propose a different solution, with different geolines than the true optimal solution.

Therefore, vehicle variables v_{lg} are introduced so that more capacity can be assigned to $y_{g'(f'-\varepsilon)}$, making this feasible. The y_{gf} variables define the *minimum* number of vehicles, and the waiting and transfer time of passengers boarding this geoline at frequency f. However, the v_{lg} define the available (passenger) capacity and operating cost, instead of the y_{gf}. The inclusion of different types of vehicles that can be assigned to one geoline can be included without the need to specify all possible combinations of assignments, as would be required in the formulation inspired by Claessens et al. (1998). Thus the problem of using vehicle variables can be solved using less frequency options, thereby greatly reducing the problem size, without the issues described above. This comes at the cost of slightly overestimating passenger transfer time and boarding time to geolines where more vehicles are assigned than the minimum number required, as an assignment of more vehicles leads to higher frequency and thus lower *PI*, which is not included in the pre-computed path costs. By defining $\mathcal{F}$ based on small increments in headways, this difference could be kept small, and results in a more accurate estimation of PI than in the previous models of Borndörfer et al. (2007) and Schöbel and Scholl (2006) that do not include frequency-dependent path costs.

Decision variables: Decision variables for passenger flow assigned to a path and number of vehicles assigned to a line are restricted to be positive by constraints (4.7) and (4.8), respectively. The inclusion of geoline g at frequency f is a binary decision variable due to constraint (4.9).

4.5 Solution Approach

This section defines two important pre-processing steps: Section 4.5.1 proposes an approach for the generation of a set of *reasonable* paths, which are required input for the model defined in Section 4.4.4. Section 4.5.2 presents a path reduction procedure that significantly reduces the number of paths and increases the computational speed, without decreasing the quality of the solution. Together the generation of reasonable paths and the path reduction generate input for the *SPLC* model, which is then solved to optimality using CPLEX 12.6.

4.5.1 Path Generation

Path generation constructs the set of *reasonable paths* $\mathcal{P}_q$ for each OD-group in a given PTN. The concept of *reasonable paths* follows Ceder and Wilson (1986), who limit the acceptable paths to some value above the absolute shortest path. We define a path as *reasonable* if its cost does not exceed the cost of the *standard path*, rather than the shortest path, by more than an increment α. The *standard path* is defined as the shortest path in the solution to the link closure closest to normal operations: a graph defined by the planned frequency of all geolines, the closure, and the standard replacement shuttle around the closure at its maximum frequency. The standard path forms a natural reference point for both passenger path lengths and the operating budget defined as the available fleet size.

The criteria and construction method that lead to a set of *reasonable* paths are defined for each OD-group, which contrasts with the global criteria generally used for column generation. A column generation approach will stop adding a new path p^* to the set of candidate paths $\mathcal{P}$ when there exists no path $p^* \in \mathrm{PTN_f}$, $p^* \notin \mathcal{P}$ that would reduce the *overall* passenger inconvenience. This global condition would allow adding paths that are purely in the interest of the global social optimum but not in the interest of the OD-group itself. Because passengers are allowed to freely choose their route in the network (within certain limits), some of these altruistic paths p^* may be unrealistic in practice. Using the incremental cost α, one could consider the set of *reasonable paths* to be the set of paths among which passengers are indifferent, and thus exclude purely altruistic paths. Defining the path set per OD-group, and not at the system level, is a better reflection of the assumption of free route choice for each passenger. As an additional advantage, this specification allows to compute the path set $\mathcal{P}_q$ for each OD-pair independently of the others, which could make calculation of these sets more efficient.

The construction uses the concept of a *geopath*. Given a path $p \in \mathrm{PTN}$, the translation of this path to a *geopath* p^γ is defined by storing only the geoline information without the frequency information for each arc in the path. The translation of a path p^γ to the corresponding set of paths in PTN is defined by the set of all possible paths in PTN that contain the same geoarcs as path p^γ. These paths can be constructed by finding all frequency-specific arcs that match the geoarcs in p^γ, and generating from these arcs all possible paths that have the exact same ordering of geoarcs as p^γ. Thus given a set of *geopaths*, these paths can be translated into a set of paths in PTN.

The intuition behind our approach is the following. For each candidate shuttle geoline we construct a graph consisting of the existing network, the line closure, and the candidate shuttle service at its maximum frequency. Note that we do *not* include the standard shuttle line in these graphs. Shortest paths for all OD-groups are calculated. The *reasonable* geopaths are then added to the candidate set, that is, all geopaths for which the estimated cost does not exceed the cost of the standard path by more than α units. Finally, the set of geopaths is translated to PTN to arrive at the full candidate set $\mathcal{P}_q$.

The concept of reasonable paths prevents passengers from being assigned to paths that make them considerably worse off than in the standard solution. However, it is not guaranteed that passengers are assigned to their shortest path. For instance, when both the standard path and a shorter path exist in the final solution for an OD-group q, a passenger from q may be assigned to either path based on what results in the lowest global passenger inconvenience given certain budget constraints. Moreover, limiting the choice set to reasonable paths, may result in a more expensive overall solution. However, when choosing a small α, passengers can be considered to be indifferent between these paths, as they are all part of the reasonable path set, and their costs differ by at most α.

4.5.2 Path Reduction

An OD-group consists of an OD-pair, a weight, and a path set. Given a set of OD-groups $\mathcal{Q}$ for a PTN, the *path reduction* constructs a new set of OD-groups $\mathcal{Q}'$. The path reduction aims to reduce the number of paths and OD-groups contained in a new OD-group set, without changing the outcome of the route assignment. Computational results for the case study show that the path reduction reduces the set of OD-groups and paths by at least a factor of two, and decreases the computation time even more.

The *SPLC* model includes demand for *all* OD-groups, as any of these may be affected by the closure: some OD-groups have multiple paths to choose from to traverse the closure, other OD-groups do not traverse the closure but find a faster alternative in one of the candidate shuttles. Moreover, OD-groups can be affected by a change in demand resulting from the closure or a change in frequency on the existing metro line. Thus, in order to estimate passenger inconvenience and required capacity correctly, demand for all OD-groups needs to be included.

Each path of each OD-group introduces a new decision variable in the *SPLC* formulation. However, for the majority of OD-groups the path choice in terms of the geographical lines and stops is fixed, but still several paths are included for the different frequencies. For these OD-groups including demand per link leads to the same demand assignment as including a set of candidate paths the demand of the groups needs to be assigned to. The intuition behind the path reduction is to split passenger demand into demand that can be geolink-based since there is only one geopath, and demand for which there are multiple geopaths available, which requires a path based assignment. This is done *within* passenger groups. Although this does not necessarily reduce the number of paths and passenger groups, our case study shows that significant practical benefits can result.

The path reduction process is based on the geopath-translation, including entrance and transfer arcs, of the path set of OD-group q, which, to improve readability, we will still denote by $\mathcal{P}_q$ in this section. Note that any geopath can be translated into a new set of paths in PTN, as discussed in Section 4.5.1.

Definition and Properties

For an OD-group $q \in \mathcal{Q}$ we define s_q^* as the last common *node* among geopaths $\mathcal{P}_q$ before a change in the stop sequence, and t_q^* as the first common *node* after s_q^*, meaning that all geopaths in $\mathcal{P}_q$ contain the arcs from s to s_q^* and the arcs from t_q^* to t. Let $\mathcal{A}^*$ be the set of all arcs between s_q and s_q^* and all arcs between t_q^* and t_q. Furthermore, we define a new geopath set $\mathcal{P}^*$ by adding the remaining sub-path of each geopath $p \in \mathcal{P}_q$ after removing all arcs $a \in \mathcal{A}^*$ from this path. Note that by the construction of $\mathcal{A}^*$ and $\mathcal{P}^*$ all paths $p^* \in \mathcal{P}^*$ connect s_q^* to t_q^*. A new set of OD-groups $\mathcal{Q}'$ is constructed by defining:

- a new OD-group $q' \in \mathcal{Q}'$ as $s_{q'} = u, t_{q'} = v, w_{q'} = w_q, \mathcal{P}_{q'} = a$ for each arc $a = (u, v) \in \mathcal{A}^*$
- a new OD-group $q' \in \mathcal{Q}'$ as $s_{q'} = s_q^*, t_{q'} = t_q^*, w_{q'} = w_q, \mathcal{P}_{q'} = \mathcal{P}^*$

These new OD-groups q' are only defined for non-empty $\mathcal{A}^*$ and $\mathcal{P}^*$. $\mathcal{A}^*$ is empty when $\mathcal{P}_q$ contains multiple geopaths with fully disjoint arc sets, and therefore $\mathcal{P}_q = \mathcal{P}^*$. $\mathcal{P}^*$ is empty when all arcs in $\mathcal{P}_q$ are contained in all geopaths of $\mathcal{P}_q$, thus when $\mathcal{P}_q$ contains only one geopath. Paths are compared on an arc basis, thus including geoline-specific transfers, and new OD-groups are defined on a node basis. Thus transferring passengers, arriving passengers, and in-train passengers can be distinguished.

Observation I: the path set $\mathcal{P}_{q'}$ is uniquely defined by the origin and destination node of the new OD-groups $q' \in \mathcal{Q}'$. The cost of a path c_p is the sum of the cost of all arcs in the path. The cost of a single arc is independent of the cost of other arcs in the path, consisting of geoline and frequency specific entrance arcs, geoline arcs, geoline and frequency specific transfer arcs and exit arcs. Thus, for any new $q', q'' \in \mathcal{Q}'$ that have the same s_q^*, t_q^*, the additional inconvenience of an assignment to any path p in the subset of paths $\mathcal{P}^*$ of either q', q'' is equal for both q', q'' independent of the OD-pairs of q', q''. Moreover any path $p^* \in \mathcal{P}^*$ will be part of both q', q'' as the concept of a *reasonable* path is defined as a fixed *incremental* cost on top of the standard path. Thus, any reasonable path of q' is a reasonable path of q'' and vice versa, and therefore the path set $\mathcal{P}_{q'}$ and $\mathcal{P}_{q''}$ are the same. It is straightforward to see that the same holds true for any OD-group defined by a single arc $a \in \mathcal{A}^*$.

Therefore, whenever there are two OD-groups q', q'' with $s_{q'} = s_{q''}, t_{q'} = t_{q''}$ we define a new combined OD-group $q''' := \{s_{q'''} = s_{q'}, t_{q'''} = t_{q'}, w_{q'''} = w_{q'} + w_{q''}, \mathcal{P}_{q'''} = \mathcal{P}_{q'}\}$ replacing q', q'' in $\mathcal{Q}'$.

Observation II: The path reduction process will not increase the number of paths by more than the number of arcs in PTN. By construction, paths are added for arcs in $\mathcal{A}^*$ and paths in $\mathcal{P}^*$. The maximum number of paths resulting from $\mathcal{A}^*$ is smaller than, or equal to the number of arcs in PTN (because of the first observation). Paths resulting from $\mathcal{P}^*$ are subpaths of the original path set of OD-group q, and therefore this number is smaller than or equal to the number of paths in the original passenger group.

However, path reduction is likely to reduce the number of paths and the number of OD-groups because of the first observation. The number of decision variables is determined by $\sum_{q \in \mathcal{Q}} |P_q|$. Thus, both a reduction in the number of groups and the number of paths will lead to a reduction in the size of the mathematical programming problem defined in Section 4.4.4.

Observation III: a minimum inconvenience route assignment is the same for $\mathcal{Q}$ and $\mathcal{Q}'$ given a PTN. By construction, paths are only split into multiple portions for those arcs that occur in all paths of the passenger group. Fixing this part of the assignment does not limit the path assignment model. Moreover, any path assignment of $\mathcal{Q}'$ can thus always be translated to a path in $\mathcal{Q}$, and vice versa. The cost of a path is defined as the sum of its arc costs, which contains transfer arcs and entrance arcs. The arc costs are independent of their position in the path. Therefore the cost of assigning a passenger to the full path in $\mathcal{Q}$ is equal to the cost of assigning a passenger to all disjunct subsets of the path included in $\mathcal{Q}'$. Therefore, the minimum inconvenience route assignments of $\mathcal{Q}$ and $\mathcal{Q}'$ are the same.

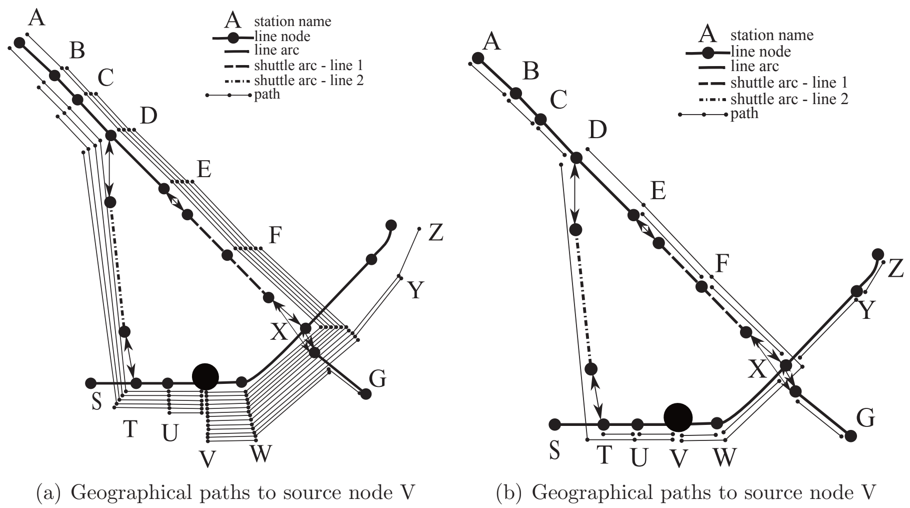
Remark: The path reduction process could be used independent of the concept of reasonable paths. However, in that case the path sets may not be uniquely defined by the origin and destination nodes s, t, possibly leading to a higher number of OD-groups.

Example

Consider the previously introduced public transport network and the associated graph given in Figure 4.2. For this network all reasonable geopaths for the OD-groups in the set $\mathcal{Q}$, where $\mathcal{Q}$ contains all passengers traveling to node V, are shown in Figure 4.3(a). This graph is again a schematic representation and arcs, nodes, and path segments representing entry and exit are omitted for reasons of clarity. Path reduction will compare the set of paths P_q for each OD-group $q \in \mathcal{Q}$ and then introduce the set of new OD-groups based on the comparison.

Take for example $(s_q, t_q) = (A, V)$. There are two reasonable paths: One passing through X and the other through T. Comparing these two paths, the last common node is $s_q^* = D$, while the first common node is $t_q^* = V$. Thus new OD-groups are introduced for (A, B), (B, C), (C, D) and (D, V) that collectively replace the original group A, V. Moreover an OD-group for the entry arc at station A is introduced (not shown in Figure 4.3(a)). A separate group for the exit arc at V will not be introduced as passengers may arrive from different directions at V. Distinguishing boarding and transfer arcs is essential to account for the waiting time and transfer time of passengers.

For each of the groups in $\mathcal{Q}$ we follow this procedure and find a new OD-group set $\mathcal{Q}'$ for which the resulting paths are shown in Figure 4.3(b). The number of paths is reduced by a factor of 5 in this example. In our case study we also find that the number of paths is significantly reduced, and as a result the computational speed is increased.



(a) Geographical paths to source node V (b) Geographical paths to source node V

Figure 4.3: Example of path reduction

A quick look of the network in Figure 4.3(a) may simply suggest cutting off all branches, such as branch A-D. However, there are several reasons why this should *not* be done. First of all, it is important for the measurement of passenger inconvenience to distinguish passengers transferring at D from passengers who are in a vehicle at D

and passengers who originate at D. Secondly, when one allows changes in the frequency on existing lines, this affects all passengers on the geoline, and thus requires considering passengers traveling outside the area of the disruption. Finally, an existing metro line could experience an increase in demand, which could lead to shortages of capacity for passengers not affected by the disruption. Therefore it is important that any translation will lead to the same passenger inconvenience as the full OD matrix. The path reduction process satisfies this requirement.

4.6 Application

In this section we apply the *SPLC* model to a real life case study of a network closure in the urban rail network of the Massachusetts Bay Transportation Authority (MBTA) in Boston, Massachusetts, in the United States. We show that the *SPLC* model is able to find better solutions than the standard practice at the MBTA which is to use a single shuttle service to replace the track section being closed for repair. Moreover, through a sensitivity analysis we show that the proposed model's solutions are relatively robust to changes in demand and changes in the trade off between passenger inconvenience and operating cost. Finally we demonstrate that the model's solutions are stable under different assumptions about passenger behavior. Although the model formulation does not specifically optimize for robustness, the use of reasonable paths, as defined in Section 4.5, contributes to this property.

The case study is based on actual data which is described in Section 4.6.1. The experimental design is presented in Section 4.6.2. The model's solutions are discussed in Section 4.6.3, and finally Section 4.6.4 reports computational performance demonstrating the improvement in computation time of the model compared to prior formulations.

4.6.1 Data

The case study uses actual data from the MBTA urban rail network in Boston. Part of the 'Red Line' will be periodically suspended on weekends between 2013-2017 due to major maintenance work on the Longfellow Bridge. On such occasions, three stations central in the network will no longer be connected by the rail line. *One in eight* of the passengers traveling by metro in Boston on these days will be affected by this closure. The following discusses the input data consisting of the Origin-Destination (OD) matrix, public transport network, and candidate shuttle lines. The problem size is indicated in Table 4.2.

OD-matrix: The OD matrix is estimated based on fare payment data on five Saturdays between August 31, 2013 and September 28, 2013. Peak hour demand is estimated from the average peak demand between 2pm and 4pm on these days. The OD-demand matrix contains 1397 OD-pairs.

Figure 4.4: Core of MBTA network

Public Transport Network: The public transport network analyzed contains 113 stations, representing the full subway system of the MBTA with just two exceptions: some stations on the Green Line were excluded due to lack of OD-information, together with some stations at the southern end of the Red Line, where very few passengers travel on the weekends. Stations are connected by 300 directed geographically distinct links under normal operations.

The core of the MBTA network is depicted in Figure 4.4. Due to the closure of the line between Kendall/MIT, Charles/MGH and Park Street, the Red Line is divided into two parts: from Kendall north to Porter which continues to Alewife, and from Park Street south to Broadway Ashmont which continues to Braintree. Thus the northern end of the Red Line becomes disconnected from the rest of the network.

Table 4.2: Problem size.

Network	113 stations, 300 trips
Shuttles	14 geolines
Passengers	1397 OD pairs

The travel times are based on the planned schedule. The translation of the network to PTN for *normal operations* results in a graph with 405 nodes and 1543 directed arcs. This graph includes nodes and arcs for transfers, entrances and exits for a single frequency for each geoline. The size of PTN including shuttles is larger and depends on the size of the candidate shuttle pool and the set of frequencies per geoline, as discussed in Section 4.4.1.

Candidate shuttle pool: The current strategy of the MBTA is to maintain connectivity along the original Red Line route by connecting the Kendall, Charles, and Park stations through a shuttle bus service running at 1 minute headways. We show that considering a broader set of candidate shuttle lines can significantly reduce passenger inconvenience with no increase in MBTA budget.

The candidate shuttle pool results from a demand analysis and an exploration of the network. In the demand analysis we identified the main attractor stations of demand for passengers traversing the link closures. The shuttle lines were constructed by connecting all attractor stations within a maximum distance of each other and requiring the shuttle lines to form one new direct connection between a station of the metro line affected by the closure and a station of another metro line, or the other part of the split line.

This procedure resulted in 14 different geolines, connecting 2 to 5 stations per geoline. Candidate shuttle lines are shown in Figure 4.5. Shorter versions of these geolines were also included in the problem. The standard shuttle, that replaces the closed section of the line, is included in this set. The 14 candidate geolines also include shuttles between stations beyond the closure. Such shuttle lines were selected in the solution of the *SPLC* model. Travel times for shuttle routes were estimated from vehicle location (AVL) data when available. The other connections were estimated based on Google maps driving times in dense traffic.

Finally, in addition to shuttle connections, we included the option of walking between selected stations that are close together, that is, less than 10 minutes walking time. Allowing passengers to walk between these stations acknowledges that the OD matrix is just an estimate of the passenger's true origin and destination, and prevents the assignment of passengers to public transport routes for parts of their journey that are easily walkable.

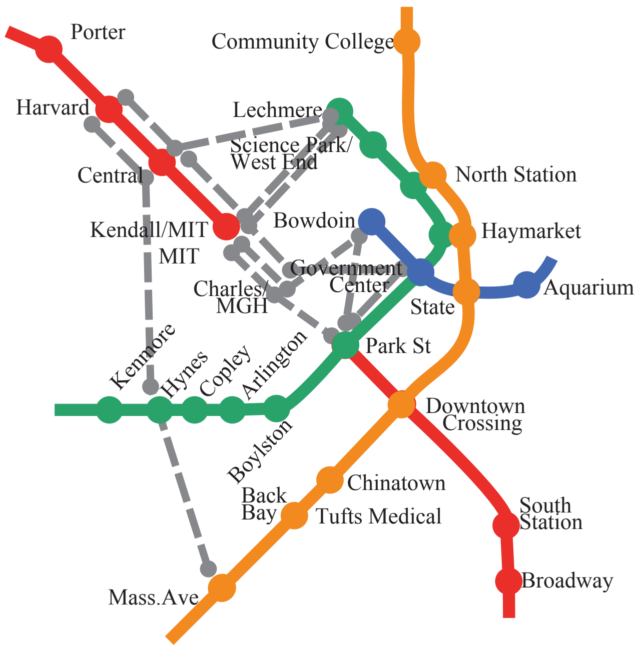


Figure 4.5: Core of MBTA network with candidate shuttle lines.

4.6.2 Experimental Design

All experiments are based on two cases: one scheduling shuttles, the second scheduling shuttles *and* allowing a redistribution of vehicles on the Red Line, as well as changing the frequencies on both parts of the Red Line. We evaluate different objective functions, different demand levels, and the robustness of the solution under different passenger behavioral assumptions. The quality of solutions is measured by the passenger inconvenience (PI), compared to PI of the standard solution ($\mathrm{Sf}_{\mathrm{st}}$) of a single shuttle replacing the closed links. OC is presented as the required number of shuttles for the solution, which defines OC as all shuttles in our case study have equal cost. An overview of the complete experimental design is provided in Table 4.3.

Shuttle Scheduling and Network Scheduling: We study two cases for the Longfellow Bridge closure. The first, *Shuttle Scheduling* ($\mathrm{C}_{\mathrm{shut}}$), considers only the introduction of shuttle lines in the current network. The second, *Network Scheduling* ($\mathrm{C}_{\mathrm{netw}}$), considers both the introduction of new shuttle lines in the current network, *and* the redistribution of vehicles and the frequency setting on both sections of the Red Line. The number of vehicles assigned to the two disconnected sections of the Red Line is limited to the current number of available vehicles for the line. Moreover, a cost is included for the change in the number of drivers a new frequency requires in comparison to the current 8 minute headway schedule. A decrease in frequency of one section of the line can compensate for the cost of an increase in frequency of the other section of the line. Finally, a budget constraint is added so that the total operating costs do not exceed the budget available for $\mathrm{C_{shut}}$. The frequency candidate set contains headways between 4 and 10 minutes in 1 minute increments.

For each shuttle line we introduce a frequency such that the headway varies between 1 and 10 minutes in 1 minute increments. The operating cost increases nonlinearly with decreasing in headways. The *SPLC* problem formulation allows assigning more vehicles to a geoline than necessary to operate the selected frequency. However, PI depends on the selected frequencies. Therefore it is more important to gradually change PI than OC for the included set of frequencies. Although a continuous set of frequencies are feasible per geoline, in Section 4.6.4 we establish that indeed the inclusion of 10 frequency options is sufficient, that is, the optimal solution does not change when the set of frequencies is defined at a finer level.

Objective function: The objective is to minimize PI due to the closure within a budget constraint on OC. However, there may be good solutions using *less* vehicles, or the maximum fleet size may not yet have been determined. Therefore three different objectives are analyzed:

- $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$: minimizing PI with a *limited* shuttle pool
- $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$: minimizing PI and OC with a *limited* shuttle pool
- $\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$: minimizing PI and OC with an *unlimited* shuttle pool.

Both PI and OC are expressed in monetary terms. MBTA bus operating costs are approximately \$140 per hour. Passenger inconvenience is expressed in terms of *value of time*, defined as the weighted total travel time, including waiting time, transfers, and in-vehicle time, multiplied by an estimate of the hourly wage. We conduct a sensitivity analysis for different assumptions about the value of time and different levels of demand. This includes three levels for the hourly wage $\omega := \{\$8, \$16, \$32\}$, ranging between the minimum and average wage in Massachusetts, and four demand levels to scale the OD matrix by $\sigma := \{0.6, 0.8, 1.0, 1.2\}$, with $\sigma = 1$ equal to the current average (peak) demand. These options reflect both a reduction in demand as the expected inconvenience may result in some passengers postponing their trips or changing mode, and an increase in demand that may be caused by a major sporting event, such as a Boston Red Sox game. Finally, the shuttle pool is limited to the number of shuttles required for the standard solution $\mathrm{Sf}_{\mathrm{st}}$ under any demand scenario.

PI is defined as the weighted sum of the costs of the arcs in the paths assigned to passengers. The waiting time to board a vehicle is defined as the expected waiting time for the first arrival based on random passenger arrivals and the scheduled frequency. For transfers between any metro or shuttle line, the waiting time is defined as the waiting time for a random arrival at the transfer-to geoline plus a fixed transfer-penalty, which reflects average transfer inconvenience in the MBTA network where arrivals of vehicles on different geolines are not synchronized to enable easy transfers and penalizes additional transfers (and waiting time) due to the closure. We define the *costs* of waiting time to be three times the cost of in-vehicle time, as first proposed in Quarmby (1967). Wardman (2004) lists more studies that find broadly similar results, although his results suggest that the actual costs may depend on other variables such as the trip purpose.

The *SPLC* model minimizes overall *PI*, and consequently not necessarily all passengers are assigned to their preferred path. The true preferred path of a passenger is unknown. Common approaches to modeling path choice are that each passenger follows the shortest path or that passengers choose one of a set of reasonable alternatives, based on some probabilistic rule. To address this we evaluate the robustness of the solution obtained under two different passenger behavior models. The first model, $\mathrm{RA}_{\mathrm{sp}}$, assigns passengers to their shortest path in the proposed network. The second model, $\mathrm{RA}_{\mathrm{prob}}$, assigns passengers probabilistically, based on a logit model to one of two candidate routes in the proposed network: (1) the shortest path and (2) the geographical route that follows the standard route most closely . The probability of choosing path p_i, $i \in \{1,2\}$, is defined as:

$$P(p_i) = \frac{e^{\theta c_{p_i}}}{e^{\theta c_{p_1}} + e^{\theta c_{p_2}}} \qquad \forall i \in \{1,2\}$$

Where c_{p_i} is the weighted travel time of the path, and $\theta = -0.2$ such that even if the difference between the p_i's is 15 minutes, 5% of the passengers still take the (longer) standard path (for example, reflecting inertia).

Both assignments, unlike the route assignment in the *SPLC* model, do not consider capacity constraints, but depend only on the 'optimal' set of geolines and their frequencies. In order to make a fair comparison between the quality of the solutions, the *OC* is recalculated such that sufficient capacity is provided for all passengers to follow their preferred route, and that all geolines are operated at a frequency no less than specified in the solution of the *SPLC* model. However, the *PI* is not adjusted for the resulting increases in frequency. Thus, conservative estimates are presented of both *OC* and *PI*,

Table 4.3: Notation for model applications.

Category	Notation	Description
Solutions	$\mathrm{Sf}_{\mathrm{mod}}$	$\mathrm{PTN}_{\mathrm{f}}$ solution from *SPLC* model
	$\mathrm{Sf}_{\mathrm{st}}$	$\mathrm{PTN}_{\mathrm{f}}$ standard solution with single shuttle bridging closure
Cases	$\mathrm{C}_{\mathrm{shut}}$	Optimizing shuttle lines operated
	$\mathrm{C}_{\mathrm{netw}}$	Optimizing shuttle lines operated and reassignment of Red Line capacity
Passenger Behavior Models	$\mathrm{RA}_{\mathrm{mod}}$	Model solution, model route assignment
	$\mathrm{RA}_{\mathrm{sp}}$	Model solution, shortest path assignment
	$\mathrm{RA}_{\mathrm{prob}}$	Model solution, probabilistic path assignment
Objectives	$\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$	*PI* and limited shuttle pool
	$\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$	*PI*, *OC*, and limited shuttle pool
	$\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$	*PI*, *OC*, and unlimited shuttle pool
parameters	ω	Value of time
	σ	Demand factor (increase or decrease)

4.6.3 Results

This section discusses the results of the case study based on the experimental design defined in Section 4.6.2. First the model solution is discussed, then the sensitivity analysis.

Solution

A solution for the *SPLC* problem defines the set of geolines to be operated and their frequencies given PTN defined by the geolines, the set of closed links, and the set of possible frequencies per geoline. Given the demand, a set of reasonable paths, and the number of available vehicles, the model identifies the set of frequencies that minimize the objective function: the weighted sum of passenger inconvenience and operating cost. A solution's quality is compared against current practice, and measures *PI* relative to normal operations, so that it is possible to conclude that a solution is not just better than the standard solution for line closures, but also a good overall solution in the event of a line closure. This section presents results for the cases $\mathrm{C}_{\mathrm{shut}}$ and $\mathrm{C}_{\mathrm{netw}}$ with objective $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$, wage $\omega=$ \$16, and demand scale σ=0.8, which we define as the *base case*[1].

[1]Note: the MBTA expects a 20% decrease in demand due to the closure. So σ=0.8 is selected over σ=1 as the base case.

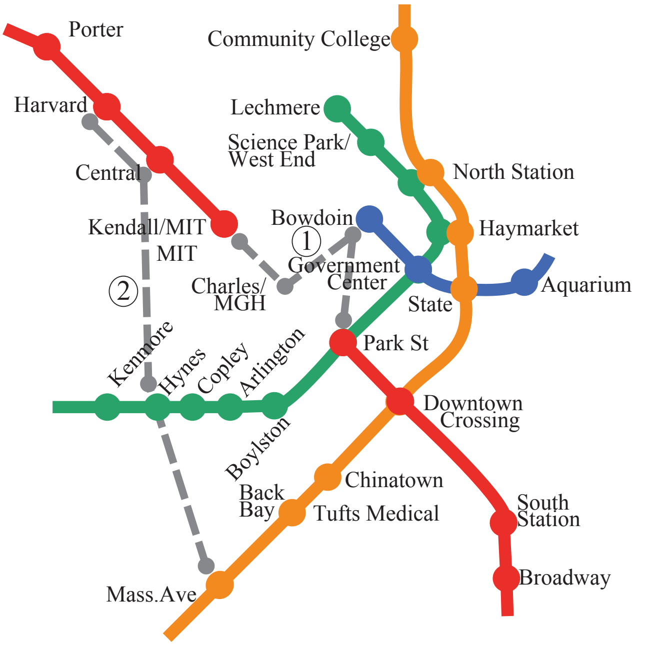


Figure 4.6: MBTA core network with shuttle lines operated in base case C_{shut} solution.

Two shuttle lines are operated in the C_{shut} solution. The resulting network is shown in Figure 4.6. The solution includes shuttle (1) operated at a headway of slightly less than 3 minutes, and shuttle (2) at a headway of 2 minutes. Shuttle (2) provides a direct high frequency connection between Harvard, Central, and Hynes: three of the major trip attractors in the network, thereby eliminating two transfers for these passengers and reducing waiting time (headways on the metro lines are 8 minutes, the shuttle runs at 2 minutes). This illustrates how shuttles beyond the closed area can significantly reduce delay, without increasing OC.

The solution for C_{netw} operates the Northern branch of the Red Line at 4 minute headways instead of 8 minutes. The 4 minute headway comes at the cost of a lower frequency of 10 minute headways on the southern branch of the Red Line and the additional need for (about) 4 drivers (based on length of route and turn around times, 8 hour shifts and the increase in frequency). The total number of vehicles on the Red Line stays the same. The solution operates shuttle (1) in Figure 4.6 at 2 minute headways, and a modified version of shuttle (2) starting at Central (i.e. omitting the Harvard section) at 3 minute headways. Although this introduces an additional transfer for all Harvard passengers, the higher frequency on this part of the Red Line compensates for this increase in inconvenience.

Table 4.4: *PI* percentage increase over normal operations, *OC* fleet size (shut= 64), $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$, ω= 16, σ=0.8

	$\mathrm{C_{shut}}$		$\mathrm{C_{netw}}$	
	PI	*OC*	*PI*	*OC*
$\mathrm{Sf_{mod}}$	15.7	61	11.1	55
$\mathrm{Sf_{st}}$	25.7	64	25.7	64

Table 4.4 shows *PI* and *OC* for the $\mathrm{Sf_{mod}}$ solution and the standard $\mathrm{Sf_{st}}$ solution for the $\mathrm{C_{shut}}$ and $\mathrm{C_{netw}}$ base cases. *PI* is expressed as the percentage increase in passenger inconvenience over standard operations. The *OC* is presented as the number of shuttle buses required, given a fixed cost of $140 per bus the *OC* follows directly from this. The *OC* of $\mathrm{C_{netw}}$ represents the total cost for shuttles and additional drivers on the Red Line in terms of shuttles. Lower values for *PI* and *OC* represent better solutions.

The model's solution for $\mathrm{C_{shut}}$, allowing bus deployment to shuttle services only, has a lower *OC* than $\mathrm{Sf_{st}}$ (61 instead of 64 buses) and a *PI* of 15.7%, reducing *PI* by 40% compared to the standard solution. For example, for a passenger who makes a 40 minutes trip under normal conditions and travels over the links which will be closed, in the standard solution the journey would be 10 minutes longer (on average), and 6 minutes (on average) longer in the model solution.

In the $\mathrm{C_{netw}}$ solution, which allows redistribution of vehicles and selecting a new frequency within a feasible range on the two Red Line sections, the passenger inconvenience is reduced to 11.1% - a reduction of 57% compared to the standard solution. This results in a delay of 4 minutes instead of 10 minutes in the previous example. The solution has a lower operating cost than both the standard solution and $\mathrm{C_{shut}}$ (55 shuttle equivalent instead of 64 or 61, respectively), while using the same number of cars on the Red Line.

The distribution of *PI* over passengers for the standard $\mathrm{C_{shut}}$ and the $\mathrm{C_{netw}}$ solutions respectively are given in Figure 4.7 as the weighted additional travel time per passenger in comparison to normal operations. Passengers with no change in inconvenience in comparison to normal operations are excluded from the graph. A unique translation of the path reduction passenger assignment to an assignment per original OD-group does not exist whenever a passenger group is assigned to multiple paths. Therefore we base the analysis of per passenger inconvenience on a shortest path assignment in the network, which has a similar *PI* as discussed in Section 4.6.3.

Both the $\mathrm{C_{shut}}$ and $\mathrm{C_{netw}}$ solutions reduce worst case delays, and distribute delay more evenly over passengers than the standard approach $\mathrm{Sf_{st}}$. In the standard solution most passengers have a weighted delay of 25-30 minutes. The $\mathrm{C_{shut}}$ and $\mathrm{C_{netw}}$ greatly reduce the number of passengers experiencing a delay of 25 minutes or more, and reduce delay to under 15 minutes for most passengers. The C_{netw} solution reduces worst case delays for more passengers than the C_{shut} at a lower *OC*, although it also has a higher number of passengers with small delays (between 0 and 5 minutes) than the C_{shut} solution.

Moreover, the C_{netw} case benefits non-affected passengers by operating a higher frequency on the Northern Branch of the Red Line, explaining the -5 minutes delay bar in the graph. The percentage of passengers experiencing inconvenience from the closure is 28% for Sf_{st}, 23% for C_{shut} and 22% for C_{netw}. Thus the C_{netw} reduces *PI* not only by providing better connections for non-affected passengers, but also by reducing inconvenience for affected passengers

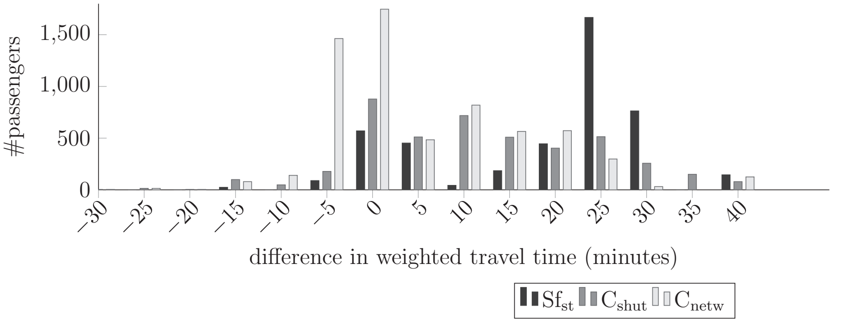


Figure 4.7: Distribution of per passenger *PI* increase for Sf_{st}, $C_{\text{shut}}$and C_{netw}.

Sensitivity Analysis

This section discusses the quality of the solution for different objective functions, demand levels, and its robustness under different passenger assignment models according to the experimental design presented in Section 4.6.2.

Objectives: The *SPLC* model has the objective of minimizing passenger inconvenience within a constrained operating cost. We compared three different formulations of the objective function: $\text{Ob}^{\text{L}}_{\text{PI,OC}}$, $\text{Ob}^{\text{L}}_{\text{PI}}$ and $\text{Ob}^{\text{N}}_{\text{PI,OC}}$. In $\text{Ob}^{\text{L}}_{\text{PI,OC}}$ and in $\text{Ob}^{\text{N}}_{\text{PI,OC}}$ *PI* is weighted by the value of time, assuming three different values: $\omega := \{8, 16, 32\}$ \$/hr. For the different objectives Table 4.5 presents the range of *PI* and *OC* over these three different values of time for both the C_{shut} and C_{netw} cases. *PI* is expressed as the percentage increase over normal operations (with the same value of time), and *OC* as the number of shuttle buses. The $\text{Ob}^{\text{L}}_{\text{PI}}$ solutions do not depend on ω.

The $\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$ uses a significantly higher number of shuttles for a relatively small increase in *PI*: 69 buses for a reduction in *PI* of 0.8 percent ($\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$) or 0.9 percent ($\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$), at a cost of respectively 5 and 7 shuttles for $\mathrm{C}_{\mathrm{shut}}$. The $\mathrm{C}_{\mathrm{netw}}$ has a higher difference in *OC* for a smaller difference in *PI*. An unconstrained fleet size thus can lead to a large variation in the number of shuttles in a solution given the relative weights assigned to *PI* and *OC* in the objective function. The advantage of $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$ is that, because the fleet size is constrained, different weights lead to smaller differences in solutions. Assigning zero weight to the *OC*, as in $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$, solutions may result in too many shuttles: 2 ($\mathrm{C}_{\mathrm{shut}}$) to 6 ($\mathrm{C}_{\mathrm{netw}}$) shuttles could be saved by increasing *PI* by 0.1% , an *OC* reduction that is 5 to 9 times as high as the resulting increase in *PI*. Therefore, $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$ can assist operators in making the right trade-off between the *PI* and *OC* without high sensitivity to the chosen weights. The results of the case study clearly illustrate that redesigning the network can reduce both *PI* and *OC*.

Table 4.5: Different objective functions for $\mathrm{C}_{\mathrm{shut}}$ and $\mathrm{C}_{\mathrm{netw}}$ cases, $\omega := \{8, 16, 32\}$ \$/hr, $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$ and $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$, shut= 64.

	$\mathrm{C}_{\mathrm{shut}}$		$\mathrm{C}_{\mathrm{netw}}$	
	PI	*OC*	*PI*	*OC*
$\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$	15.5	64	10.4	64
$\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$	15.6 - 17.7	50 - 62	10.5 - 12.0	54 - 58
$\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$	14.7 - 17.7	50 - 69	10.1 - 11.7	54 - 81

Demand: The base case assumes a demand loss of 20% due to the closure. Although this is MBTA's best estimate, demand could be lower when passengers can easily postpone their trips, or have access to other modes. However, when the added passenger inconvenience is small the resulting decrease in demand may also be small. Major sports events could even increase demand. Because the demand is uncertain, we evaluate the sensitivity of the solutions for demand scaled by $\sigma = \{0.6, 0.8, 1.0, 1.2\}$.

The *PI* and *OC* for all scenarios are given in Table 4.6 for the mixed objective with limited fleet size, $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$. Both an increase and a reduction of demand (slightly) increases *PI* in comparison to the base scenario (0.8) for both $\mathrm{C}_{\mathrm{shut}}$ and $\mathrm{C}_{\mathrm{netw}}$. The increase in *PI* at higher demand levels is caused by the limited fleet size of 64 shuttles, which is not enough to provide a similar service, especially at a 20% demand increase. Increasing the fleet size reduces *PI*, but requires a significant extension of the fleet (77 and 84 buses for $\sigma = \{1.0, 1.2\}$ for $\mathrm{C}_{\mathrm{shut}}$). *PI* also increases when demand decreases, as a decrease in demand reduces the relative benefit of operating lines at a higher frequency, and less vehicles are therefore employed than at higher demand levels, resulting in lower OC and also a slightly higher PI for $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$ and $\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$.

In terms of shuttle services for $\mathrm{C}_{\mathrm{shut}}$, at $\sigma = 0.6$ the same lines are proposed as in the base case ($\sigma = 0.8$), but operating at lower frequencies. The resulting public transport network is shown in Figure 4.6. For $\sigma = \{1.0, 1.2\}$ a third shuttle connecting the Red Line to Lechmere station is proposed in addition to shuttle (1), and a shorter version of shuttle (2) operating from Central Square to Hynes/Massachusetts Avenue is included. The short lines (2) and (3) help cope with the increased demand using the same number of shuttle buses. The PI and OC of the solutions with original shuttles (1) and (2), and the solution with three shuttle lines, are fairly similar. Thus the base solution is satisfactory even with higher demand, as long as the frequencies are adjusted accordingly. Results for $\mathrm{C}_{\mathrm{netw}}$ are similar, with higher frequencies on shorter lines, and a connection to Lechmere at high demand.

Table 4.6: Different demand levels for $\mathrm{C}_{\mathrm{shut}}$ and $\mathrm{C}_{\mathrm{netw}}$ cases, shut=64.

	$\mathrm{C}_{\mathrm{shut}}$		$\mathrm{C}_{\mathrm{netw}}$	
OD scale	PI	OC	PI	OC
0.6	16.7	47	12.6	42
0.8	15.7	61	11.1	55
1.0	16.9	64	13	62
1.2	19	64	15.2	64

Route Assignment: The model optimizes over all *PI*. The path assignment is restricted to *reasonable* paths, between which, one could argue, passengers are indifferent - but still does not fully reflect free route choice. This section therefore investigates the robustness of the solution under different assumptions on passenger route choice behavior.

The PI and OC for the model's route assignment $\mathrm{RA}_{\mathrm{mod}}$, the shortest path route assignment $\mathrm{RA}_{\mathrm{sp}}$, and the probabilistic route assignment $\mathrm{RA}_{\mathrm{prob}}$ in the network of the model's solution are shown in Table 4.7 for the base case $\mathrm{C}_{\mathrm{shut}}$. PI is not very sensitive to the route assignment model. Actually PI is within 0.4% of the model's estimated *PI*. The OC for the two different route assignment models increases. However, the OC is a conservative (upper bound) estimate of costs, as it estimates costs of geolines based on the maximum vehicles per geoline needed for either the *SPLC* solution or the new passenger assignment solution. If the frequency of geolines are reduced to mirror the decrease in demand due to the changed route assignment models, the increase in OC would be lower.

In the standard solution all passengers are assigned to the shortest path in the network. Also, in our case study, there exists in the standard solution only one path per passenger group. Therefore the PI (25,7) and OC (64) do not change for different route assignment models. This could be different for networks that are more dense, where even in the standard solution more paths could exist.

The delay distributions of $\mathrm{RA_{sp}}$ and $\mathrm{RA_{prob}}$ for the base case $\mathrm{C_{shut}}$, shown in Figure 4.8, are similar. In comparison to the standard solution, both route assignment models reduce passenger inconvenience by reducing the worst case delays. Results are similar for both the $\mathrm{C_{shut}}$ and $\mathrm{C_{netw}}$ cases at different levels of ω and σ, and for other objective functions.

Table 4.7: Route Assignment $\mathrm{C_{shut}}$

	$\mathrm{C_{shut}}$ PI	$\mathrm{C_{shut}}$ OC
$\mathrm{RA_{mod}}$	15.7	61
$\mathrm{RA_{sp}}$	15.3	63
$\mathrm{RA_{prob}}$	15.8	65

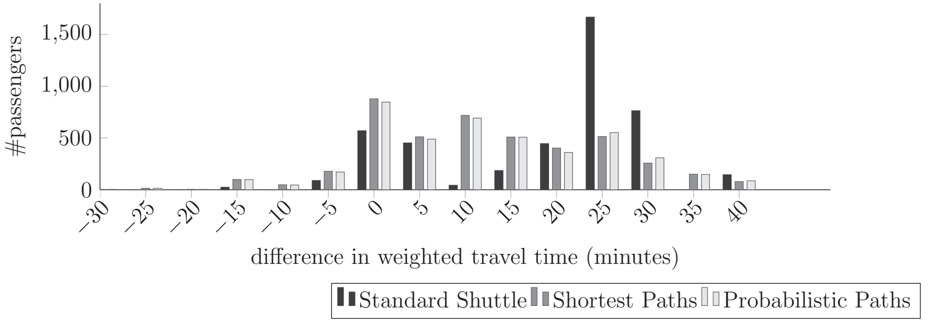


Figure 4.8: Distribution of per passenger PI increase for assignment in the Standard Shuttle solution, and Shortest Path and Probabilistic Path assignment for the $\mathrm{C_{shut}}$ (shut= 64, $\mathrm{Ob^{L}_{PI,OC}}$, ω= 16, σ=0.8) solution.

4.6.4 Computational Considerations

The computational benefits of the new formulation using *vehicle variables* and the *path reduction* preprocessing step are evaluated in this section. Two formulations for the *SPLC* problem are compared: 1) *SPLC*(y, v), containing both vehicle variables v and combined geoline and frequency variables y, and 2) *SPLC*(y), containing the combined geoline and frequency variables y only, which is a more straightforward adaption of Claessens et al. (1998) to the *SPLC* problem. All computational experiments were run using CPLEX version 12.6 on an Intel I7 3.07GHz processor using the default settings assigning 0.5GB of memory to the program.

Path reduction: The path reduction process reduces the number of OD groups by 75 % (from 1397 to 320). The number of different paths is reduced by more than 50 %. For example, with 10 frequency options per shuttle line the number of paths is reduced from 59,237 to 25,179 (reduction of 57%), while with 40 frequency options per shuttle line the number of paths is reduced from 224,666 to 99,726 paths (reduction of 56%). The number of x_{pq} decision variables is thus greatly reduced, thereby almost equally reducing problem size as the great majority of decision variables result from x_{pq}. Moreover, many of the new paths are 'simple' paths that traverse a single geo-arc. This might further contribute to decreasing the computation time.

The CPLEX optimization running time ($\mathrm{T_{opt}}$) and the total running time including preprocessing ($\mathrm{T_{tot}}$) for solving the problem with and without path reduction are given in Table 4.8. The candidate frequency set for both the $SPLC(\mathrm{y})$ and $SPLC(\mathrm{y,v})$ formulations are chosen such that the resulting solutions are comparable. For both formulations, the path reduction process reduces computational time significantly: it is 58 times faster for the $SPLC(\mathrm{y})$ case and 10 times faster for the $SPLC(\mathrm{y,v})$ case, without changing the problem definition or optimal solution value. Therefore, in the discussion that follows, it will be used in all reported computation times.

Table 4.8: Computation times (seconds) ($\mathrm{C_{shut}}$, $\mathrm{Ob^{L}_{PI}}$, ω=16, σ=0.8, shut = 64)

		Path reduction:			
Model	Number of	No		Yes	
	Frequencies	$\mathrm{T_{opt}}$	$\mathrm{T_{tot}}$	$\mathrm{T_{opt}}$	$\mathrm{T_{tot}}$
$SPLC(\mathrm{y})$	40	3297	3517	56.6	82
$SPLC(\mathrm{y,v})$	10	96.4	115	9.53	12

Vehicle variables: We search for the number of frequency settings per model to arrive at comparable solutions. We find that at 40 options the $SPLC(\mathrm{y})$ and $SPLC(\mathrm{y,v})$ models propose the same shuttle lines, with a difference in objective value of only 0.1%. The computation times for optimizing through CPLEX ($\mathrm{T_{opt}}$) and the total run time including preprocessing ($\mathrm{T_{tot}}$) shown in Table 4.9 are for different frequency options of the two formulations $SPLC(\mathrm{y})$ and $SPLC(\mathrm{y,v})$. The $SPLC(\mathrm{y,v})$ solves the model 5 times faster, in 9.53 seconds instead of 56.6 seconds respectively, as it requires only 10 frequencies to arrive at the same solution as the $SPLC(\mathrm{y})$ formulation with 40 frequencies. The addition of vehicle variables itself does not speed up the computation time, solving $SPLC(\mathrm{y},\mathrm{v})$ with 40 frequencies in 871 seconds is slower than $SPLC(\mathrm{y})$. But the $SPLC(\mathrm{y},\mathrm{v})$ formulation with 10 frequencies finds the same solution as the $SPLC(\mathrm{y},\mathrm{v})$ with 40 frequencies. Thus, because the $SPLC(\mathrm{y},\mathrm{v})$ requires less frequencies it is significantly faster than the $SPLC(\mathrm{y})$ formulation. The $SPLC(\mathrm{y},\mathrm{v})$ formulation together with the path reduction are able to solve the model 345 times faster, from 3297 seconds to 9.53 seconds as shown in Table 4.8.

Table 4.9: Computation times (seconds) (C_{shut} , $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$, ω=16, σ=0.8)

Model	Frequencies	T_{opt}	T_{tot}
$SPLC(\mathrm{y})$	40	56.6	82
$SPLC(\mathrm{y},\mathrm{v})$	40	871	894
$SPLC(\mathrm{y},\mathrm{v})$	10	9.53	12

Cases and Objectives: Computation times for the C_{shut} and C_{netw} cases are presented in Table 4.10. For all objective functions, the $SPLC(\mathrm{y},\mathrm{v})$ formulation is faster than the $SPLC(\mathrm{y})$ formulation. It computes C_{shut} in a minimum of 9.53 seconds, versus 39.48 for the $SPLC(\mathrm{y})$ formulation, thus 4 times faster. For the more complex case C_{netw} computing time is 28.2 seconds and 1192 seconds respectively, thus $SPLC(\mathrm{y},\mathrm{v})$ computation time is around 40 times faster than the $SPLC(\mathrm{y})$ formulation, 10 times more than the speed increase for the C_{shut} case. These results suggest that the benefit of the $SPLC(\mathrm{y},\mathrm{v})$ formulation increases as the problem complexity increases.

There are significant differences in computation times for different objective functions as shown in Table 4.10. $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$ is fastest, $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$ is 1.5 times as long and the $\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$ is 3 times as long as the $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI}}$. We were not able to solve the $SPLC(\mathrm{y})$ formulation with objective $\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$ due to insufficient memory. By estimating an appropriate upper bound on the number of vehicles, the $\mathrm{Ob}^{\mathrm{N}}_{\mathrm{PI,OC}}$ could be solved using the $\mathrm{Ob}^{\mathrm{L}}_{\mathrm{PI,OC}}$ for different fleet sizes, thus increasing the computation speed.

4.7 Conclusion and Discussion

This chapter presents a new analytic model for the design of shuttle services for planned closures in high frequency urban transportation networks. A new formulation is proposed that allows the selection of the frequency for new and existing lines, while minimizing passenger inconvenience, including frequency dependent transfer and waiting costs, within a

Table 4.10: Computation times (seconds)(Sf_{mod}, σ= 0.8, ω= 16). *-instances were not solved due to insufficient memory.

Settings		$SPLC(\mathrm{y}, \mathrm{v})$		$SPLC(\mathrm{y})$	
Instance	Cost Shuttle	T_{opt}	T_{tot}	T_{opt}	T_{tot}
C_{shut}	Ob^{L}_{PI}	9.53	12.27	39.48	57.46
C_{shut}	$Ob^{L}_{PI,OC}$	15.4	18.08	74.68	92.74
C_{shut}	$Ob^{N}_{PI,OC}$	34.2	37.03	1436	1461
C_{netw}	Ob^{L}_{PI}	28.2	52.00	1192	2588
C_{netw}	$Ob^{L}_{PI,OC}$	36.2	60.33	1421	2790
C_{netw}	$Ob^{N}_{PI,OC}$	65.6	91.26	*	*

budget for operating cost. A sensitivity analysis including different demand levels, different objective functions, and different assumptions about passenger route choice behavior is included. It is shown that the proposed formulation is able to find good solutions quickly for real life cases of planned closures, making this model a candidate for real time application. The solutions are better both in terms of passenger inconvenience and operating cost in comparison to the standard practice.

The proposed model formulation combines the ideas of Borndörfer et al. (2007) of a path formulation with the idea of Schöbel and Scholl (2006) to include transfers, and the idea of Claessens et al. (1998) to combine the capacity assignment and the opening of geolines' (services having the same sequence of stops) into one decision variable. We extend these ideas with the introduction of additional vehicle decision variables that relax the assignment of capacity to a geoline, while still including integer decision variables for which geolines to operate. This allows the specification of a minimum frequency for a geoline that is operated, as well as frequency dependent costs of path assignments.

The model is somewhat limited by the assumption that demand and frequencies are not time dependent. Although this assumption is fair and common in high frequency networks with cyclic timetables, it might not be valid for all public transportation networks. Future research could focus on extending the model formulation to time dependent problems. For more complex problems, the proposed model could be combined with a dynamic column generation approach. The combination of column generation with the proposed path reduction process could be an interesting area of research for any multi-commodity flow model. The proposed path reduction process assumes there is sufficient capacity available to transport all demand. In real time disruptions capacity shortages may arise, leading to competition amongst passengers for seats. How to include this competition in the model and path reduction, specifically preventing unrealistic altruistic behavior of passengers to reach a social optimum, is identified for future research.

Finally, the introduction of the concept of *reasonable* paths is a first step towards including realistic passenger behavior in systems with free route choice. Future research could extend on this, for instance extending the ideas proposed in Schmidt (2012) for an arc-formulation to the path formulation used in this chapter.

Chapter 5

Passenger Guidance and Rolling Stock Rescheduling under Uncertainty for Disruption Management

This chapter has appeared as the ERIM Technical report Van der Hurk et al. (2015a) and will have been submitted for peer review by the time of publication of this thesis.

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5.1 Introduction

Major disruptions resulting in the closure of one or more links in a public transportation system can cause significant inconvenience for many passengers. These disruptions occur several times a week in large networks such as Netherlands Railways (NS), Transport for London, and the Massachusetts Bay Transportation Authority's urban rail system. They can be caused by malfunctioning rolling stock, infrastructure failure, or accidents. At the start of a disruption the duration of the disruption is often unknown. Given this uncertainty, passengers need to adjust their journeys, and the operator needs to adjust its logistic schedule.

In this chapter we propose a model for minimizing passenger inconvenience through the novel idea of combining individual route advice to passengers with rolling stock rescheduling. We study a transportation system without seat reservation. That is, the passengers are allowed to freely choose their route in the system and therefore they are not obliged to follow the advise provided. Consequently the train capacities may not be sufficient to carry everyone on their preferred route.

The ability to provide individual support to passengers may become crucial to operators aiming to maintain their licence to operate, which is often based on their performance. This performance is increasingly based on passenger service measures rather than on-schedule performance. Indeed, new technologies, such as smart card ticketing, allow direct measurement of actual service experienced by passengers. Other technological advancements, such as the wide adoption of smart phones and the availability of wireless communication, allow for direct communication with passengers. In this chapter we will demonstrate that operators can greatly improve passenger service by providing individual route advice to passengers that anticipates a possible longer length of the disruption and warns of overcrowded trains – and may even prevent overcrowding.

The operator does attempt to adjust the capacity provided by rescheduling their rolling stock. However, these measures have a limited and delayed impact: even if there is spare capacity (which is not always the case), it can take quite some time for the additional rolling stock to arrive at the required location. In contrast, travel advice is communicated instantly. Therefore passenger guidance can greatly reduce the inconvenience resulting from a disruption.

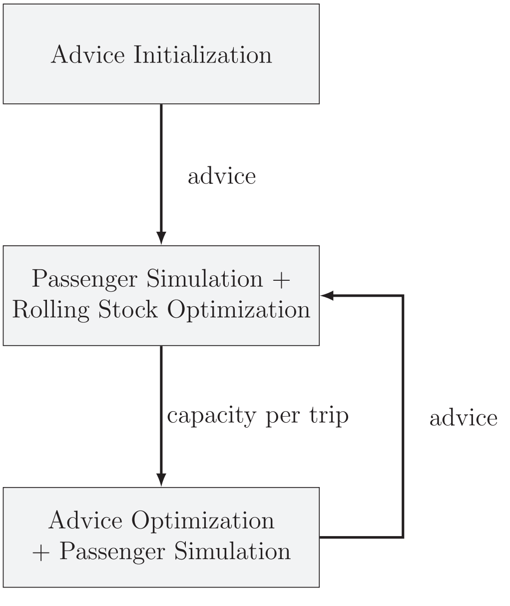

Figure 5.1: Solution Approach

In this chapter we present an optimization based approach to Passenger Advice and Rolling Stock Rescheduling under Uncertainty for Disruption Management. The model is to be run by an operator when a disruption occurs. It provides passenger guidance in the form of individual route advice, and an updated rolling stock schedule.

Uncertainty is captured by assuming a fixed set of disruption scenarios, where the scenarios differ only in the length of the disruption. The exact length of the disruption is unknown at the start, but is revealed at a fixed time during the disruption. Our approach computes initial advice and an initial rolling stock schedule based on a first estimate of the length of the disruption. When the true length is known, both the advice and the rolling stock schedule are updated.

Passengers receive individual advice based on their origin, destination, and planned departure time. The objective is to minimize the expected passenger inconvenience over all possible disruption scenarios. A passenger's inconvenience in a disruption scenario depends on the difference in waiting time, in-vehicle time, and number of transfers between the planned path and the realized path resulting from the advice, and the fact that the length of the disruption is unknown.

The solution approach is shown schematically in Figure 5.1. After the initial advice, we iterate between rolling stock optimization and advice optimization. Both optimization modules are based on mathematical programming models. Both aimed at finding a social optimum, minimizing overall passenger inconvenience. Real passengers, however, do not behave altruistically, and will compete for seats in their preferred timetable services. Therefore we evaluate the quality of each rolling stock schedule and of each passenger advice in a passenger simulation module.

We want to emphasize that the iterative framework is modular: the passenger behavior model, the underlying rolling stock rescheduling model, and even the advice optimization model can be replaced. Therefore our approach can be adjusted to the disruption management problems at a wide variety of public transport operators. To illustrate the benefit of the framework, we present computational results based on realistic problem instances of Netherlands Railways, the largest passenger railway operator in the Netherlands.

The key contributions of this chapter can be summarized as follows

- We study the disruption management problem with an uncertain disruption duration.
- We present a novel optimization based approach aiming to minimize expected passenger inconvenience by providing individual route advice and by rescheduling the rolling stock.

- We evaluate solutions under realistic assumptions on passenger behavior in a system with free route choice, such as the competition for seats in case of capacity shortages and the freedom to choose an alternative route rather than the one recommended.
- We carry out computational tests on realistic problem instances.
- We demonstrate that the provision of advice can greatly reduce passenger delays.

This chapter is organized as follows. Section 5.2 provides a literature overview. Section 5.3 illustrates the problem by an example. Section 5.4 presents the formal problem definition and framework, while in the next Sections 5.5, 5.6 and 5.7 the modules Passenger simulation, Advice optimization, and Rolling stock rescheduling respectively are discussed. Results for a case study based on data of Netherlands Railways are presented in Section 5.8. Finally Section 5.9 provides conclusions and a discussion.

5.2 Literature Review

Disruption management aims to reduce passenger inconvenience and operational costs by adjusting the pre-set schedules to the new circumstances. So far, both research and practice focus on resource rescheduling: adjusting the timetable, the rolling stock schedule and the crew schedule to reduce the effects of the disruption, as described in Jespersen-Groth et al. (2009). The overview of Cacchiani et al. (2014) shows that minimizing inconvenience for passengers resulting from the disruption is commonly modeled by minimizing the deviation from the planned schedule. However, minimizing the deviation does not necessarily minimize passenger inconvenience, as passengers preferred paths may also change as a result of changes in the timetable caused by the disruption.

Recent research has therefore modeled passenger behavior in more detail, distinguishing between unplanned and planned disruptions. For unplanned disruptions, Kroon et al. (2014) use an iterative framework for rolling stock rescheduling, where the passenger inconvenience cost are estimated based on a detailed simulation of passengers traveling in the system and competing for seats in case of insufficient capacity. Veelenturf et al. (2013) adopt a similar framework for minimizing passenger inconvenience by also allowing minor changes to the timetable. Cadarso et al. (2013) present a model for timetable and rolling stock rescheduling where passenger inconvenience is minimized based on a dynamic assignment of demand in the resulting schedule.

In case of planned disruptions, such as result from planned maintenance of the infrastructure, often the introduction of alternative shuttle busses is considered. Jin et al.

(2013) provide a model that combines the generation of candidate shuttle lines with the selection of such lines. Van der Hurk et al. (2014) study a similar problem for which they present a model that integrates the shuttle line selection and the frequency selection, which they evaluate under different assumptions on passenger behavior.

An explanation for the recent attention to passengers and passenger behavior is the increase in data on their behavior generated by automatic fare collection systems such as ticketing through smart cards. Pelletier et al. (2011) provide a review of research on smart card data. Sun et al. (2012) estimate the location of passengers over time based on smart card data containing origin and destination in the Singapore MRT system. Both Kusakabe et al. (2010) and Van der Hurk et al. (2015b) present methods for deducing route choice from smart card data. Van der Hurk et al. (2015b) validate their method based on a data sample of Netherlands Railways and thereby show that indeed route choices can reliably be deduced from smart card data. Van der Hurk et al. (2013) further demonstrate that passenger demand can be predicted reasonably accurately based on this data. All this supports the assumption made in this chapter that information on passenger demand and their preferred route is available.

5.3 Example

The concepts of passenger behavior and provision of advice to passengers are illustrated by the following example. Figure 5.2 displays part of a public transport network containing three lines: line ① connects stations A, B, and D, line ② connects station B with C, and line ③ connects stations A, C and D. The travel time between any two stations is also given in Figure 5.2.

A disruption occurs on line ③ between stations C and D, which prevents trains running on this section. As a result, the operator needs to adjust the logistic schedule: the timetable, the rolling stock circulation, and the crew schedule. Moreover, passengers need to alter their routes. We will assume an adjusted timetable to be available based on a contingency plan; our method adjusts only the rolling stock schedule.

The length of the disruption is unknown at its start. However, a discrete set of possible lengths of the disruption is known by the operator, say, increasing by 30 minute intervals. When the timetable adjustment is such that all trains with a departure time within the length of the disruption are canceled, such a discrete set of scenarios is naturally defined by the scheduled departure times of trains on the disrupted link. We assume that, when time reaches the shortest possible disruption length, the exact length is revealed – for instance after an inspection of the cause of the disruption. Once the actual length is

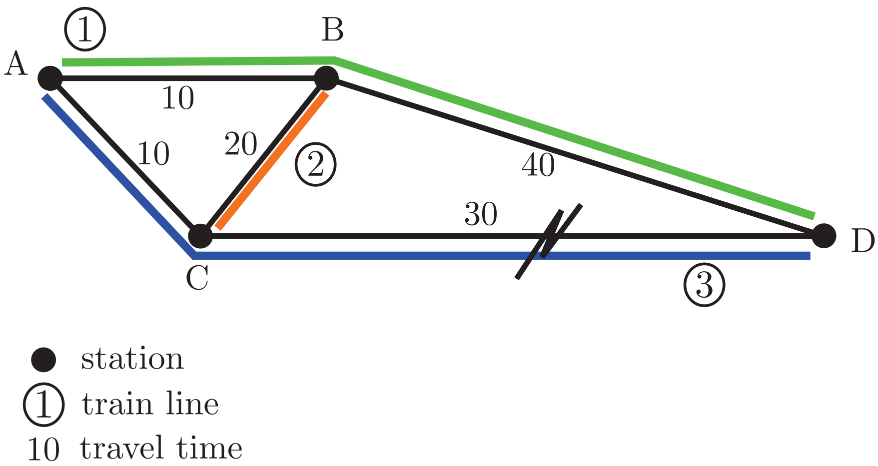

Figure 5.2: Public Transport network

known, passengers may adjust their initially planned path and the operator may adjust the initially adjusted rolling stock circulation.

Consider some passengers at A and C traveling to D who would normally travel on line ③. They need to decide whether to wait until the disruption is over, or to use lines ① and/or ②. The route advice of the operator supports passengers in this decision when the disruption length is still uncertain by recommending a specific sequence of timetable services. The advice may depend on the origin, destination, and (planned) departure times of the passengers.

The choice that passengers travelling from C to D need to make is illustrated by the time-space diagram of Figure 5.3. The horizontal axis represents time, and the vertical axis space. Trains, represented by the diagonal lines, connect stations in space and time. During the disruption there are no trains between C and D.

The uncertainty about the length of the disruption concerns the 3 direct services between C and D. In the shortest scenario (Scen 1), all 3 trains can run. In the scenario with medium length (Scen 2), the earliest service is canceled, the two later ones run. Finally, the long scenario (Scen 3) cancels the first 2 direct services, only the last one runs.

The inconvenience a passenger will experience depends on the advice, the initially chosen path at the start of the disruption, and on the actual length of the disruption. Although passengers need to make an initial travel decision when they start their journey, they are free to change their travel plan once the end of the disruption is announced. It is assumed that the actual length is known at the earliest end time of the disruption. In

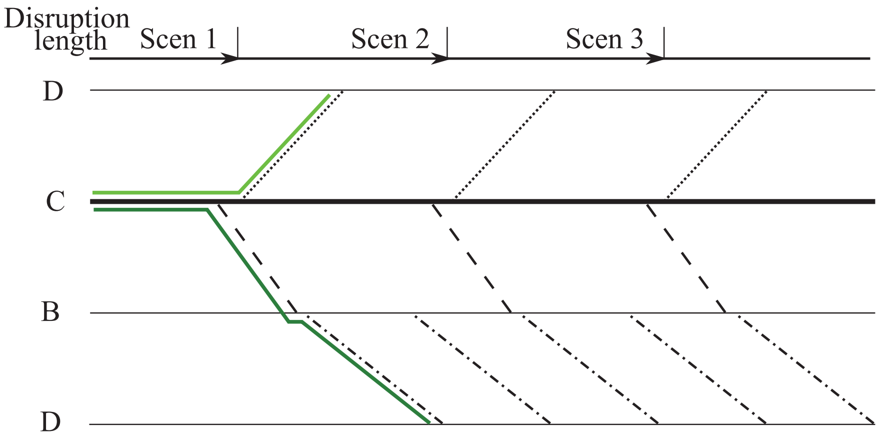

Figure 5.3: Time-space representation of the timetable between stations C and D. (Note that two time-lines are associated with station D in order to avoid crossing lines.)

the example this announcement is after the departure of the first detour option via B. Passengers traveling from C to D that initially decided to wait, will embark on the first departing direct train of line ③ in case of Scenario 1 or 2. However, in case of Scenario 3 with a longer disruption, they will change their planned path to reroute via B as this leads to an earlier arrival time than waiting for line ③.

Insufficient train capacities may also cause a difference between planned and realized paths. Passengers waiting at C to take the direct line ③ to D may not be able to board the train if it has already filled with passengers from A to D. As a result, passengers waiting at C might only obtain a seat in the second train of line ③ running after the disruption. In case of capacity shortages, delays may also arise for passengers not directly affected by the disruption. The operator's advice is a way to save unnecessary delay by recommending routes with spare capacity.

Passenger inconvenience thus results from a complex interaction between passengers themselves and the provided capacity. Because there is the interaction between capacity and passengers, the problems of providing advice and rescheduling rolling stock are integrated into a single framework.

5.4 Problem Definition and Framework

The starting point is a timetable, defined as a set of trips, where *trip* is a train ride between two consecutive stops. The timetable graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is an acyclic time-space graph. It contains a node $v \in \mathcal{V}$ for the departure and arrival of a trip at a station. The arc set $\mathcal{E}$ contains an arc for every trip $t \in \mathcal{T}$, and arcs connecting the nodes at the same station to a time-line; the latter arcs represent the option of waiting at this station. A straightforward modification of this intuitive graph allows us to account for transfers.

A disruption causes the cancelation of a set of trips during its length. As the length of the disruption is uncertain, we define a set of disruption scenarios $\mathfrak{D}$, where each disruption scenario $\delta \in \mathfrak{D}$ defines a possible length of the disruption. An adjusted timetable $\mathcal{T}^\delta$ is given for each scenario. Note that the timetables $\mathcal{T}^\delta$ are identical between the start of the disruption (denoted by τ_{start}) and the earliest end time of the disruption (denoted by $\tau_{\min}$), and also after the end time of the longest scenario.

In this chapter it is assumed that it is known at the beginning of the disruption that the actual length will be known at time τ_{com}. In this chapter τ_{com} is assumed equal to the earliest end time of the disruption time $\tau_{\min}$. The method allows however for a rolling horizon approach to take additional uncertainty into account.

Passengers are given as a set $\mathcal{Q}$ of *passenger groups* where a passenger group q represents w_q passengers, departing at time τ_q, traveling from the same origin station to the same destination station. A *rolling stock circulation* defines the capacity for each trip $t \in \mathcal{T}$. An *advice* recommends a path in the timetable graph $\mathcal{G}$ for every passenger group $q \in \mathcal{Q}$. Thus a path contains an ordered set of arcs in $\mathcal{G}$, which can be translated into a sequence of trips t in the timetable.

At the start of the disruption, the actual disruption scenario δ is unknown, and consequently the timetable $\mathcal{T}^\delta$ is uncertain. Therefore the calculation of the rolling stock schedule at τ_{start} requires an initial estimate of the disruption duration $\delta_r^{\text{I}} \in \mathfrak{D}$. We will investigate whether it is better for this estimate to be optimistic or pessimistic .

The model for computing the advice minimizes the expected total passenger inconvenience over all scenarios $\delta \in \mathfrak{D}$. Based on the estimated inconvenience per disruption scenario, the model selects a single recommended path per passenger group that will be provided at τ_{start}. The estimated inconvenience per passenger depends on the recommended path, the disruption scenario, the available capacity per trip, *and* the recommended paths for other passengers. The calculation of inconvenience recognize that the actual disruption length is uncertain between τ_{start} and $\tau_{\min}$, and capacity shortages may arise.

In addition, the same *communicated* disruption length δ_q^{I} is supplied to all passengers at τ_{start}. Some passengers may need to deviate from the advice between τ_{start} and $\tau_{\min}$ (for reasons discussed in Section 5.3). These passengers replan their route themselves based on the timetable graph for the communicated disruption length. In the case study we will investigate the best setting of δ_q^{I}; note that δ_q^{I} is not necessarily equal to the estimation δ_r^{I} used for rescheduling the rolling stock.

A solution is evaluated based on its performance over all scenarios $\delta \in \mathfrak{D}$. In this chapter we assume that every scenario has an equal probability of occurring. However, one could assign specific probabilities to the scenarios, indeed a worst-case evaluation would be possible within our framework.

Framework

The advice provision and rolling stock rescheduling problem is solved in the iterative framework presented in Figure 5.4. Input is the set $\mathfrak{D}$ of disruption scenarios, the passenger demand defined by the set $\mathcal{Q}$ of passenger groups, the timetable $\mathcal{T}$, an assumed length of the disruption δ_r^{I} for rolling stock scheduling, and a communicated length δ_q^{I}. Within the framework, advice will be calculated for each passenger, based on all possible outcomes for δ.

Note that the values δ_r^{I} and δ_q^{I} can be considered as high-level decision variables. A real-life implementation of our method could select the best settings over all possible choices of these two variables by evaluating the framework over all possible settings, or base this choice on pragmatic implementation considerations. A sensitivity analysis of these settings is included in the computational study presented in Section 5.8.

The advice and rolling stock schedule are optimized iteratively, and evaluated through a simulation model. The optimization model strives to find a social optimum. The objective of the simulation model is to evaluate a solution defined by the advice and the rolling stock schedule under more realistic assumptions on passenger behavior. Moreover, the simulation model serves as a tool for generating columns for the advice optimization: it generates candidate advice paths that can be provided to passengers. The simulation framework is presented in Section 5.5.

The advice optimization minimizes expected passenger inconvenience over all scenarios $\delta \in \mathfrak{D}$, given the available rolling stock capacity and uncertainty on the length of the disruption, while the rolling stock schedule minimizes capacity shortages for the anticipated per-trip demand. To initialize the model, the advice is optimized assuming an infinite seat capacity on each trip. The advice for this initial solution represents the preferred path for each individual passenger.

If the rolling stock module is able to find a solution without any capacity shortages for all possible disruption scenarios $\delta \in \mathfrak{D}$, then a solution with the absolutely minimal expected passenger inconvenience has been found, and therefore further iterations can

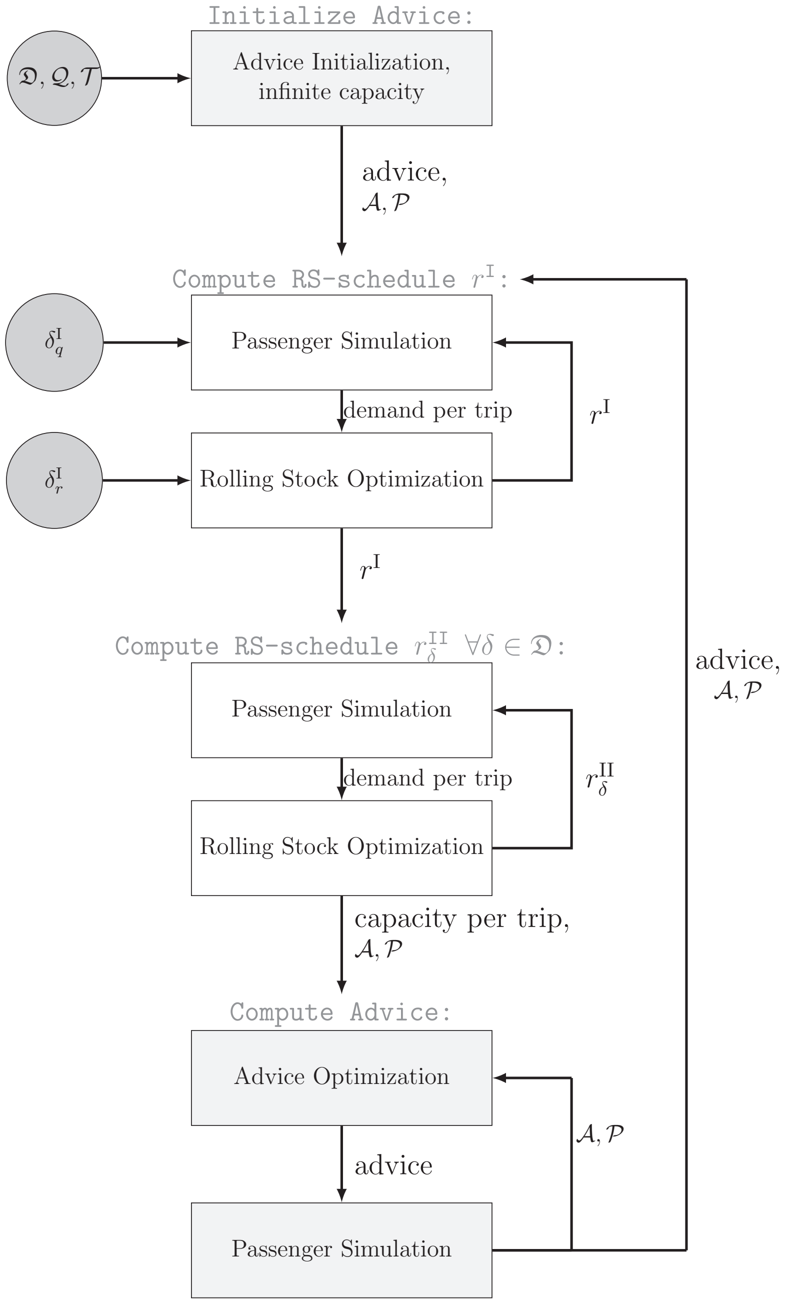

Figure 5.4: Solution Approach

not improve it. A different choice of δ^{I}_r or δ^{I}_q would also not result in a better solution. Indeed, the values δ^{I}_q and δ^{I}_r are only relevant in case of capacity shortages.

When capacity shortages do arise, advice optimization is invoked to warn passengers about these shortages, thereby reducing their delay. After that, the rolling stock schedule is adjusted to accommodate the changes in passenger flows due to the advice. Iterations continue until no further improvements are found, or until a maximum number of iterations is reached.

The following sections discuss the passenger simulation (Section 5.5), advice optimization (Section 5.6), and rolling stock rescheduling (Section 5.7) in detail.

5.5 Passenger Simulation

The threefold goal of the simulation module is to (*i*) evaluate a solution under realistic assumptions on passenger behavior, (*ii*) serve as a tool for generating columns for the advice optimization, and (*iii*) provide input for the rolling stock rescheduling. The solution quality is calculated by summing the inconvenience of all passengers in all scenarios, weighted by the probability of a scenario. A single passenger's inconvenience is defined by a weighted sum of the difference in waiting time, in-vehicle time, and transfers between the realized path calculated in the simulation and in the planned path in the undisrupted situation.

Input for the simulation consists of advice (providing recommended path to all passengers), a rolling stock circulation (specifying the capacity per trip), and the communicated length δ^{I}_q. In essence, the simulation computes the realized paths of passengers in a specific scenario δ. By collecting additional information on the fly, the simulation provides the following data for a specific scenario $\delta \in \mathfrak{D}$:

- Solution quality of the advice and rolling stock schedule (derived from the path decomposition).
- Input for Rolling Stock rescheduling:
  - demand per trip (defined as the total flow on a trip arc).
- Input for Advice optimization:
  - additional candidate paths for passenger groups $q \in \mathcal{Q}$;
  - realized paths for the recommended path to passenger group $q \in \mathcal{Q}$.

Section 5.5.1 describes the general outline of the simulation model, and passenger behavior is defined in Section 5.5.2. The concept of advice and the role of the simulation in the advice optimization are discussed in Section 5.6

5.5.1 Simulation Outline

The passenger simulation model is a discrete event simulation with three phases as shown in Figure 5.5. In Phase 0, before the start of the disruption, passengers travel along their planned paths, which may be derived and forecast based on smart card data, as shown in Van der Hurk et al. (2015b) and Van der Hurk et al. (2013). Phase I starts at τ_{start} when the disruption occurs. At τ_{start} the operator provides advice, which contains a recommended path per passenger group, and adjusts the rolling stock circulation given the disruption. Phase II starts at τ_{com}, in this chapter assumed equal to τ_{min}, when the actual length δ^* of the disruption is assumed known and the passengers update their route, and the operator updates the rolling stock schedule. The adjustment of passenger routes is calculated within the simulation, while the update of the rolling stock schedule is calculated outside the simulation using a rolling horizon approach discussed in Section 5.7. Phase II lasts until the end of the planning horizon.

The outcome of the simulation is deterministically defined by the input of the passenger groups, the advice, the rolling stock schedules (for Phases 0, I, and II), the start of the disruption τ_{start}, the announcement time of the actual length τ_{com}, the communicated length δ^{I}_q, and the actual length δ^*. Note that the latter three, together with the set of possible disruption scenarios $\mathfrak{D}$, influence the resulting inconvenience, but are outside the control of the operator and passenger.

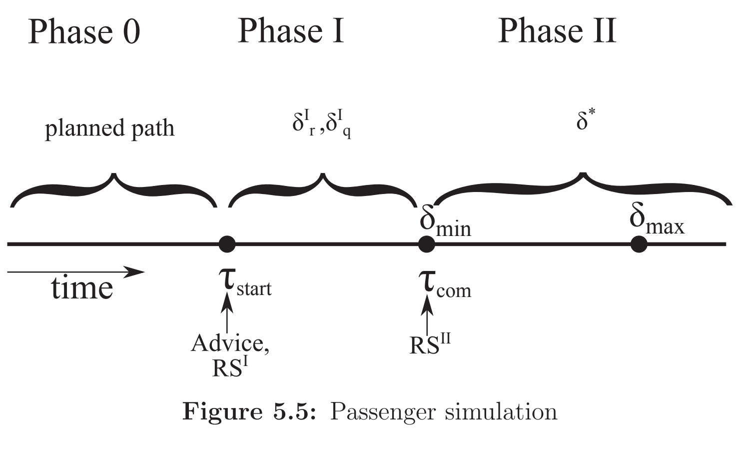

Figure 5.5: Passenger simulation

5.5.2 Passenger Behavior

Every passenger group is associated with three types of path. The *planned* path is the path passengers intend to travel on if there is no disruption, and is the base for measuring inconvenience. The *recommended* path is provided to passengers by the operator at the start of the disruption. Finally, the *realized* path is the path that represents the actual journey of a passengergroup. This realized path results from a complex interaction between previous components, and is therefore computed in the simulation. The simulation computes a single realized path per passenger. The realized paths determine the inconvenience of passengers, measured as the difference in the weighted sum of waiting time, in-vehicle time, and numbers of transfers between the realized and the planned path. Each passenger group has a single planned path, receives a single advice, but can have multiple realized paths, as will be discussed below.

At the start of the disruption, all passenger groups receive a recommended path which they may follow with a certain probability. Within the advice optimization model, we assume that all passengers follow the advice. However, afterwards we perform a sensitivity analysis in which the probability of following the advice is either fixed or depends on the available alternatives. Any passenger not following the recommended path aims to travel on a minimum inconvenience path in the current timetable graph, which is based on the communicated length δ_q^{I} between τ_{start} and τ_{min}, and on the actual duration δ^* after τ_{min}.

Passengers follow the path as long as there is sufficient capacity available. In case of insufficient capacity, the entering passengers compete with each other for the empty seats. All entering passengers then have an equal chance of boarding the train. Passengers losing this competition will replan their path to a minimum inconvenience path in the current timetable graph from their current location. That is, a passenger group is split into two groups if some of its members can enter the train while others cannot. This mechanism is identical to that of Kroon et al. (2014). For implementation reasons, we assume passengers leave the system immediately when the expected inconvenience exceeds a maximum tolerated inconvenience.

A simulation is run assuming a specific disruption scenario δ^*, and therefore the uncertainty about the length is modeled according to the 3 phases defined in Section 5.5.1. At the start, all passengers follow their planned path in the undisrupted timetable. At τ_{start} the disruption starts, passengers receive a recommended path and travel as described until at τ_{min} the actual length of the disruption is known. At τ_{min} all passengers may update their path to a minimum inconvenience path in the timetable graph of the actual length δ^* based on their location at τ_{min}. The inconvenience resulting from a specific recommendation and rolling stock schedule is thus evaluated for a specific scenario δ^* recognizing the initial uncertainty about the duration.

5.6 Passenger Guidance and Advice Optimization

This section presents the mixed integer linear programming formulation for advice optimization in the framework of Figure 5.4. The advice optimization model is solved to optimality for a given set of candidate paths and a given rolling stock schedule. The solution for the advice is evaluated through the passenger simulation for all disruption scenarios in $\mathfrak{D}$.

The advice optimization aims to model realistic passenger behavior by considering only a limited set of candidate paths. These paths are discussed in Section 5.6.1. Section 5.6.2 presents the mathematical optimization model which is solved to optimality within the framework. This model is solved using a column generation framework as described in Section 5.6.3.

5.6.1 Candidate Paths

A candidate path is a consecutive set of trips in the timetable. Out of all available candidates, the advice optimization selects a single recommended path per passenger group. The recommended path may be individual based on the origin, destination, and planned departure time of the passenger group. Passengers are not obliged to follow the advice, because we consider a system with free route choice. Therefore, to increase the chance of passengers accepting the advice, we restrict the set of candidate advice paths to paths of the following two classes.

- Minimum inconvenience paths given a disruption scenario δ.
- Low inconvenience paths because they avoid overcrowded sections in the network.

Minimum inconvenience paths are minimum cost paths in at least one of the timetable graphs defined by $\mathcal{T}^\delta, \delta \in \mathfrak{D}$. If capacities are infinite, all passengers can travel on minimum inconvenience paths. In case of capacity shortages, a path avoiding the overcrowded sections can lead to less inconvenience than a minimum inconvenience path in the timetable. Paths of this second type are also good candidates for a recommended path, we discuss them in detail in Section 5.6.3.

The operator's objective to minimize the overall inconvenience conflicts with the passengers' objective to find their personal minimum inconvenience path. Passengers may therefore not follow a recommendation that does not seem to be in their best interest. However, it is extremely difficult for a passenger to determine the best path, as this depends on the available capacity, the (unknown) length of the disruption, and the route choice of all other passengers. Consequently, optimizing advice ignoring passengers' reactions may lead to a worse outcome.

By limiting the advice to paths that are arguably attractive to passengers, it is more likely that passengers will follow the advice, and thereby it allows the operator to look for a feasible social optimum. Thus we expected that the calculated passenger inconvenience in the optimization model of Section 5.6.2 will be close to the actual passenger inconvenience as measured in the simulation.

5.6.2 Model for Advice Optimization

A solution to the advice optimization model defines a recommendation, which contains a single recommended path for each passenger group $q \in \mathcal{Q}$ such that the overall expected passenger delay is minimal over all scenarios. Per scenario capacity constraints are considered within the optimization. The underlying model resembles a capacitated multi-commodity flow model per disruption scenario $\delta \in \mathfrak{D}$ where the capacities are defined by the rolling stock schedule. The flow assignment and passenger inconvenience calculation are based on realized paths instead of recommended paths, to better reflect the actual inconvenience. The assignment to realized paths depends on the selected advice for passenger group q and the disruption scenario δ.

The advice optimization requires a set of disruption scenarios $\mathfrak{D}$, a set of passenger groups $\mathcal{Q}$, a candidate path set $\mathcal{A}$, a set of realized paths $\mathcal{P}$, and a rolling stock schedule r. The rolling stock schedule defines the capacity k^{δ}_{tr} of trip t in scenario δ. Note that the sets $\mathcal{P}$ and $\mathcal{A}$ can be extended whenever the simulation module is executed, as described in Section 5.6.3.

We use the following notation. Recall that w_q denotes the number of passengers in passenger group q. Let c_{qp} be the inconvenience of a single passenger of group q when traveling on realized path p. Let ϕ^{δ} be the probability that disruption scenario δ occurs, with $\sum_{\delta \in \mathfrak{D}} \phi^{\delta} = 1$. Furthermore, $\mathcal{A}_q$ denotes the set of all candidate paths for passenger group q, $\mathcal{P}^{\delta}_{qa}$ denotes the set all realized paths for candidate path a that are eligible for passenger group q in scenario δ, and $\mathcal{P}^{\delta}_{t}$ denotes the subset of all realized paths containing trip t in scenario δ.

Decision variables. The binary decision variable y_{qa} represents the decision to select one candidate path $a \in \mathcal{A}_q$ per passenger group q. Continuous decision variables x_{qp}

represent the numbers of passengers of passenger group q traveling along realized path p of the passenger assignment. Then the model is expressed as follows.

$$\min \sum_{\delta \in \mathfrak{D}} \phi^{\delta} \sum_{q \in \mathcal{Q}} \sum_{a \in \mathcal{A}_q} \sum_{p \in \mathcal{P}^{\delta}_{q,a}} c_{qp} x_{qp}$$

subject to:

$$\sum_{a \in \mathcal{A}_q} y_{qa} = 1 \qquad \forall q \in \mathcal{Q} \tag{5.1}$$

$$\sum_{a \in \mathcal{A}_q} \sum_{p \in \mathcal{P}^{\delta}_{qa}} x_{qp} = w_q \qquad \forall q \in \mathcal{Q}, \forall \delta \in \mathfrak{D} \tag{5.2}$$

$$\sum_{p \in \mathcal{P}^{\delta}_{qa}} x_{qp} \leq y_{qa} w_q \qquad \forall q \in \mathcal{Q}, \forall a \in \mathcal{A}_q, \forall \delta \in \mathfrak{D} \tag{5.3}$$

$$\sum_{q \in \mathcal{Q}} \sum_{p \in \mathcal{P}^{\delta}_{t}} x_{qp} \leq k^{\delta}_{tr} \qquad \forall t \in \mathcal{T}, \forall \delta \in \mathfrak{D} \tag{5.4}$$

$$x_{qp} \geq 0, y_{qa} \in \{0, 1\} \qquad \forall q \in \mathcal{Q}, \forall p \in \mathcal{P}_q, \forall a \in \mathcal{A}_q \tag{5.5}$$

Objective. The objective function minimizes the overall expected delay of the passengers. Straightforward extensions include minimizing worst case delay (using a min max formulation). The objective represents the operator's desire to minimize overall inconvenience - the passenger's interests are modeled by the limitation to recommended paths, the assignment based on realized paths, and the evaluation based on the simulation, as discussed in Section 5.5.

The objective function is calculated as the weighted sum of inconvenience over all scenarios, thereby acknowledging that inconvenience is dependent on the disruption scenario δ. For each scenario, the inconvenience is calculated based on the assignment of passengers to *realized* paths rather than *recommended* paths. The recommended paths are required to be the same independent of the scenario, as the scenario is unknown at τ_{start} when the advice is provided to passengers. The realized paths, which are scenario specific, capture the inconvenience resulting from following the advice, including the fact that passengers may change their route at $\tau_{\min}$, in a specific scenario. Moreover, they aim to reflect the paths that result from competition for space when there is insufficient capacity for passengers on the recommended route.

Constraints. Constraint (5.1) states that a single recommendation is made by the operator for each passenger group. Constraint (5.2) distributes the passengers among all possible realized paths in each scenario $\delta \in \mathfrak{D}$. Constraint (5.3) links the path assignment to the advice: the path assignment is limited to the set of realized paths belonging to the provided advice $\mathcal{P}_a^\delta$ for each scenario $\delta \in \mathfrak{D}$. Constraint (5.4) ensures that the path assignment does not exceed the available capacity per trip. The latter restriction could result in an infeasible solution when $\mathcal{P}$ is incomplete. To make sure that a feasible solution always exists, we extend the set of realized paths for each recommendation to include paths that do not use capacity. These additional paths do incur a delay; they model the journey of a passenger who is not able to board a train on the maximum inconvenience path, thereby forced to wait for the next one.

Advice Initialization. The advice initialization, at the start of the framework of Figure 5.4, is a special case. The assumption of infinite capacity translates the capacitated multi-commodity flow model into an uncapacitated one which is solved efficiently by independent shortest path computations per passenger group. The sets $\mathcal{A}$ and $\mathcal{P}$ are initialized by these shortest paths; this ensures that the true preferred paths of passengers are always valid travel options.

5.6.3 Column Generation Framework

Motivation. The advice optimization model uses a path based formulation, instead of an arc based formulation, for the multi-commodity flow component. An arc based assignment requires a polynomially bounded, yet large number of decision variables, namely one decision variable per arc per commodity, rendering the model slow or even intractable. The number of possible paths per commodity may be even larger than this, possibly even exponential. Still, dependent on the structure of the problem, the path based formulation may be solved much faster by including only a selection of all paths. Therefore, dependent on the structure of the problem, a path based formulation can be solved much faster than an arc based formulation.

An alternative advantage of the path based formulation, is that it allows us to model passenger behavior more realistically than an arc based formulation by using an alternative method to generate paths. Altruistic behavior can be limited or prevented, to some extent, by including only the candidate paths of the two classes defined in Section 5.6.1 and by basing the path assignment on realized paths. The inclusion of realized paths also allows modeling the uncertainty about the disruption length, and thus the dependency of the advice and the scenario in calculating the inconvenience. Therefore, the path based formulation allows us to model passenger behavior more realistically than an arc based formulation.

Our heuristic solution approach iterates between generating more paths and solving the mixed integer programming model described in Section 5.6.2. We use the simulation model to generate the candidate advice path set $\mathcal{A}$ and the realized path set $\mathcal{P}$, based on the current solution for the master problem, as they result from a complex interaction between passengers, the uncertain disruption length, and the rolling stock schedule. Thereby we prevent the generation of implausible paths, like paths where passengers disembark their direct train, thus contributing to modeling realistic passenger behavior.

Although the mixed integer programming problem is solved to optimality, there is no guarantee that the solution found by this procedure is the optimal solution because of the restricted set of paths, and because the generation of paths is done heuristically in the simulation. In most column generation applications, new columns arise from solving a pricing problem. Typically for flow models, this pricing problem corresponds to solving a minimum cost path problem in a graph where the costs of the arcs depend on the dual values of the current master problem solution. When no new paths are found, the current solution is optimal. For this specific application, such an approach would not allow to (easily) model passenger behavior constraints (like people not disembarking their direct train). Moreover, the standard column generation approach would concern the linear relaxation of the problem, which would require additional techniques to come to a valid integer solution for the optimization model (Section 5.6.2). Therefore we leave the exploration of a more traditional column generation approach for future research.

Method The set of candidate paths $\mathcal{A}$ and the set of possibly realized paths $\mathcal{P}$, containing a mapping from candidate paths to realized paths in a specific scenario, are generated in the simulation based on the current solution of the mixed integer programming model (Section 5.6.2) including the rolling stock rescheduling solution. For $\mathcal{P}$, each simulation run computes at least one realized path for passenger group q in the evaluated scenario δ^* and the recommended path for this passenger group at τ_{start}, according to the process described in Section 5.5. Thus the method iterates between generating new paths and solving the mixed integer programming model, until either no new paths are found in the simulation, or a maximum number of iterations has been reached.

The candidate path set $\mathcal{A}_q$ of a passenger group q is extended by paths that avoid overcrowded sections of the network for passengers that needs to compete for seats in the simulation. For those passengers, a search algorithm is called that finds alternative paths that would lead (in expectation) to less inconvenience than their current path, and avoids all so-far overcrowded trips in the timetable. Such paths can be found by a standard shortest path search in the timetable graph. Note that these alternative paths do not need to share any trips with the path realized (so-far) by the passengers currently competing for space. We apply the search algorithm only for passengers who lose the competition for space, thus the newly added path is available only for passengers who may directly profit from the detour.

The sets $\mathcal{A}$ and $\mathcal{P}$ can be initialized straightforwardly outside the simulation by assuming infinite available capacity through a set of shortest path computations following the three stages in the simulation to account for the uncertain disruption length. For any new paths added to $\mathcal{A}$ a mapping in $\mathcal{P}$ can be calculated similarly. The addition of these paths based on infinite capacity ensures that the true desired path of a passenger is part of the possible set of realized paths.

5.7 Rolling Stock Rescheduling

In this section we discuss the rolling stock rescheduling model. We use the rolling stock rescheduling model of Kroon et al. (2014) as a base model; it computes a rolling stock schedule for a disruption of known length. This base model is solved iteratively, jumping back and forth between passenger simulation and an integer programming model.

We embed the base model in a rolling horizon setting in order to deal with the uncertain length of the disruption. We note that the rolling horizon approach is generic in that it can be built around any deterministic base model for rolling stock rescheduling. Moreover, a completely different rolling stock optimization model could be used within our framework because the framework is fully modular.

5.7.1 Rolling Stock Rescheduling Model

When a disruption occurs, the current timetable and rolling stock schedule become infeasible and therefore need to be adjusted. The rescheduling is based on an adjusted timetable, the planned rolling stock circulation, and the expected number of passengers per trip. Within the context of this chapter, we assume the first two are available, and compute the number of expected passengers per trip based on the passenger simulation, including advice, as described in Section 5.5.

We have selected the rolling stock rescheduling model of Kroon et al. (2014) as the base model because it minimizes *both* passenger inconvenience and operational cost when calculating a new feasible circulation. Specifically, it allows minimizing passenger inconvenience based on a dynamic assignment that may be simulated or calculated outside the optimization model itself. Because of this modular approach, the model of Kroon et al. (2014) is very well suited for combination with the defined passenger behavior resulting from advice and the uncertainty about the duration of the disruption.

This chapter follows the approach of Kroon et al. (2014) for constructing a new rolling stock circulation. However, in Kroon et al. (2014) the disruption length is known at the start of the disruption, and the option of passenger guidance is not included. Therefore we make two important modification to the Kroon et al. (2014) model.

1. The number of passengers per trip is estimated based on the new simulation model of Section 5.5, that includes advice and uncertainty on the disruption duration

2. The model is embedded in a rolling horizon setting, to deal with the uncertain duration of the disruption.

As a result of the rolling horizon approach for rolling stock rescheduling, this process contains two phases as presented in the framework in Figure 5.4. In the first phase, we select an *estimated* duration δ_r^{I} for rolling stock rescheduling, as the actual length of the disruption is uncertain at time τ_{start}. Based on this estimate and on the expected demand per trip, we compute an initial rolling stock schedule r^{I} that is feasible in scenario δ_r^{I} from τ_{start} until the end of the planning horizon. The schedule r^{I} is obtained from the base rescheduling model. We report the sensitivity on the choice of δ_r^{I} in Section 5.8.

In the second phase, the rolling stock schedule is updated at time $\tau_{\min}$ when the actual length δ^* is revealed. We use the base model again, yielding the schedule $r_{\delta^*}^{\mathrm{II}}$. For rolling stock rescheduling only, one would need to compute $r_{\delta^*}^{\mathrm{II}}$ only at time τ_{start}. However, the advice optimization at time τ_{start} requires a rolling stock schedule r_{δ}^{II} for all possible scenarios $\delta \in \mathfrak{D}$ in order to calculate the expected inconvenience. That is, the rolling stock optimization module results in a single solution δ_r^{I} combined with $|\mathfrak{D}|$ solutions r_{δ}^{II}, as shown in Figure 5.6.

Similarly to Kroon et al. (2014), the iterations in the base model are terminated if a maximum number of rounds occur with no improvement , or if a maximum number of iterations has been reached. Kroon et al. (2014) find that solutions that are initialized based on passengers' preferred routes converge quickly. This is one of the reasons that our framework starts with initialization of demand.

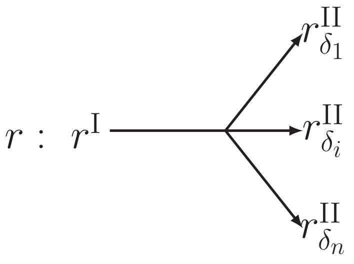

Figure 5.6: Schematic representation of rolling stock solution: a common part in Phase I is followed by a scenario-dependent part in Phase II.

5.8 Computational Results

Results are obtained for a realistic case study based on data of NS, the largest passenger rail operator in the Netherlands. We use the instances presented in Kroon et al. (2014), which are based on the Intercity network of NS, covering the heavily used core part of the Dutch network. It contains 14 Intercity stations and 2324 train trips. Over 10,000 passenger groups are included in the test instances, representing over 400,000 passengers.

5.8.1 Experimental Design

In the case study, we analyze the sensitivity to, and dependence on, the following four components:

- disruption location,
- uncertain disruption length,
- passenger behavior, and
- advice.

We analyze 5 different disruption cases corresponding to the cases described in Kroon et al. (2014), which, following their notation, are referred to by D1 to D5. These cases represent disruptions at different locations in the network depicted in Figure 5.7. The locations of the disruptions are as follows. D1 is between Rotterdam (Rtd) and The Hague (Gvx), D2 is between Gouda (Gd) and Utrecht (Ut), D3 is between Utrecht (Ut) and Amersfoort (Amf), D4 is between The Hague (Gvx) and Leiden (Ledn), and finally D5 is between Amsterdam (Asd) and Utrecht (Ut). Note that D2 and D5 provide the most opportunities for passengers to travel around the disruption, which explains why we will

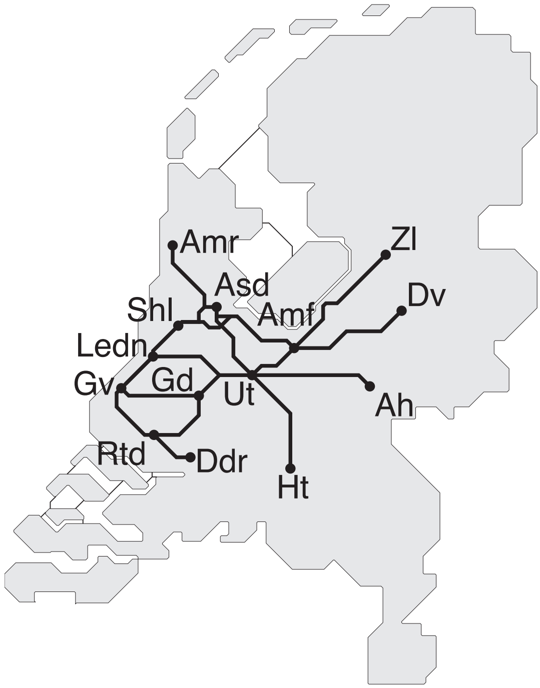

Figure 5.7: The network considered in the test instances, as included in Kroon et al. (2014).

find that our approach of providing advice is most effective in these cases. We consider disruptions during peak hours, as this is when capacity constraints become most stringent. Although the results presented here are based on the cases described in Kroon et al. (2014), they are not directly comparable due to the uncertain duration of the disruption added in this chapter, and a few different assumptions in our passenger simulation model. To study the uncertain duration of the disruption, three disruption scenarios are introduced for each case: Short, Medium, and Long, reflecting a disruption duration of 2, 2.5, and 3 hours respectively. The choice of three scenarios allows us to compare an optimistic estimate of the length at time τ_{start} for δ^{I}_r and δ^{I}_q with a pessimistic estimate or an average estimate, each having (approximately) equal weight.

Our proposed framework provides Optimized Personalized Advice (*OPA*) to passengers. This method minimizes expected inconvenience by providing a *recommended* recommended route for each passenger group, taking into account both the *uncertain* disruption duration and the *limited available seat capacity* per trip. To illustrate the value of this approach, we compare the *OPA* solutions to two different models: Uniform Advice (*UA*) and Simple Personalized Advice (*SPA*).

UA contains no advice optimization and therefore also does not include any capacity limitation when computing the advice. *UA* is a direct translation of the model of Kroon et al. (2014) to include an uncertain disruption duration. In both models passengers follow their personal minimum inconvenience path assuming infinite capacity. The only difference is that in Kroon et al. (2014) passengers compute their minimum inconvenience path knowing the exact duration of the disruption. Because the disruption duration is uncertain in our problem setting between time τ_{start} and τ_{min}, passengers in *UA* follow a minimum inconvenience path based on the communicated length δ_q^{I} in this time interval. They may update their paths once the actual disruption length becomes known at τ_{min}. Thus, given a fixed δ_r^{I} and δ_q^{I}, *UA* is a base case where advice is neither optimized for the uncertain duration nor for the limited available capacity.

SPA optimizes advice given the uncertainty in the duration of the disruption, but without the consideration of seat capacity constraints. It provides individual advice minimizing expected delay assuming infinite available capacity. Thus it reflects the true individual preference of passengers. *SPA* is the advice resulting from the advice initialization in the framework of Figure 5.4, which results from solving the advice optimization model of Section 5.6 assuming infinite capacity per trip.

Thus, the value of individual advice follows from the comparison of *UA* with *OPA* and *SPA*. The comparison of *SPA* and *OPA* allows an estimate of the benefit of taking capacity constraints into account in addition to the uncertain duration of the disruption.

Within the framework of *OPA* it is assumed that all passengers follow the advice. This is a plausible assumption given the restriction on the candidate paths aiming to make the advice in the passengers' best interest, as discussed in Section 5.6.1. Still it could be that in practice not all passengers follow this advice. Therefore we perform a sensitivity analysis evaluating the solutions under different assumptions on passenger behavior.

In total, 5 cases $\times$ 3 disruption scenarios $\times$ 3 advice optimization models (*UA*, *SPA*, *OPA*) $\times$ 3 settings for $\delta_r^{\text{I}} \times$ 3 settings for $\delta_q^{\text{I}} \times$ 6 behavioral settings = 2430 solution values are compared.

5.8.2 Solution Quality

We evaluate the solution quality based on the relative gap between the passenger inconvenience PI in the solution and a lower bound LB. This lower bound is calculated as the minimum passenger inconvenience given infinite capacity and perfect information about the disruption length. The PI and LB depend on the disruption scenario δ. The relative gap, minimized in the objective function, is calculated as $r = \frac{\sum_{\delta \in \mathfrak{D}}(PI_\delta - LB_\delta)}{\sum_{\delta \in \mathfrak{D}} LB_\delta}$, where PI_δ and LB_δ represent the passenger inconvenience and lower bound in scenario δ, respectively. Moreover we report the relative gap per scenario $r_\delta = \frac{PI_\delta - LB_\delta}{LB_\delta}$. The LB represents absolutely unavoidable inconvenience. However, because of uncertainty in the disruption duration and limited available capacity, it is likely that there does not exist a solution with a 0% relative gap. Note that the gap does *not* represent an optimality gap, but provides insight into the current quality of the solution, and an upper bound on the maximum potential for improvement of the solution.

Settings		Relative Gap (%)				Mean Delay (min)			Delayed Passengers (Nr)		
Case	Advice	Total	S	M	L	S	M	L	S	M	L
D1	*UA*	8.33	11.22	6.49	7.67	34.4	33.7	34.2	12942	14217	15342
D1	*SPA*	8.23	11.21	6.49	7.40	34.4	33.7	34.2	12945	14217	15325
D1	*OPA*	7.92	10.19	6.48	7.39	34.0	33.7	34.2	12949	14216	15324
D2	*UA*	35.83	45.16	32.26	31.54	53.8	53.4	54.4	26196	27214	28899
D2	*SPA*	33.63	36.03	31.33	33.78	51.9	52.4	54.9	25436	27534	29127
D2	*OPA*	14.31	14.57	13.45	14.91	48.4	50.0	52.0	22961	24936	26373
D3	*UA*	6.55	12.84	2.92	4.95	47.2	47.0	48.5	9223	9862	10831
D3	*SPA*	5.74	10.70	2.92	4.45	47.6	47.0	48.4	8976	9862	10792
D3	*OPA*	5.25	11.16	2.53	3.15	47.9	46.8	47.8	8954	9865	10795
D4	*UA*	8.86	14.16	6.36	6.88	41.9	42.3	43.3	17486	18358	19611
D4	*SPA*	8.58	13.53	6.36	6.63	42.1	42.3	43.2	17290	18358	19593
D4	*OPA*	6.13	10.44	3.89	4.71	42.0	42.3	43.3	16856	17967	19202
D5	*UA*	88.90	86.21	88.21	91.74	46.0	48.4	51.3	20496	22100	23117
D5	*SPA*	94.37	94.18	98.16	91.04	48.2	50.0	50.9	20397	22531	23191
D5	*OPA*	8.90	11.27	9.89	6.06	34.9	34.9	34.8	16128	17932	18854

Table 5.1: Summary of solution quality for *UA*, *SPA*, and *OPA*

Table 5.1 presents the relative overall gap, and relative gap per disruption duration scenario for all cases (D1 to D5), and for each advice optimization model (*UA*, *SPA* and *OPA*. The smaller the gap, the smaller the delay resulting from uncertainty and capacity constraints. A lower relative gap within a column per case indicates a better solution. Comparing relative gaps between cases and columns only indicates the difference in delay resulting from the uncertain duration and the limited available capacity. However, here a higher relative gap does not necessarily indicate a worse solution, as part of the delay due to capacity constraints and uncertainty may be unavoidable. Furthermore, Table 5.1 includes the average delay per affected passenger per scenario, and the total number of passengers affected by the disruption per scenario. A longer disruption duration doe snot necessarily lead to longer average delays, but does increase the number of affected passengers. Results are presented for the best settings of δ_q^{I} and δ_r^{I} per case and per advice optimization. The table thus allows comparison of the relative and absolute impact of the proposed method on passenger inconvenience.

The results in Table 5.1 show that *OPA* provides consistently better solutions than *SPA* and *UA*, and generally *SPA* performs slightly better than *UA*. Especially in case of large inconvenience, as in scenarios D2 and D5, *OPA* solution provides solutions with a much lower passenger inconvenience than *SPA* and *UA*. In case of D2, the *OPA* solution significantly reduces inconvenience, in comparison to both *SPA* and *UA*, while *SPA* is slightly better than *UA*. It reduces the average delay of *affected* passengers by up to 10%, and also reduces the *number* of affected passengers by around 10%.

In case of D5, the *OPA* solution reduces delay dramatically, while *SPA* is slightly worse than *UA*. It reduces the relative gap by a factor up to 10. The number of affected passengers is reduced by 20%, while average delay of affected passengers is reduced by up to 30%. An explanation of this dramatic difference is that the advice helps passengers to avoid traveling into a bottleneck where capacity shortages lead to large delays. Indeed, the number of passengers needing to compete for seats is much lower in the *OPA* solution than in the *SPA* and *UA* solutions.

In cases D1, D3 and D4 the advantage of using *OPA* is small, and the benefit of using *SPA* is even smaller. Improvements result from a small reduction in the average delay of affected passengers, and/or a reduction in the number of affected passengers by the disruption. Kroon et al. (2014) found that the delay reduction for these cases resulting from rolling stock rescheduling is small, and therefore it is likely that not much more improvement is possible, as the relative gaps are also fairly small. We can thus conclude that the benefit of the method is dependent on the location of the disruption. A more extensive case analysis would be required to conclude whether or not the methodology provides a benefit in the majority of disruptions an operator experiences.

The results in Table 5.1 are based on the best settings for δ_q^{I} and δ_r^{I} selected per case and per advice optimization model. These settings represent either an optimistic or pessimistic estimate of the length of the disruption. In analyzing these settings we find that the best choice for δ_q^{I} and δ_r^{I} depends both on the case and the optimization model. The performance of *UA* depends most on these settings, with a difference of up to 24 percent points in the relative gap. It generally performs best on medium estimates for both δ_q^{I} and δ_r^{I}, where the selection of δ_q^{I} influences the results the strongest. *SPA* varies the least over the selection of δ_q^{I} and δ_r^{I}. For most settings, therefore, *SPA* outperforms *UA* by a much larger margin than based on the best settings, as presented in Table 5.1. In contrast to *UA*, the performance depends most strongly on the selection of δ_r^{I} rather

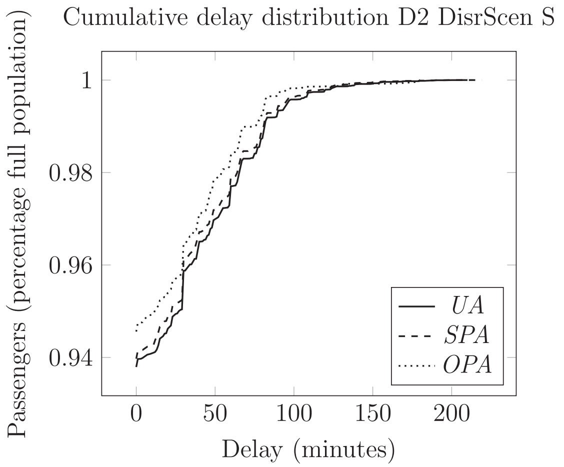

Figure 5.8: Cumulative Delay distribution for Case D2, scenario S

than δ_q^{I}. However, there is no dominant setting for δ_r^{I} over all cases. Finally the sensitivity of the *OPA* solution is in between those of *UA* and *SPA*. The *OPA* solutions also depend strongly on δ_r^{I}, and are generally *not* best for a medium selection for δ_q^{I} and δ_r^{I}. There is however no dominant strategy, e.g. to be pessimistic or optimistic, in the selection of δ_q^{I} and δ_r^{I}. Therefore, currently the best performance is obtained by analyzing all values for δ_q^{I} and δ_r^{I}.

That *OPA* solutions perform better by reducing the number of affected passengers, the average delay per passenger, and the worst case delay, can also by deduced from the cumulative delay distribution represented in Figure 5.8. This graph represents the cumulative delay distribution of solutions *UA*, *SPA* and *OPA* for the short scenario and case D2, with the horizontal axis reflecting the delay per passenger, and the vertical axis the percentage of passengers that have experienced at least this amount of delay. Results for other cases and scenarios are similar. The *OPA* solution has a higher percentage of passengers with zero minutes delay, and the left-shift in comparison to *UA* and *SPA* shows that it also has fewer passengers with long delays.

5.8.3 Behavioral Sensitivity Analysis

As passengers are not obliged to follow the advice, we further evaluate the *OPA* solutions in the simulation under two different behavioral assumptions:

- a *fixed* probability of passengers following the advice

- a probability dependent on the quality of the alternative path relative to the recommended path

Passengers not following the advice compute the minimum inconvenience path based on the expected length δ^{I}_q. Each passenger group q is split into two groups according to the probability of following the advice. The new path, computed by passengers not following the advice, could still be the recommended path.

For the fixed probability, we evaluate the percentage of passengers following the advice in the range of $\{0\%, 20\%, 40\%, 80\%, 95\%, 100\%\}$. For the probability dependent on the quality of the alternative path, we use a logit model. The probability of choosing path p_i, $i \in \{1, 2\}$, is defined as:

$$P(p_i) = \frac{e^{\theta c_{p_i}}}{e^{\theta c_{p_1}} + e^{\theta c_{p_2}}} \qquad \forall i \in \{1, 2\}$$

Here c_{p_i} is the weighted travel time of the path, and θ is a externally defined parameter. For our experiments, we have selected θ such that when two paths differ by 10 minutes, 95% of passengers select the shortest path, and 5% choose the longer path.

Table 5.2 presents the total relative gap per behavioral model over all disruption scenarios for a single case: D1. Each column contains results for a single behavioral model. The rows represent different settings for δ^{I}_q and δ^{I}_r. All settings of δ^{I}_q and δ^{I}_r are included in the table because the *best* setting depends on the expected behavioral model of passengers.

Comparing the logit model with the *OPA* solution (100% of passengers following the advice), we find that the difference between the two solutions depends strongly on the selection of δ^{I}_q and δ^{I}_r. Specifically, for the selection of δ^{I}_q as long, the difference is small – while if δ^{I}_q is short, the difference is large. So large even that the solution is worse than the *best* (not necessarily the same) setting solution of either *UA* or *SPA* for this case, as provided in Table 5.1. Moreover, the best setting for *OPA* with 100% of passengers following the advice does not necessarily have to be the best setting for the model with the logit behavior. The small difference between the two behavioral models if δ^{I}_q is long can be intuitively understood from the fact that in this case the alternative path is less attractive than in case δ^{I}_q is short – and therefore when δ^{I}_q is long more passengers are willing to follow the advice, thus leading to a better solution. This small difference between the logit model and all passengers following the advice also shows that indeed our solution approach is capable of recommending paths to passengers that are attractive to them, and reduce their delay in comparison to an non-optimized approach.

Settings		Passengers following the advice							
δ_q^{I}	δ_r^{I}	Logit	100%	95%	80%	60%	40%	20%	0%
S	S	14.24	8.51	8.69	9.35	10.44	11.75	13.59	15.42
S	M	13.97	7.92	8.02	8.72	9.95	11.35	13.37	15.30
S	L	12.86	8.09	8.11	8.54	9.50	10.69	12.32	13.94
M	S	8.59	8.51	8.52	8.54	8.57	8.60	8.63	8.67
M	M	8.00	7.92	7.93	7.99	8.08	8.16	8.25	8.35
M	L	8.18	8.09	8.10	8.13	8.18	8.24	8.29	8.35
L	S	8.52	8.51	8.55	8.67	8.82	8.98	9.13	9.29
L	M	7.93	7.92	7.97	8.13	8.35	8.57	8.79	9.01
L	L	8.10	8.09	8.13	8.27	8.45	8.64	8.82	9.01

Table 5.2: Summary of solution quality for different behavioral settings case D1.

When assuming a fixed rate of passengers following the advice, we see that the solution quality slowly decays when fewer passengers follow the advice. Thus, for *OPA* to provide better solutions, not all passengers need to follow, or even receive, an advice - although the solution performs better when everyone does. As before, the choice of δ_q^{I} is important for the solution quality, where a long δ_q^{I} leads to better solutions than a small δ_q^{I} in case of D1. This is generally true for all cases except for D2, where the selection of δ_r^{I} is more important. In some cases the *OPA* solution when no passengers follow the advice is even better than *UA* and *SPA*. It may be that the alternative passenger flows, estimated based on passengers following the advice, allows the rolling stock rescheduling model to find better or more robust solutions. We leave this investigation for future research.

Results for other cases are similar to those of D1. Although differences between different behavioral models for D2 and D5 are slightly larger than for D1, the *OPA* solution still outperforms the *UA* and *SPA* solutions given probabilistic route choice when a significant number of passengers follows the advice. An important observation is that the best setting for δ_q^{I} and δ_r^{I} depends on the behavioral model. For example, the best settings for the probabilistic logit model differ from the best settings for full compliance to the advice. Hence when selecting the best solution for implementation, it is important to consider the expected passenger behavior.

5.8.4 Convergence and Computation Time

In this section we discuss convergence and computational speed. All computational experiments were run using CPLEX version 12.6 on an Intel I7 3.07GHz processor. The algorithm is implemented in Java.

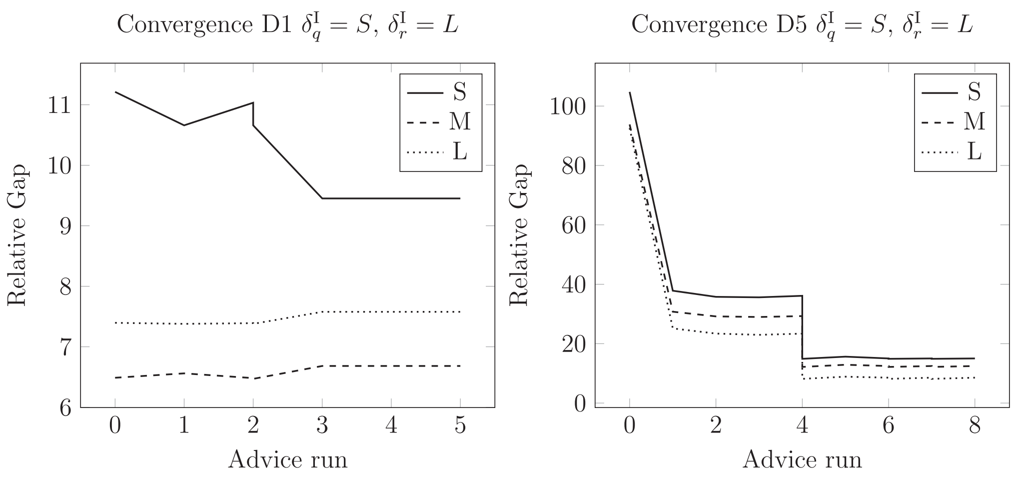

Figure 5.9: Convergence over advice optimization loops

Convergence. *OPA* solutions are computed by iterating between advice optimization and simulation in the inner advice optimization loop, and advice optimization and rolling stock rescheduling in the outer optimization loop. To analyze convergence we allowed for a maximum of 4 iterations for each of these loops. The process stopped when either no improvements were found, or the maximum number of iterations was reached. Figure 5.9 presents the convergence over the advice optimization loops in the *full* solution process on the horizontal axis, and the relative gap of the solution for the scenarios S, M, and L. Thus, a maximum of 16 runs could be included on the horizontal axis. A straight vertical drop or increase represents a change in the solution value due to the call to the rolling stock rescheduling component. Our solution approach is heuristic. Therefore, the best solution of the advice optimization is reported to the outer loop, which does not necessarily result from the last run.

We note that for the majority of the solutions, the advice optimization finds the best solution in the first, or second, iteration of the internal loop, and the first or second iteration of the outer loop. Re-scheduling the rolling stock after the advice optimization module often leads to the best solution. Both the advice optimization and the rolling stock module therefore contribute to the improvement of the quality of *OPA* solutions.

Figure 5.9 shows two typical convergence patterns. In the case of D1, only small improvements are found for the short scenario, while the medium and long scenarios are relatively stable. As the initial solution is already relatively good, we do not expect that large improvements are possible. Thus this result is expected. In case of D5 there is a large gain from the advice optimization. The advice optimization call causes quite dramatic inconvenience decreases for all scenarios. In the outer loop, adjustment of the rolling stock schedule contributes to an improvement in the solution (in the graph at advice optimization run 4) after which the solution stabilizes. This thus indicates that, specifically in case large delays result from the combination of uncertainty about the disruption length and the limited available capacity, our framework can improve the solution quality, – and that this improvement is obtained through the combination of advice optimization and rolling stock rescheduling.

Computation time. Individual components of the framework are fast. Specifically, the simulation runs average 6 seconds, with a range of 2 to 23 seconds. The advise optimization model takes on average 46 seconds, with a range of 23 to 74 seconds. The full advice optimization loop, including simulation, runs on average in 3 minutes, and varies between 1 and 8.5 minutes. The rolling stock rescheduling runs on average in 2 minutes, with a range of 1.5 to 4 minutes.

The *OPA* solutions are on average computed in 20 minutes given the current setting for the maximum number of iterations. However, for three out of four cases a solution is found in less than 16 minutes. In one case, and one setting for the δ^{I}'s, however, computation time was 54 minutes.

The long computation time is generally a result of the number of iterations, which, given our convergence analysis, could be reduced as good solutions are found early. Therefore, in case of time constraints, one could limit the number of iterations or computation time, and still find good, and very likely the same, solutions. Indeed, the worst case computation time was reduced from 54 minutes to around 20 minutes by bringing back the number of iterations, while the solution stayed within one percent of the previously found solution. For the other cases computation time was significantly shorter, and a fairly standard computer was used. Moreover, further computational speed up can be obtained from more efficient implementation than implemented by the authors for evaluation of the method, e.g. using a parallel implementation of (some parts of) the algorithm. Therefore we believe the presented framework, with some further focus on efficient implementation and better stopping criteria, could and model to be sufficiently fast to be considered for implementation in practice.

5.9 Conclusion and Discussion

This chapter proposes a novel optimization based framework for providing individual route advice to passengers, in combination with rolling stock rescheduling, for major disruptions with an uncertain duration. The presented modular framework iteratively solves the advice optimization and the rolling stock rescheduling model. Solutions are evaluated under realistic passenger behavior assumptions in a simulation model. A computational study based on realistic cases of Netherlands Railways shows that providing individual travel advice that takes into account both the uncertainty in the disruption duration and the limited available capacity can strongly reduce passenger inconvenience in terms of average delay, worst case delay, and number of affected passengers, and that the solution framework is fast enough for implementation in practice.

A key aspect of the proposed method is that it finds good quality solutions under realistic passenger behavior assumptions in a system with free route choice. To prevent the advice optimization from finding unrealistic socially optimal solutions, it is solved in a column generation framework where the simulation generates new candidate paths according to certain behavioral restrictions. The sensitivity analysis shows that, indeed, our model is successful in finding good quality solutions with attractive paths for passengers under different behavioral assumptions. That our method manages to find attractive paths for passengers in the advice optimization, is demonstrated by the small difference in passenger inconvenience between all passengers following the advice, and passengers accepting the advice probabilistically, given careful consideration to the communicated expected disruption length to passengers.

Our results suggest that the advice optimization finds solutions with lower passenger inconvenience than solutions without advice optimization, even when the majority of passengers do not follow the advice. Thus, it improves the rolling stock solution. This may be a result of a different input in the rolling stock model, as the expected demand per trip when assuming that passengers follow the advice may be different from a situation where no passengers follow the advice. These flows that anticipate shortages of capacity and a longer (or shorter) disruption duration increase the robustness of the rolling stock rescheduling, and therefore the quality of the solution itself. Moreover, it may steer rolling stock to provide additional capacity on alternative routes that would otherwise not have been found. Future research could look into quantifying the cause of these differences, and possibly improving the rolling stock rescheduling model itself.

The model assumes that all passengers can receive individual advice at the start of the disruption. However, in practice, passengers will have to either actively ask for this advice, or have signed up for some service before the operator may be able to recommend a path. Note however that at the start of the disruption, passengers need to adapt their route. Therefore, it is plausible that they will actively ask for advice, e.g. by using an app on their smart phone. The behavioral study also showed that when only a fraction of the passengers follows (and therefore received) the advice, the solution quality is good. There are however alternative ways in which an operator could actively contact passengers, e.g. through the usage of broadcasting systems in trains and at stations. However, such systems would not allow for as much personalization. Future research could focus on how to provide advice to passengers when opportunities for personalization are limited, and the cost of less available personalization in terms of passenger inconvenience.

The rolling stock is rescheduled according to a rolling horizon approach. The initially estimated length of the disruption has the strongest influence on the solution quality, apart from the behavioral model. This suggests that possibly robust rolling stock rescheduling could further improve the quality of the full framework. Future research could focus on including a *robust* optimization model for rolling stock rescheduling.

The proposed solution approach assumes that all possible disruption scenarios are known and that also the probability distribution over these scenarios is known. In practice however often little is known about the possible set of disruption scenarios. Moreover, even if this information is available, one could question whether in practice the expected minimum inconvenience is the best measurement for passenger inconvenience. This measure implies that a route with a long travel time in one scenario can be less bad if it has a shorter travel time in another scenario. In practice, passengers' preferences may be more binary: if the destination is not reached before a certain time limit, the journey may have lost its purpose. Future research may look into how these types of constraints could be taken into account, either in the pricing of the paths, or by for example taking a quasi-robust optimization approach such as for instance proposed for crew rescheduling in Veelenturf et al. (2015). Such a quasi-robust approach focuses on finding (almost) always feasible solutions, and therefore does not require a probability distribution over the possible scenarios. So far we performed a sensitivity analysis of the solution under different behavioral assumptions. One could however experiment with including this behavior within the optimization framework, with possible new ways to update the column set for the advice optimization. This updating could possibly consist not only of the extension of this set, but also of the reduction of this set based on the alternatives found. Furthermore, one could also study the personalization of the communicated length to passengers, as well.

We found that the relative gap between the presented lower bound and the passenger inconvenience of the solution is small. However, it is unknown what the exact optimality gap is. Future research could focus on calculating better lower bounds that take into account the uncertain length of the disruption and realistic assumptions on passenger behavior.

Chapter 6

Summary and Conclusions

This thesis studies if, and to what extent, public transport operators can improve passenger service during disruptions by using new sources of detailed information on passenger journeys, given the limited flexibility in the logistic operations, and the limited influence on passenger's route choice. Automated fare collection systems generate large amounts of detailed data on individual passenger journeys that was never available on this scale before. Moreover, the wide adoption of smart phones and the availability of wireless communication provide new opportunities for direct communication between the operator and passengers. This thesis shows that the availability of this information can have a substantial positive impact on passenger service in case of disruptions.

Operators can anticipate passenger demand using the new data. Moreover, the operator can substantially influence passengers route choice through providing route advice and through the adjustment of the logistics plan. This influence is however constrained by the limited flexibility of the logistic schedule: for example, an additional vehicle must be moved to the location in need of more capacity before it can be used.

Additionally, the operator's influence is limited by the free route choice of passengers: passengers are free to choose, within certain limits, their own route, which may differ from the advice. The operators objective to reduce total passenger inconvenience may not align with passengers' desires to minimize their own inconvenience, specifically in case of limited capacity. For example, overall passenger delay might be less if some passengers disembark from their direct train in favor of others, but such altruistic behaviour is not realistic. Still, in many cases it might be difficult for passengers to know which route is in their best interest, as the available capacity on a route depends on the number of other passengers that also select this route, and all passengers need to select their paths almost simultaneously. Therefore route advice that aims to anticipate other passengers' route choices can help passengers to reduce their delay.

In this thesis data analysis to derive (Chapter 2) and anticipate (Chapter 3) passenger route choice is combined with the development of new quantitative models to help operators improve passenger service using this new information. The novelty of these models is that they use detailed data on passenger demand to anticipate passengers' reactions to new capacity allocations, and aim to influence this demand, specifically the route choice, through capacity rescheduling (Chapter 4) and individual travel advice for passengers (Chapter 5).

The following sections provide an summary of the main findings of the thesis by chapter, discuss scientific and managerial relevance, and provide suggestions for future research.

6.1 Main Findings

Chapter 2 proposes a method for passenger route choice deduction from smart card data. Smart card data from an automated fare collection system only registers the origin station, destination station, and travel time of a journey. However, it does not record the route the passenger traveled. Knowledge about route choice is important for evaluation of service, both for evaluating service retrospectively and for developing passenger route choice models that are used to evaluate alternative schedules. We therefore propose a method that deduces the passenger's chosen route by linking data on passenger journeys with data on the realized timetable. We use a data set of conductor checks to validate this method. We compare several methods for generating candidate passenger routes, and various models for selecting a route. We find that our method is able to select the correct route for about 90% of the journeys in our sample of journeys of Netherlands Railways.

A framework for forecasting passenger flows is proposed in Chapter 3. The framework is specifically intended to support an operator during a disruption by obtaining insight into where and how passengers are affected by a specific disruption. The three-step framework proposes to (1) derive route choice from smart card data to determine the number of passengers per path for previous dates; (2) forecast the number of passengers per planned path, based on the data derived in (1), and (3) use a simulation model to calculate how the flows change due to the disruption under realistic passenger behavior. The full framework provides forecasts of the number of passengers per train. Additionally, a preprocessing step is proposed that may provide insight into when and where passengers are affected by the disruption and, for example, need route recommendation. Moreover it may help to reduce computation time of future applications of the model. A computational experiment was conducted on a 10-month smart card data sample from the introduction period of the smart card at Netherlands Railways. As a result, data quality was not yet sufficient to derive definitive conclusions. Results based on this data are however indicative that accurate forecasts on passenger demand can be derived from smart card data.

Chapter 4 concerns the planning of shuttle services during a planned link closure in an urban public transport network. Link closures occur due to, for example, planned maintenance. When closures cause a part of the network to become disconnected, standard practice is to use a shuttle to replace the closed link and thereby restore connectivity. However, such shuttles have a lower speed and may require additional transfers. Therefore better passenger service may be obtained when considering other possible shuttle locations in the network to accommodate passenger demand as defined by the origin-destination flows, rather than using them to accommodate the link-demand. Within this research a new mixed integer programming formulation is proposed for the shuttle planning problem that includes a dynamic passenger assignment model. The model takes into account inconvenience resulting from transfers, and aims to reflect passengers' free route choice. Solutions define both the location and frequency for the selected shuttles minimizing passenger inconvenience under budget constraint. Computational experiments for a real life case study of a link closure at the Massachusetts Bay Authority Transportation show that the model provides solutions with much lower passenger inconvenience at the same or lower operational costs as the standard practice solution. The solution quality is stable under different passenger behavior assumptions. Moreover, our results show that, thanks to a new formulation and the preprocessing step proposed in this chapter, solutions can be generated quickly enough to consider the model for use in real time applications.

In Chapter 5 we evaluate the benefit of providing individual travel advice to passengers, supported by rolling stock rescheduling, in case of large disruptions with uncertain durations. We consider a public transport system with free route choice, where the operator can guide passengers through route recommendations. Passengers need to decide whether to wait to the end of the disruption, or to reroute. Moreover, passengers may want to avoid overcrowded trains as they incur more delay when they are unable to board a train in case of a capacity shortage. The route advice provided by the operator is meant to help passengers anticipate the impact of different disruption durations, and helps them to avoid capacity bottlenecks in the network. Although the objective of the model is to minimize overall passenger inconvenience, our proposed model aims to recommend paths that are in the passengers' best interest. In practice passengers do not need to follow the recommendations. Therefore the solution quality is evaluated under the assumption that not all passengers follow the advice. An agent based simulation model is used to evaluate the solution in terms of passenger service as it results from interaction between passengers and the logistic system, and the influence of the uncertainty about the disruption duration. Computational experiments for realistic cases of Netherlands Railways suggest that the provision of advice can significantly reduce passenger inconvenience resulting from a disruption, even when not all passengers follow the advice. Even more, sometimes the overall passenger service is better when not all passengers follow the advice. In all of our experiments, it was better to provide individual advice rather than providing the same type of advice for all passengers. Moreover, the results suggest that, with future research focused on a computational efficient implementation of the algorithm, the model might be solved fast enough to be considered for implementation in practice.

6.2 Scientific Relevance

The objective of this thesis is to find how information now typically available on passenger journeys can help public transport operators improve passenger service during disruptions, given the limited flexibility in the logistic operations, and the limited influence on passenger's route choice. In this research we intended to combine knowledge from the field of Operations Research and complexity theory to answer this question. A three-step framework is proposed to answer this question. First of all, past passenger behavior is analyzed using the new data. Secondly,the question of whether future passenger flows can be forecasted based on this data is investigated . Finally, the question of how this information can be used in new models for disruption management aimed at supporting operators in improving passenger service during disruptions is studied .

It was indeed found that data on passenger journeys, where only the origin, destination, and travel time are registered, does provides sufficient information to deduce the route choice of passengers retrospectively. Therefore this data can be used to obtain insight into passenger behavior and the experienced service quality. Moreover, results based on an early sample of smart card data suggest that forecasts can be derived from this data, allowing the information on passenger demand to be used in applications for planned or real time disruption management. The two applications in this thesis showed that indeed passenger service could be improved by using detailed information about passenger demand and by providing individual route recommendations to passengers.

The aim was to combine the fields of complexity and Operations Research to answer this research question. It is difficult to say whether the research in this thesis would have used different methods if there was no initial intention to combine these two fields of complexity and Operations Research in the disruption management application. The modeling of the central concepts of free route choice and emerging service levels through an agent based model fits with approaches in the field of complexity, that also often use agent based models. However, the use of simulation is not new in Operations Research. For example Chapter 5 extends previous research that used simulation to solve the rolling stock rescheduling problem.

However, when considering complexity as a field that first of all brings a perspective through which a problem is studied, rather than a set of field specific tools, one could argue that indeed our research is a result of the combination of the fields of complexity and Operations Research. A central topic in this thesis is the evaluation of passenger service as it emerges from the interaction between the passengers and the capacity available in the network. This interaction is complex due to the free route choice of passengers in a system with limited capacity, in which a passengers' experienced service may be positively or negatively influenced by the route choices of other passengers. The strong emphasis on this passenger behavior is new in comparison to previous research in disruption management. To our best knowledge, Chapter 5 is the first to investigate the benefit of individual travel advice in case of disruptions *and* to propose a model that supports the operator in what advice to provide. Chapter 4 also aims at modeling free route choice of passengers and includes a sensitivity analysis to different assumptions on passenger behavior.

The research has therefore made contributions to both fields. For the field of complexity, the research shows that Operations Research techniques are valuable tools to understand how to influence systems with emerging behavior in order to obtain better solutions. This is an important addition to the field that so far rarely uses these techniques and has mostly focused on descriptive models rather than decision support models. This research thus forms an important contrast with the many descriptive models so far studied within the field of complexity that may increase understanding, but do not provide concrete solutions to practitioners.

For the field of Operations Research, this research has shown that practically relevant solutions for complex problems can be derived quickly by combining mathematical programming formulations with simulation models for both the solution and evaluation of these models. Although the general concept is not new, our research illustrates the practical relevance for a different application. Moreover, the use of the simulation to model behavioral constraints in a column generation framework is to our best knowledge new, at least in the field of disruption management. For this application our approach shows that measuring passenger inconvenience under realistic passenger behavior indeed leads to better solutions for passengers than previous models for this application.

6.3 Managerial Relevance

This thesis shows that accurate data on passenger movements benefits passengers, as it enables operators to improve passenger service in case of disruptions. Better passenger service can be reached within the same operating constraints because these data help the operator to better match the provided service to the demand and desires of the passengers.

First if all, this thesis shows that smart card data provides deep insight into passengers' travel behavior. By linking different data sets, the actual route choice of passengers can be deduced in hindsight (Chapter 2). These data therefore enable retrospective analysis of the passengers' experience of service. Chapter 3 proposes a model for forecasting passenger demand based on smart card data, such that detailed information on passenger demand can also be used in real-time applications. Results of computational tests on a limited set of smart card data, derived from the introduction phase, are indicative that accurate forecasts on passenger demand are likely to be derived from these data. Reliable estimates of the expected number of passengers per train enable an operator to better match the available capacity and the demand, thereby increasing the efficiency of the capacity allocation. Data on passenger route choice allows one to define and calculate performance measures based on the service experienced by passengers, rather than to derive these from, for example, the punctuality of the operated vehicles. Combining smart card data with other data sources, such as information on the number of passengers per train, or the number of passengers embarking and disembarking a train at a station, could further improve the information available on past passenger behavior, and thereby also improve the forecasts derived for future passenger flows from these data. Moreover, the increase in speed in which smart card data becomes available to the operator might enable new real-time forecasting models to provide even better estimates of passenger demand.

Secondly, the provided passenger service during disruptions can be improved by adjusting the operations to expected passenger demand, rather than to the previous schedule. In case of link closures in public transport networks, it has been shown that employing shuttle buses to accommodate expected passenger demand, rather than simply to restore the original network structure, improves passenger service without increasing operational costs. Computational results for a real-life case study, presented in Chapter 4, show that using new available data on passenger journeys to adjust the network to the anticipated demand can reduce both average and worst case passenger delays.

Finally, it is demonstrated that passenger service can be improved by providing individual route recommendations to passengers in case of a disruption. Specifically in cases when insufficient capacity is available, such advice may reduce passengers' delays as indicated by the computational experiments for realistic test cases for Netherlands Railways in Chapter 5. It may also help passengers to make decisions in case the disruption duration is uncertain. The results show that combining individual travel advice with rolling stock rescheduling can reduce worst case delay, average delay, and the number of passengers affected by a disruption.

In summary, the research of this thesis has shown that especially passengers benefit from a better knowledge of their desires and behavior, which can be obtained from smart card data. Better passenger service can be obtained, within the same operating constraints, when this information on passenger demand is taking into account in the planning, management and operations of the public transport system.

A first step towards practical application would be to validate these results in practice. For this validation, the proposed method of Chapter 2 could be used to evaluate passenger service in hindsight using smart card data, if such data is available. Alternatively, more extensive simulation models could be used to evaluate the practical value of the results, which also take into account other parts of the disruption management process, such as the adjustment of the timetable and the rescheduling of crew duties.

6.4 Future Research

We believe there are many promising directions for future research. In addition to the suggestions made in each chapter, we list three general areas for extension here.

Behavior

Originally, we planned to deduce passengers' reactions to a disruption from the passenger journey data: do they wait, reroute, or not travel? Indeed Chapter 2 made a start on this by proposing a method for route deduction from smart card data. Results allow analysis of passengers' route choice, and therefore also their experienced service, retrospectively.

However, to be able to deduce actual passengers' reactions to a disruption in terms of waiting, rerouting, or not traveling, more research and possibly more data are needed. Deducing a route in hindsight (Chapter 2) does not explain why a passenger chose this route. For example, a longer waiting time at the departure station could indicate both a delay or a deliberate choice of a passenger to engage in a different activity, such as getting a cup of coffee. Even the existing paths in the timetable are not an error free measure of the delay of passengers, as in case of disruptions passengers may not have had sufficient information to choose the shortest path. For regular travelers, a change in behavior could be an indication of the reaction to a disruption. This however requires forecasting models that can predict individual passengers' journeys.

There are three reasons for not studying this behavior further within this thesis. First of all, at the time this research was started, data was incomplete and insufficient for analysis at this level of detail since the smart card system was still in the introduction phase. However, now this data is of much better quality and may be sufficient to continue this line of research. Secondly, analyzing this data in such detail, specifically the development of models that forecast individual passenger behavior, should always be done taking great care to protect the privacy of passengers. Whether the development of such forecasting models by an operator is desirable is still in debate both within the operator holding this data and in society as a whole. Therefore a method to improve passenger service during disruptions with minimal invasion of passenger privacy is a preferred solution to the main research question of this thesis. Finally, current passenger behavior may not result in the travel choices that minimizes passengers' own inconvenience in case of a disruption, for example because passengers currently have insufficient information to make those decisions that are in their best interest. Altering passenger route choices from their current behavior, for instance by helping them to avoid capacity bottlenecks, may improve the service experienced by passengers. Therefore better passenger service may result when the proposed disruption management policy supports passengers in selecting the best travel strategy, rather than estimating (and accommodating) current passengers' imperfect reactions to a disruption. Consequently, such a model does not require knowledge of the current reaction of passengers to a disruption.

Although current passenger reactions may not be needed to improve passenger service, the models proposed in this thesis assume an understanding of passengers' paths preferences. The models in Chapters 4 and 5 allow for different passenger behavior models. The models were evaluated under different behavioral assumptions, such as the assumption that passengers prefer the shortest path, prefer a path that is geographically similar to the planned path, and a situation where passengers are divided among a set of attractive paths based on a logit model, as information on passengers' preferences was not yet available. This sensitivity analysis showed that even under slightly different passenger behavioral assumptions, the models still provide good solutions.

Future research could focus on deriving passengers' paths preferences. For example, passengers' preferences may be influenced by aspects other than travel time such as crowdedness, number of transfers, or reliability of the arrival time. Moreover, these preferences may differ over passengers. Further analysis of smart card data, possibly combined with other sources, could define these preferences and show whether there are heterogeneous groups of passengers. These findings could be used to validate, adjust, or extend the behavioral assumptions made in the models of Chapters 4 and 5. Extending the behavioral models of passengers in these methods is possible because of the agent based simulation approach. Alternatively, one could investigate to what extent different behavioral assumptions change the results found in Chapters 4 and 5, thereby extending the sensitivity analysis.

Furthermore, future research could include the study, and possible integration of, multiple data sources. For example, data resulting from weighing in trains, the number of people using the (often free) wifi connection in the train, passenger counts, and surveys could together provide great insight into route choice, crowdedness, and real-time forecasts of passenger demand. An important second branch of research is therefore how to combine different data sources to obtain information on passenger behavior.

Disruption Management

The disruption management process consists of timetable adjustments, rolling stock rescheduling, and the adjustment of crew schedules. The models in Chapters 4 and 5 do not consider all these components. Future research could extend existing models for timetable adjustments and crew rescheduling with a dynamic passenger assignment and realistic behavior, as proposed in this thesis. The benefit of such an approach would be that the then proposed disruption management actions are taken with more attention to the effects on passenger service. The optimization in Section 5 could possibly be extended to include the other components of timetable adjustment and crew rescheduling as well. The challenge will be to integrate these models efficiently so that they are fast enough to be considered in a real-time application.

Application beyond disruption management

The models in Chapters 4 and 5 both concern capacitated multi-commodity flow models. Other application areas dealing with network design and flow optimization could profit from the models and techniques proposed in this thesis. Possible applications could include goods logistics plannings, workforce scheduling that aims to optimize employee satisfaction, and service logistics where packages are delivered at a time most convenient for the customer.

The model of Chapter 4 could be valuable for network (re)design questions in transportation in general. It would also be suitable for strategic network design planning within and outside public transportation. The principle of the proposed preprocessing step in this chapter could also be used to reduce the number of commodities for other applications when the number of paths available per commodity is very limited.

The model in Chapter 5 combines capacity assignment and flow assignment in a multi-commodity flow network into a single model. However, the proposed model formulation is more specific to the application of disruption management in public transport than the model in Chapter 4. For example, the concept of passengers having free route choice is an aspect likely unique to the application in public transportation. However, the proposed solution approach, consisting of a combination of column generation and simulation, may also be used in other applications when they involve restrictions on the flow that are easy to reflect by limiting the path choice set, but hard to capture in constraints in an optimization model.

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Summary in English

Around the world millions of passengers depend on public transportation systems, which provide a relatively sustainable option for transportation. In the Netherlands around 1,1 million journeys are made by train every day. Unfortunately, disruptions happen regularly due to malfunctioning rolling stock or infrastructure, extreme weather conditions, and accidents. The most important choice a passenger needs to make when faced with a disruption is whether to wait or reroute. As a student I commuted by train daily, and selecting the best strategy became something of a sport. The best decision was not obvious, especially as I did not yet have a smart phone with an Internet connection. On my arrival at the station it was uncertain whether the disruption would last for hours to come, or be over in the next ten minutes. However, I could be certain that a detour would at least add an hour to my journey time, as well as two transfers. It was not only the duration of the disruption, but also the routes chosen by my fellow passengers which could affect the inconvenience of my journey: If we all chose the same route, the resulting overcrowded trains would lead to further delay for passengers who were unable to board, and a less pleasant journey for the passengers that did embark.

It was during disruptions like these that I often wondered: Why does Netherlands Railways not help me to make good travel decisions? Disruption Management is the field of research that aims to mitigate the effects of disruptions on passenger service. A decade ago, Netherlands Railways didn't have detailed information on where its passengers were and where they were traveling to. Additionally, means of communicating with passengers were limited to announcement systems in trains and on stations, which do not allow for detailed and customized travel advice. This may explain why, at the time, route choice support to passengers was very limited. However, recently detailed information on customers' journeys has become available through Automated Fare Collection Systems (such as the OV-chipkaart in the Netherlands), and personalized communication has become possible through the wide availability of wireless communication technology (for instance through applications on smart phones). Thus, indeed, the personal support of passengers during disruptions is possible nowadays.

This thesis concerns the question of how new information on passenger behaviour, such as that resulting from Automated Fare Collection Systems, can be used to improve passenger service in case of major disruptions in public transportation systems. To improve service, the operator can adjust the assignment of vehicles in the network, and provide route advice to passengers. However, flexibility in the assignment of vehicles is limited, and passengers are not obliged to follow the route advice of the operator. This thesis combines research in extracting information from newly available data on passenger demand and behaviour with research on how this information may be used to improve passenger service during major disruptions in public transportation systems within the above-mentioned limitations. Indeed it was found that this new information, together with the option to provide route advice to passengers, could significantly improve service during major disruptions.

Passengers

Collection of data on passenger behaviour in the Netherlands started with the introduction of the OV-chipkaart , a smart card, although similar systems were already in use in, for example, Hong Kong, Singapore, Tokyo and London. Smart card data is unique in that it stores the origin, destination, and time of journey for all journeys made by smart card. This information was never before available at this combined scale and level of detail. However, the route which the passengers select is not stored. The route choice is important, for example to calculate train occupancy or evaluate passenger service in hindsight. In Chapter 2 a method is proposed to deduce the selected route of passengers based on smart card data and information on the logistical operations. The validation set shows that the proposed method is able to select the correct route for over 90% of journeys in the sample.

Disruption management requires insight into current and near future demand for travel. Chapter 3 proposes a framework for deriving forecasts based on historic smart card data. At the time of analysis the data was incomplete as the card was still in the introduction phase. However, results from this framework are indicative that sufficiently accurate forecasts could indeed be derived from this data, and future studies using the current data could provide more definite conclusions.

Information during Disruptions

Next, models have been developed that aim to improve passenger service during disruptions, based on detailed information on passenger flows, by adjusting the logistic schedule to the anticipated passenger demand. These models support public transport operators to best make use of the limited flexibility in the logistic schedule to reduce the inconvenience passengers experience due to the disruption. Specifically, these models aim to take into account the free route choice of passengers, and the fact that a change in the transport schedule may also lead to passengers changing their route. Moreover, the models take into account capacity constraints, and thus also that passengers route choice may be affected by other passengers' route choices in case of insufficient capacity. Models have been developed for two applications: (1) the scheduling of shuttle services during planned link closures in public transport networks and (2) the adjustment of rolling stock scheduling combined with the provision of personalized travel advice during real time disruptions.

Link closures, closing a segment of the network, are regularly necessary for maintenance. Standard practice uses shuttle buses to replace the currently closed link in the network. Although this ensures that all passengers will be able to reach their destination, other shuttle lines may be better capable of reducing the inconvenience to passengers. Deciding which set of shuttle lines to operate is a complicated problem, as the benefit of one shuttle line depends on what other shuttle lines will also be operated. Passengers will therefore only be able to choose their best route once the schedule of all shuttle lines is available. Moreover, given a limited budget, the opening of one line will reduce the options for opening other lines. Chapter 4 proposes a new mixed integer programming model that can assist an operator in the decision of which shuttle lines to open and at what frequency. The model includes a dynamic passenger assignment model that aims to assign passengers to those paths that are in their personal best interest, rather than the paths that, because of the limited capacity, would best suit the operator. Results from a real-life case study of a link closure at the Massachusetts Bay Transportation Authority indicate that different shuttle lines can provide a solution with a much lower passenger inconvenience than standard practice.

Moreover, providing personalized route advice to passengers that helps them to avoid capacity bottlenecks and anticipates an uncertain disruption duration is possible thanks to the availability of information on current and future passenger demand. Chapter 5 proposes a new optimization-based model that combines rolling stock rescheduling with the provision of personalized route advice to passengers. The rolling stock is rescheduled with the aim of providing sufficient capacity for the demand of each trip. However, flexibility in scheduling rolling stock is limited because there are few spare units, and it may take a long time before re-assigned vehicles can arrive at the location where they are needed. Therefore personalized route advice may be more effective in the short term, as it can help passengers to avoid bottlenecks in which they would incur even more delay.

This route advice should be such that it is attractive for the passengers to follow, as the operator cannot force passengers to follow the advice. Computational experiments were conducted based on realistic case studies of the Netherlands Railways network. Indeed it is found that, even under different assumptions on passenger behaviour, route advice can substantially reduce passenger inconvenience. In some cases, a better solution may even be found if not all passengers follow the route advice.

Conclusies & Recommendations

In summary, this thesis has shown that new information on passenger behavior, such as that resulting from automated fare collection systems, is extremely valuable for operators to evaluate their service in hindsight, and can be used to improve passenger service in case of disruptions in public transportation systems. Specifically, better service is obtained when the transport schedule is adjusted to meet passenger demand as it reacts to the new situation in a disrupted network. Moreover, the support of passengers during disruptions through travel advice also substantially improves service, even in case of systems with free route choice. The recommendation to the research field is therefore to strengthen research in the area of demand-driven transportation planning. The recommendation to public transport operators is to use the currently available data in daily planning and evaluation of service, and increase effort in providing travel information and route advice to passengers during disruptions in connection to the logistic rescheduling. The models proposed in this thesis could be used to support public transport operators in this task in practice.

Nederlandse Samenvatting (Summary in Dutch)

Miljoenen mensen maken elke dag gebruik van het openbaar vervoer, dat een belangrijke duurzame optie is voor transport. In Nederland verzorgt de Nederlandse Spoorwegen (NS) dagelijks circa 1,1 miljoen reizen. Helaas verlopen niet al deze reizen vlekkeloos. Defecten aan het materieel of de infrastructuur, extreme weersomstandigheden en ongelukken zorgen regelmatig voor grote verstoringen die leiden tot veel vertraging en ongemak voor reizigers. Een verstoring maakt een deel van de materieelplanning, dienstregeling en personeelsdiensten onuitvoerbaar. Ook reizigers moeten hun reis aanpassen. Disruption Management (management van verstoringen) is een onderzoeksveld dat zich bezighoud hoe deze processen het beste aan te passen tijdens een verstoring. Voorheen was de focus in dit onderzoeksveld voornamelijk op het aanpassen van de logistieke planning. In de laatste jaren is steeds meer data beschikbaar gekomen over de reizen van de passagiers, bijvoorbeeld door het gebruik van automatische ticketing systemen. In dit proefschrift is onderzoek gedaan naar hoe deze informatie gebruikt kan worden om het ongemak van passagiers tijdens een verstoring zo veel mogelijk te beperken.

Ten eerste is onderzocht welke informatie over reisgedrag verkregen kan worden uit de nieuwe data die gegenereerd wordt door elektronische ticketing systemen zoals de OV-Chipkaart. In Hoofdstuk 2 wordt een methode voorgesteld die uit de OV-chipkaart data en de gereden dienstregeling de door reizigers gekozen route per reis afleidt. Deze methode wist voor ruim 90% van de reizen in een validatie smart card data set van de NS de correcte route af te leiden. In Hoofdstuk 3 wordt daarom een raamwerk voorgesteld om op basis van smart card data van voorgaande dagen een voorspelling te maken voor de huidige vraag. De positieve resultaten in dit hoofdstuk op basis van een eerste kleine test set zijn een indicatie dat deze data inderdaad geschikt is om zulke voorspellingen op te baseren.

Vervolgens zijn modellen ontworpen die, gebruik makend van de gedetailleerde informatie over reizigersstromen, tot doel hebben de reizigersservice te verbeteren tijdens verstoringen. Er zijn wiskundig gemengd integer programmeringsmodellen ontworpen

voor twee toepassingen: (1) het plannen van shuttle bus services in het geval van een geplande, tijdelijke, sluiting van een gedeelte van het netwerk (in Hoofdstuk 4); en (2) het aanpassen van materieel in combinatie met het geven van reisadvies tijdens grote, onverwachte verstoringen (in Hoofdstuk 5). In beide gevallen wordt rekening gehouden met het feit dat passagiers zelf hun route mogen kiezen en daarom reisadvies niet hoeven op te volgen. Ook capaciteitsbeperkingen zijn gemodelleerd, net als de concurrentie onder passagiers in het geval van capaciteitstekorten. De resultaten in Hoofdstuk 4 voor een case studie op basis van het metro netwerk in de Boston regio laten zien dat het plannen van shuttle bussen op basis van de reisvraag van passagiers leidt tot minder vertraging voor reizigers zonder dat de operationele kosten daarvoor hoeven toe te nemen. Experimenten op basis van realistische case studies voor de NS in Hoofdstuk 5 tonen aan dat het geven van persoonlijk reisadvies aan passagier hun vertraging substantieel kan verminderen in vergelijking met het uitsluitend aanpassen van de materieelomloop, zelfs als niet alle reizigers het advies opvolgen.

Het onderzoek in dit proefschrift heeft laten zien dat de nieuw beschikbare informatie over reizigersgedrag van grote waarde is om de reizigersservice tijdens verstoringen te verbeteren. De data is zeer geschikt voor het gedetailleerd analyseren van de geboden service en reizigersroutekeuzes in het verleden. Tijdens verstoringen kan de reizigersservice substantieel verbeterd worden wanneer de logistieke planning wordt aangepast op basis van de kennis van huidige en verwachte toekomstige reizigersstromen en door reizigers te ondersteunen met reisadvies. De hieruit volgende aanbeveling aan onderzoekers is om het onderzoeksgebied omtrent vraag-gestuurde transportplanning te versterken. Openbaar vervoerders wordt aanbevolen gebruik te maken van de beschikbare data en tijdens verstoringen de informatievoorziening aan reizigers een meer centrale plek te geven naast de aanpassingen van de logistieke planning. De in dit proefschrift voorgestelde modellen kunnen openbaar vervoerders daarbij in de praktijk ondersteunen.

Curriculum Vitae

Evelien van der Hurk (1985) has a master's degree in Econometrics and Management Science, specialization Quantitative Logistics and Operations Management, (cum laude) from the Erasmus University Rotterdam. She started her PhD research within the Netherlands Science Foundation (NWO) project 'Complexity in Public Transport' in September of 2010 at the Rotterdam School of Management. Her main research interests are in analyzing human behavior based on large data sets and including human behavior in combinatorial optimization models, specifically with the application to resilient network planning and design in transportation. Within her PhD, she has focused on analyzing passenger behavior based on large data sets on passenger journeys, and modeling realistic passenger behavior in decision support models for disruption management in public transport.

In 2013, Evelien visited Prof. Nigel Wilson, Prof. Joe Sussman at the Civil Engineering Department, and Prof. Dick Larson at the Engineering Systems Division, of the Massachusetts Institute of Technology.

The research that is described in this thesis has been presented at many international conferences, such as IFORS, CASPT, TRISTAN and the IEEE Conference on Intelligent Transportation Systems. One of the chapters has been published in IEEE Transactions. Two others are currently under review at *Transportation Science*.

From April 1, 2015, Evelien will be working as an assistant professor at the Technical University of Denmark, where she will continue to work on research in transportation.

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PASSENGERS, INFORMATION AND DISRUPTIONS

Passengers traveling in public transport generate a detailed digital track record of their journey through using automated fare collection systems and carrying mobile devices. This information on passenger behavior has only recently become available to public transport operators. This thesis addresses the question how this new information can be used to improve passenger service in case of disruptions in public transportation.

Major disruptions cause the current logistical schedule of the operator to be infeasible. Adjusting this schedule to the disruption is a complicated planning problem. Passengers will adjust their journeys to the new schedule, and may need to adjust their route choice due to the route choice of other passengers in case of capacity shortages. Therefore the passenger service results from a complex interaction between passengers themselves, and between passengers and the schedule.

This thesis proposes new models for improving passenger service in case of major disruptions by adjusting the schedule while anticipating passenger's reactions, and also by supporting passengers during disruptions through the provision of route advice. This research is combined with a study on passenger behavior based on the new data sources. The models are evaluated using data and case studies of the passenger rail network of Netherlands Railways and the urban rail network of the Massachusetts Bay Transportation Authority. It was found that indeed this new information, together with the option to provide route advice to passengers, could significantly improve service during major disruptions.

This research is part of the Netherlands Science Foundation (NWO) project 'Complexity in Public Transport'.

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