Analysing the impacts of peak demand and traffic rescheduling in high frequency metro networks

Master Thesis

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Master Thesis

Analysing the impacts of peak demand and traffic rescheduling in high frequency metro networks

by

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Cover image by author

Preface

In front of you lies the result of the final result of my Thesis project at TU Delft and RoyalHaskoningDHV. With this Thesis I am concluding my time as a student in Delft and my time as Transport, Infrastructure and Logistics student at the Delft University of Technology. A time I really enjoyed. With a desire to explore public transport related research and to discover what it is like to work in an engineering consultancy firm, my Thesis became a combination of both. It was a challenging time to write my Thesis, for which I spent most of my time working from home. Though it was definitely challenging everything from home and sometimes weird that the people who helped me out so much writing this Thesis, I never even met in real life, I definitely learned a lot in this process both personally and professionally. I would like to take this opportunity to thank everyone who helped me achieve this result.

First of all I would like to thank RoyalHaskoningDHV with providing me with the tools and guidance for this research. Especially with providing me with all the possibilities to continue my research from home when we all had to stay at home as much as possible. Special thanks go out to my daily supervisor, David Koopman, for getting me up to speed on this study and providing me with a critical view and practical help where possible. Even though we didn't meet in person very often, we definitely were in close contact and spent a lot of time improving my research. Your help and feedback helped shaping a great deal of my Thesis. Also special thanks to Rob van Neerrijnen and Laura Pardini Susacasa for answering my many questions concerning the OpenTrack model and programming issues.

Secondly I would like to thank my supervisors at TU Delft for assisting me throughout the entire process and helped me stay motivated when it was sometimes getting hard. A special thanks goes out to my daily supervisor Nikola Bešinović who provided me with many critical views but at the same time motivated me to keep raising the overall level of my Thesis. Also your feedback helped to shape a great part of my Thesis. We definitely spent a lot of time on Zoom working everything out and addressing my concerns. Next also special thanks to Oded Cats, who is excellent at delivering feedback in a motivational way and also provided me with additional motivation when I was having a difficult time. Also I would like to thank Yousef Maknoon for his critical view and questions to further improve my work and Serge Hoogendoorn for being willing to chair my thesis committee. For all my committee members: thank you very much for all your contributions, feedback and motivational support throughout the entire process, it wouldn't have been possible without you!

Thirdly I would also like to thank Halmar Kranenburg from RET and Alex Bruijn from NS for kindly providing all the data needed to perform this research. Also I would like to thank Nadia Huerlimann from OpenTrack to provide me with the much needed API licence to enable me to continue my research working from home. Without your contributions this Thesis also wouldn't have been possible, thank you very much!

Finally I would like to thank everyone else, which is an extensive list of people too long to name here, who supported me throughout this entire process by providing me motivational or professional support, it was really much appreciated!

I hope you enjoy reading this report!

Olmo Müller
Delft, July 2021

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List of Abbreviations

API	Application Programming Interface
ATA	Actual Time of Arrival
ATD	Actual Time of Departure
AVL	Automatic Vehicle Location
IC	InterCity
KPI	Key Performance Indicator
NS	Nederlandse Spoorwegen
Pax	Passengers
RET	Rotterdamse Elektrische Tram N.V.
SBTM-MN	Simulation Based Traffic Management for Metro Networks
SPR	Sprinter
STA	Scheduled Time of Arrival
STD	Scheduled Time of Departure
TSM	Transport Simulation Model
TSM-RW	Transport Simulation Model of the Real World
TRM	Train Rescheduling Model

Summary

With the increasing demand for public transport systems worldwide and also a lot of these systems running at their maximum capacity, there is a strong need for finding ways for these systems to operate in a more efficient way. In recent transportation research there is an increasing attention for operational conditions and the impact of passenger-vehicles interaction on the timetables of urban rail networks. Passenger-vehicle interaction can have a strong impact on the operational conditions of an urban rail line as a large part of the dwell time of a vehicle can be explained by the number of boarding and alighting passengers.

A lot of urban rail networks have connections to national or even international rail services. These services often run at a lower frequency than the urban rail networks. When a national train arrival occurs at a transfer station to the urban rail network, this can cause a sudden peak in demand for the next arriving urban rail vehicle. As passengers can have a strong impact on the dwell time of a vehicle, it is likely that a temporary peak in demand can cause the next urban rail vehicle to have a longer dwell time, possibly causing delays and an uneven headway. These expected correlations are depicted in Figure 1. When there is known upfront what the impact of such a peak in passenger demand is, there are possibilities to reduce the impact of these peaks in demand using real time rescheduling measures.

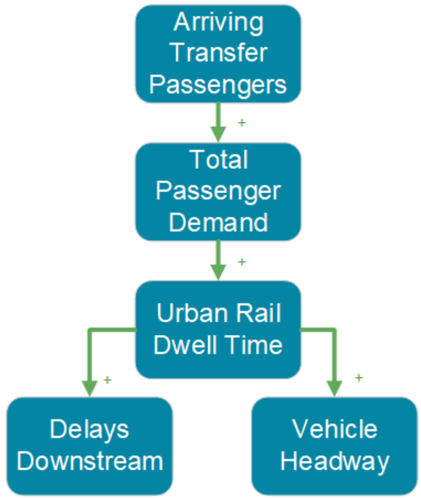

Figure 1: Schematic overview of the correlation analysis

The goals of this research are to quantify the impact of transfer passengers on reliability of an urban railway network in the case of a difference in service frequency and to find what rescheduling measures are recommended to reduce time impact of these peaks in demand. The main research question of this research is:

"What impact do transfer passenger flows from lower frequency railway transportation mode have on disturbances in high frequency urban railway networks and which control and rescheduling methods are recommended to minimise these disturbances?".

To answer this question first correlation analysis is performed with data from a case study. This case study concerns the metro network of Rotterdam. In this metro network there are several transfer stations with connections to the national railway network of The Netherlands. Based on several parameters one transfer station, Rotterdam Blaak, is selected as case study transfer station on which this study focuses. This station is serviced by metro lines A, B and C in the network, which thus also the lines under review in this study. The correlation analysis is performed with the four steps presented in Figure 1. For each step a separate analysis is performed to quantify each step and determine the impact of each step on the next step, which is done as follows:

- **Passenger demand - Number of transfer passengers:** using smart card data and the check-in location of passengers there can be determined whether a passenger arriving at the researched transfer station is a transfer passenger or a originating passengers. The share of transfer passengers in the demand per minute is calculated using this data to determine to what extent peaks in passenger demand are caused by transfer passengers.
- **Passenger demand - Metro dwell time** That passenger numbers impact the dwell time of a vehicle has already been established in literature. However, to what extent can differ strongly for each situation. Therefore for this specific case study parameters are obtained describing the impact of passenger demand on the dwell time

- **Metro dwell time - Delays Downstream** With variations in dwell time in mind the dwell time at the researched transfer station is correlated to delays downstream to determine to what extend variations in dwell times at the transfer station can cause delays in the network.
- **Metro dwell time - Headway deviation** These same variations in dwell time are also correlated to headway deviations downstream to determine to what extend these variations in dwell time can cause headway deviations and possibly bunching in the network.

With the parameters obtained using this correlation analysis a modelling study will be carried out. This is done using an existing simulation framework. This framework simulates (part of) a metro network and hereby takes into account passenger vehicle interactions by taking into account passenger numbers at each station and calculating the dwell time accordingly with these passenger numbers. This yields a much more representative picture of delay development on the line. With this accurate representation of reality this model is then also used to iteratively come up with a rescheduled timetable which reschedules the timetable for the benefit of the passenger. This way the simulation framework can be used to come up with rescheduling strategies to correct for the impact of transfer passenger flows.

The passenger-vehicle interactions calculated by the model are updated with the parameters obtained from the correlation analysis. The framework is adapted to work with metro lines A, B and C of the metro network of Rotterdam. Passenger arrival data from Rotterdam Blaak is used to simulate train arrivals to the network and the framework is update to handle these passenger numbers accordingly. Data from the data set provided by the RET is then used to validate the model.

With a correct representation of the metro line and the arrival of transfer passengers to the network several scenario's are then simulated to come up with: timetable improvements in the base scenario and estimate the impact of the following situations: an increased number of transfer passengers, a total increase of passenger numbers and a change in train frequency.

There are clear quantifiable correlations between the number of transfer passengers and passenger demand for the next metro, with 94% of the peaks in passenger demand being explained by arriving transfer passengers during the morning peak. There is also a clear correlation between passenger demand and the dwell time of a metro, with about 45% of the dwell time being explained by the number of boarding and alighting passengers during the morning peak. The correlation between passenger demand and delay is less clear. As the dwell time is strongly influenced by the number of boarding and alighting passengers, passenger demand and therefore also a higher demand due to transfer passengers, can cause a longer dwell time, but this doesn't necessarily cause a delay for the metro. If a metro is already delayed it can contribute to an increasing delay. The average delay of metros affected by transfer passengers also lies 17 seconds higher than for other metros. The same also holds for headway; a flow of transfer passengers can contribute to an increasing deviation in headway, but doesn't necessarily cause large headway deviations.

With the set of increasing/decreasing running time between two stations, increasing the dwell time or dispatching a metro earlier or later for departure, an improved schedule can be obtained. The recommended rescheduling actions strongly depend on the situation at the transfer station as well as the surrounding stations. For each situation a recommended solution can be obtained through the TRM. Next to the base scenario also a scenario is ran in which the arrival distribution of transfer passengers from historical data is increased with 20% to test what the impact would be on the rescheduling decisions made by the TRM. From this scenario can be concluded that compared to the base scenario a similar pattern in rescheduling decisions can be found as compared to the same data from the base set, but that the decisions are somewhat intensified. For example a metro that is already scheduled earlier in the base scenario will now get scheduled even earlier. Also in this case the rescheduling decisions remain strongly dependant on the situation. Also a scenario is ran in which the overall passenger numbers are increased. From this scenario can be concluded that without optimizing the timetable dwell times and delays will increase with raising passenger numbers. Through the TRM also an optimized timetable for this scenario can be obtained, however the possible improvements do not increase the same as the dwell times and delays in the network. From the different runs with the base scenario could already be concluded that different distributions of arriving transfer passengers can lead to very different optimal timetables. This is also the case for running the optimization with an altered train frequency.

In this study is found that transfer passenger flows from a lower frequency railway transportation mode can significantly impact the demand and dwell time of the next arriving urban rail vehicle. However no strong indications were found that such a peak in demand alone can cause disturbances in the urban rail network. A peak in demand caused by transfer passengers flows can however contribute to the development of delays over the network. A combination of three different rescheduling methods is used to obtain the optimized schedule for several transfer passenger arrival distributions. Though there are some indications that generally urban rail vehicles that deal with a peak in transfer passengers tend to get rescheduled earlier than other urban rail vehicles, each distribution resulted in different rescheduling decisions and improvement possibilities. Through the usage of the SBTM-MN framework recommended rescheduling decisions can be obtained for each situation.

Overall the scientific contributions of this study can be summed up as follows:

- The analysis and quantification of the impact of peaks in passenger demand caused by transfer passengers in case of a difference in service frequency on the reliability of the high frequency system. This research quantified the relation between peaks in (transfer)passenger demand and delays and headway deviations in a high frequency metro system.
- Develop adaptations to a simulation-based framework to simulate the impact of peaks in passenger demand and simulate their impact on dwell time and delay development over the line in combination with simulating for according passenger numbers and dwell times on other parts of the simulated networks as well.
- Develop insights in the usage of rescheduling measures in the context of peak demand at transfer stations in a high frequency metro network.
- Explore several possible scenarios in the case study to estimate the impact of increasing numbers of transfer passengers, an increasing number of passengers on the entire line and a change in frequency on the train side.

And the societal contributions of this study can be summed up as follows:

- Providing a clear insight for the operators in the impact of transfer passenger flows and to what extent they are able to cause disturbances in their networks.
- How to reschedule the timetable for the benefit of the passenger, reducing the overall travel time of passengers while looking out for operational schedule adherence.
- Providing some insight in possible development of dwell times and delays for future growth scenario's.

1 Introduction

With increasing urbanisation and cities throughout world becoming more crowded, the need for efficient public transport systems continues to rise. These systems are under increasing pressure to work in an attractive and efficient manner. However, using current infrastructure, these high-frequency transportation systems are frequently operating at near-maximum capacity, particularly during rush hour. This is the case, for example, with Rotterdam's metro system (Velzen, 2019). On the other hand, expanding the infrastructure of urban rail networks in densely populated areas is very costly and has a significant impact on the urban area and living space. Examining ways to make better use of existing infrastructure would be a far more cost-effective strategy.

1.1. Problem statement

There are many ways to increase the efficiency of urban rail or metro systems. This can be done on a strategical (long term), tactical (medium term) and operational (short term) level. Examples of measures to increase efficiency or capacity in metro systems in the short to medium term include: reducing dwell time, homogenize train speeds or adapting shorter block sections to reduce buffer times between consecutive trains (Dicembre & Ricci, 2011). When considering timetables for metro networks, the technical requirements of the systems and the optimal alignments in transportation planning are frequently considered. However, usually relatively little attention is paid to understanding operational conditions, such as the time required for passengers boarding and alighting at stations (Harris & Anderson, 2007). This despite research by Harris and Anderson (2007) concluding that these boarding and alighting rates are very important in determining the line capacity and reliability, and play an important part in causing (small) disturbances and delays. Traditional models assume that these (small) delays can be caught up using buffer times. The model developed by Pardini-Susacasa (2020), that includes passenger interactions with the vehicle, concludes that delays cannot be caught up or can even worsen during the remainder of the journey when these passenger interactions are included. Therefore solving seemingly unimportant delays and disruptions can in the end still have a large impact on the network as a whole.

One of the causes of small delays can be a strong fluctuation in passenger demand per vehicle. Passenger demand can not only fluctuate throughout the day, but also between specific vehicles. Peaks in passenger demand can have a strong impact on the dwell time of a vehicle, as the number of boarding and alighting passenger explains most of the dwell time of a train (Suazo-Vecino, Dragicevic, & Muñoz, 2017). When the demand in general is higher for a longer period of time, for example during rush hour, this can be accounted for in the timetable. However, this is harder for temporary and more unpredictable peaks in demand. One of the causes for a peak in demand can be the arrival of a large batch of transfer passengers from another line or even another mode. Usually metro lines have such a high frequency that passengers do not necessarily account for the timetable but rather arrive at a stop at random (Ingvardson, Nielsen, Raveau, & Nielsen, 2018). This would normally lead to relatively even arrival patterns. However, in higher frequency metro networks with transfer stations to lower frequency (intercity) rail networks this arrival flow can vary strongly in a short period of time when a lot of transfer passengers arrive at the same time from (intercity) trains (Sun, Jin, Lee, Axhausen, & Erath, 2014). An intercity or national rail network often runs at a lower frequency and with higher capacity vehicles than the metro network, causing peaks in demand with transferring passengers when a large train arrives at one of the transfer station of the metro network. These peaks in demand can have an impact on the dwell time and crowding level of the next metro vehicle as passenger demand is suddenly higher than it would have been without transfer passengers. When the dwell time of an metro vehicle is influenced by this transfer process, this is not accounted for in the timetable. As the dwell time and crowding level of vehicles can be strongly influenced this way, this can cause (small) disturbances in the network. Research by Pardini-Susacasa (2020) pointed out these passenger interactions can cause delays that then easily propagate throughout the network creating an increased amount of delays.

By better understanding how these flows of transfer passengers can impact the schedule of the metro network, measures can be taken to mitigate or even prevent disturbances and delays caused by these transfer passenger flows. The impact of disturbances can for example be mitigated using real-time rescheduling methods. These methods are used to reschedule the timetable up until the last second and real time to cope with disturbances that happen in the network. For example, if a train gets (slightly) delayed due to passenger holding the door, it will fall (slightly) behind schedule. Real-time rescheduling methods are then used to adjust the timetable with this delay factored in. This is then used to decide what the best strategy for this train and other trains around this train to recover from this delay. Examples of real-time rescheduling methods include; increasing or decreasing driving speed, short turning a train, skipping a stop or increasing or decreasing the dwell time (Altazin, Dauzère-Pérès, Ramond, & Tréfond, 2020). These real-time rescheduling methods can be applied with different optimization objectives in mind, for example; minimizing passenger waiting time, adherence to the timetable (Hassannayebi, Zegordi, Yaghini, & Amin-Naseri, 2017), transfer synchronization control (Gavriilidou & Cats, 2019), reducing delays or increase stability to increase capacity (Lüthi, 2009). Advice is then given to the traffic controller and train driver in what way the driving strategy should be adjusted. Although several successful experiments have been carried out with real-time rescheduling methods, the number of practical applications remains limited (Altazin et al., 2020).

1.2. Research setup

By describing the purpose of this research and constructing the major research question and its relevant sub-questions, the problem statement addressed in the previous section will be made more concrete in this section. This is done by first describing the goal of this research, followed by the formulation of the main research question and supporting sub-questions.

1.2.1. Research goal

This study contributes to existing research by studying the impact of transfer passenger flows from a lower frequency rail mode on the development of delays and headway deviations in an high frequency metro network. The goal of this research can be seen twofold. The first goal is to quantify this effect. With this quantification the aim is to identify circumstances under which these transfer passenger flows can cause disturbances. Secondly, with this knowledge, there can be looked at how these disturbances can be predicted and what measures can be taken to minimise these disturbances. This is done using real time rescheduling methods.

1.2.2. Research questions

This research aims to combine three separate research fields that are closely related but are rarely combined in one research; dwell time and vehicle bunching, the behaviour of (transfer) passengers and real time traffic control strategies. The main goal of this research is to gain understanding into the interaction between passenger demand on metro lines due to arrivals of transfer passengers at a specific moment and the possibility that these passengers cause delays and headway deviations in this metro network. With a better understanding of this interaction effect a methodology can be developed for mitigating disturbances and delays caused by these transfer passengers. Based on these insights in train dependent passenger demand, further developments can be made on the rescheduling strategies developed by Pardini-Susacasa (2020). The main research question of this research is defined as follows:

What impact do transfer passenger flows from lower frequency railway transportation mode have on disturbances in high frequency metro networks and which control and rescheduling methods are recommended to minimise these disturbances?

To answer this main research question, several sub-questions need to be answered first. They are formulated as follows:

1. *Using smart card data, what correlations between transfer passengers from lower frequency rail mode and disturbances in an higher frequency metro network can be found and how can this be quantified?*
2. *What control and rescheduling strategies to minimise disturbances are currently used in railway networks and what KPI's are used to asses their performance?*
3. *Which control and rescheduling methods can best be applied to minimize disturbances and delays caused by transfer passenger flows?*
4. *What is the impact of a change in frequency on the train side on the impact of transfer passenger flows?*

The first sub-question aims to identify what correlation can be found between transfer passengers from a lower frequency railway and disturbances in an high frequency metro network. More specifically a quantification is sought for the impact of transfer passenger flows in terms of for example passenger volume and vehicle occupation on the dwell time and thereby the schedule of the metro network. This analysis is made based on available smart card data, from which transfer passengers can be identified based on their check-in location.

The second sub-question aims to identify which rescheduling methods are currently already in use and to what extent and under what circumstances these rescheduling methods are used. This is necessary to identify which rescheduling measures would be most appropriate in case of an expected disturbance caused by transferring passengers at certain stations, or that it is necessary to develop new rescheduling strategies. Also, to asses the performance rescheduling methods, the Key Performance Indicators (KPI's) that can measure the performance of the current situation and the proposed scenario are identified.

With the results of the first and the second sub-question there can be identified what control and rescheduling measures would be suitable in which situations. These rescheduling measures are used in a simulation and optimization framework by Pardini-Susacasa (2020) to identify what combination of rescheduling measures would benefit the passenger the most.

The last sub-question aims to determine to what extent the results of this research are still applicable should the frequency of the lower frequency line change, or to what extent it is applicable in other systems with different frequency combinations.

These sub-questions each cover the different parts of the research in order to be able to answer the main research question. To answer these sub-questions and eventually answer the main research question.

1.3. Research scope

This research focuses on finding real time rescheduling strategies by better understanding the dynamic interaction between transfer passengers from a lower frequency transport mode to a higher frequency transport mode. The main goal of better understanding this relation is to find a quantification for the amount of transfer passengers and vehicle sizes on both the intercity and metro networks, and the influence this has on metro vehicle dwell time. The research on this correlation focuses only on the transfer from (lower frequency) train to (higher frequency) metro. The correlation the other way around is not considered. Also specifically the correlation between train and metro is considered, transfers from and to other transportation modes are not considered. It is also assumed that the metro line generally utilizes smaller vehicles than the train line.

In this research a case study is used. The results of this study are therefore mainly applicable to the researched case study. There is discussed to what extend results are applicable to other transport networks, but as each transportation network in the world has its very own unique characteristics application of the results to other case studies should be done with careful considerations.

This research is performed during a worldwide pandemic which drastically changed the behaviour of people in public transport (Tirachini & Cats, 2020). However, data from a period before this pandemic are used. Therefore its conclusions are relevant to 'normal' travel circumstance. To what extend the results will be applicable in the future will depend on how travel behaviour will develop in a post-Covid-19 situation. The results of this change in behaviour will not be taken into account in this study.

1.4. Relevance

In this section the relevance of this research to as well society as to scientific knowledge is be discussed. This is done with the outcome of this thesis in mind: a quantified correlation between transfer passengers and the dwell time of metro vehicles and recommended rescheduling measures for this effect.

1.4.1. Societal relevance

Because metro systems all over the world are becoming more and more crowded it is essential to continuously search for ways to improve efficiency of these systems as expansion of railway infrastructure is often very expensive, especially in an urban environment. With finding recommended rescheduling strategies, the aim of these strategies is to shorten the travel time for passengers and to reduce the number and duration of delays in the network. Reducing the duration and the frequency of delays in the network results in two improvements: improved service reliability and the more efficient use of resources in the network.

Service reliability is perceived as key quality indicator for public transportation (van Oort, 2014). When being able to improve the reliability of the network, overall passenger satisfaction will increase and there is a greater possibility of attracting additional passengers, also from other modes. As attracting more passengers to an urban public transport network as opposed to people travelling to the urban area with a car is often a more desirable situation, this research can contribute to societal benefits this way.

Secondly when improving the overall reliability of the network, the network can also be used more efficiently. Having fewer delays or when being better able to predict delays, the schedule can be tightened and this can eventually result in a higher line capacity without having to expand the infrastructure.

1.4.2. Scientific relevance

There are several scientific research topics this study will touch upon. In this section is discussed briefly what the contribution of this research to each field will be mentioned. A more in depth analysis of the relevant study fields and available academic knowledge is discussed in section 2.

The first topic this research will touch upon is the modelling of transfer passengers. There are some studies that already looked at transfer passengers in the context of different service frequencies, however what has not been researched yet is this correlation in the context the effect on delays and headway deviations of the metro line. This also yields the second topic this research will touch upon: dwell time. A lot of research has already been done into dwell time. There are many researches into the important factors that can explain the variability in dwell time. The main contribution of this research in this field lies in correlating peaks in passenger demand to dwell time variance, and dwell time variance to delays further down the line.

The next field this research touches upon is rescheduling methods. Using an existing model of delay propagation of the selected case study by Pardini-Susacasa (2020) at RoyalHaskoningDHV this research will contribute to finding rescheduling strategies in the context of predicted peaks in passenger demand.

1.5. Report outline

The outline for the remainder of this thesis is presented in Figure 1.1. An explanation of the figures used can be found at the bottom of this Figure. In chapter 2 a literature review is presented to get a clear view of the existing knowledge and gain insight in the previous work this thesis builds on. In chapter 3 the method for analysing the input data is described, as well as the method for obtaining the parameters that are used as input for the framework described in chapter 4. This will be applied in a case study and with this case study experiments will be performed, as presented in chapter 5. In this chapter also the obtained results are analyzed. In the final chapter 6 the conclusions and recommendations are presented.

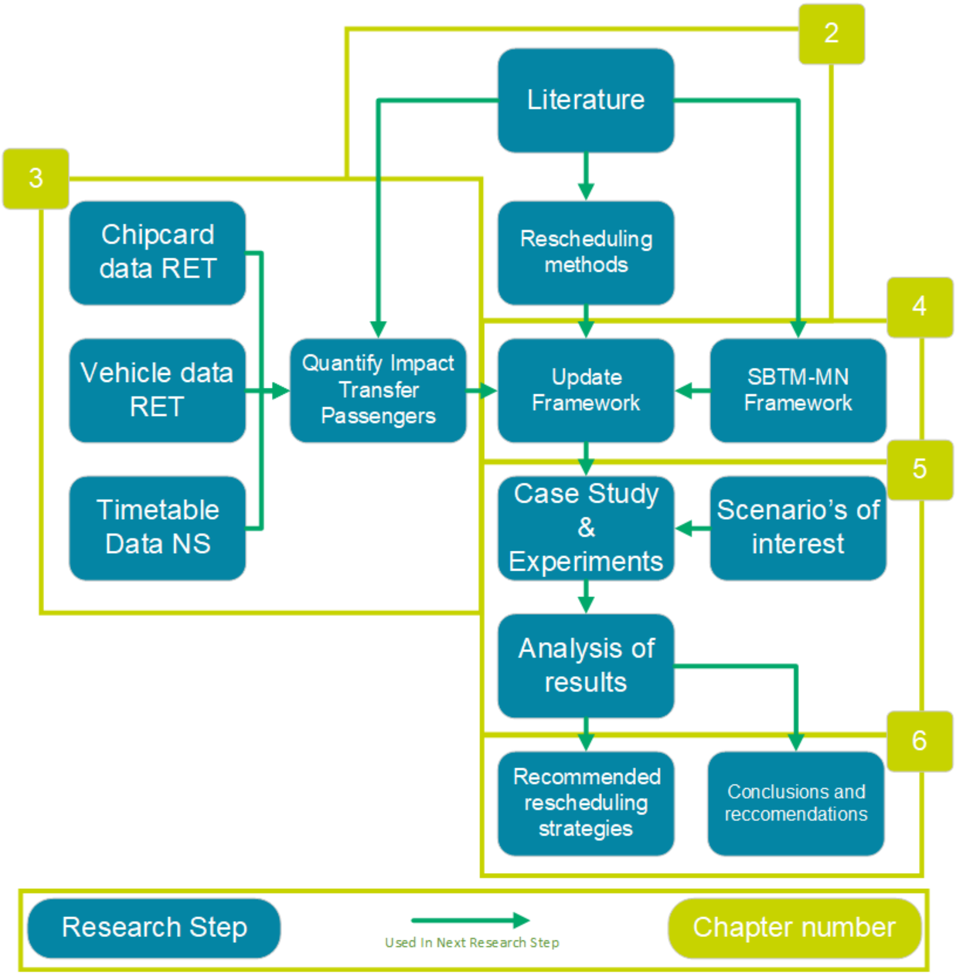

Figure 1.1: Thesis outline

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Literature Review

This research touches upon several relevant research fields. Considering the main research question and looking at a transfer from a passenger perspective, relevant existing literature can be categorized into five different categories. Considering a transfer from lower frequency rail mode to higher frequency rail mode, a passenger will start the transfer process by alighting the heavy rail vehicle walking towards the platform of the metro line. This yields the first two research topics: **analysis of transfer passenger flows** and **impact of difference in service frequency**. Arriving at the platform of the metro line there are multiple passengers arriving there at the same time trying to board the next metro vehicle with leads to the next research topic: **passenger demand and vehicle dwell time.** This vehicle dwell time is an important variable for the reliability of a metro line, yielding the next topic: **vehicle bunching**. Last this study aims to study mitigation actions for possible disturbances, resulting in the last topic: **real time rescheduling methods.** This research aims to combine knowledge these different research topics. For each topic relevant literature is studied and used as input for this research.

2.1. Transfer passenger modelling

With the increasing availability of smart card data, it becomes easier to analyse the travel behaviour of passengers throughout a public transport system. This also includes the choices people make when it comes to transfers. One of the first researches investigating transfer journeys using smart card data was performed by Hofmann and O'Mahony (2005). In this research an algorithm was developed for identifying transfer journeys from a pool of single journeys, creating a rule based framework for assigning transfer journeys. Since then a lot of research has been done in this area and additional frameworks have been developed.

A main distinction can be made between models that use smart card data as input to model individual behaviour or models that use this data to model a macroscopic flow of passengers. For example Kusakabe, Iryo, and Asakura (2010) use smart card data to predict which train a passenger is going to board. Their method relies on GPS tracking of passengers or the weighing of trains assuming their punctuality. Another recent application of smart card data to determine which train passengers took was developed by Zhu, Koutsopoulos, and Wilson (2017). In this research smart card data was combined with automatic vehicle location data to assign passengers to individual trains and this way calculate indicators such as train loads and number of passengers that were denied boarding. However, this model is only applicable for single lines and cannot be used to determine the routes for transfer passengers. A framework in which there is accounted for passenger train assignment with possible transfers in the network is presented by Hörcher, Graham, and Anderson (2017). In this paper an methodology using a framework with probabilities is used to calculate passenger assignment characteristics using real time vehicle data and passenger smart card data.

Besides train assignment models to describe the behaviour of transfer passengers in the network, also a lot of research has been done into describing the behaviour of transfer passengers at transit stations themselves. These pedestrian traffic assignment models are used to describe local travel activities, way finding and movements of passengers. These models can be categorised in macroscopic, mesoscopic and microscopic. Macroscopic models consider pedestrians as a continuum, mesoscopic models consider individual pedestrians but describe their movements in terms of macroscopic relationships and microscopic models consider individual pedestrian movements (Hänseler, van den Heuvel, Cats, Daamen, & Hoogendoorn, 2020).

These two research fields, train assignment modelling and pedestrian traffic assignment modelling have been combined by Hänseler et al. (2020). A transit model is presented in which pedestrian movements in stations and vehicle specific train ridership distributions are modelled based on automated fare collection data and train tracking data. This research shows that it is only very recent that pedestrian behaviour and vehicle ridership have been combined into one study and emphasises that research into passenger and vehicle interactions is a promising research area. Suggested usage for their model include crowding estimation, transit optimization and disruption management, and can therefore provide useful input for this research.

Another important factor in capturing the behaviour of (transfer) passengers are the different walking speeds of passengers. A lot of factors can be of influence on the walking speed: demographic characteristics such as age, gender or physical condition are of importance. Additionally, also environmental aspects such as platform design, presence of stairs and crowding are important determinants of the walking speed of a passenger (Bosina & Weidmann, 2017). For this research the most relevant aspect is that an estimation of the distribution of walking speeds needs to be made in order to be able to determine arrival of transfer passengers at the platform based on their smart card data. Leurent and Xie (2017) developed a stochastic model to capture two major factors of in-station walking times; individual speed and walking distance. With such a model passenger smart card data can be linked to individual passengers and an estimation can be made on which passengers arrive at the platform at a certain time and thereby construct a passenger arrival distribution and a crowding estimation at the platform.

What has not been researched yet are the previously mentioned factors in combination with the impact of transferring passengers on stations, especially in the case of a difference in service frequency. Assuming the availability of smart card data, an extensive analysis of behaviour of transfer passengers can be performed and can be used to analyse passenger behaviour on the system, with routing choices and passenger volumes being the most important factors. These factors are important variables to research the impact of transfer passengers on the dwell time of metro vehicles, which is next step in the transfer passenger journey.

2.2. Difference in service frequencies

An important factor in this research is the difference in service frequency between the metro line and the intercity rail line. However, not a lot of literature is available on this topic. One of the researches that has been performed in this area is by Guo, Bai, Hu, Zhuang, and Feng (2020). In this research a mathematical optimization method was developed to minimize the waiting time of passengers at the connecting station. Their optimization can provide useful input for this research considering the way the timetable was optimized to minimise the passenger waiting time. However, as the interest of this research lies more in the propagation of delays throughout the network and also consider passengers downstream of the transfer station it fundamentally differs from the research by Guo et al. (2020).

Sun et al. (2014) researched a demand-driven timetable for metro services. They conclude that current peak/off-peak based schedules may fail to meet the dynamic and temporal nature of passenger demand. Using smart card data, they propose three optimization models to design demand driven timetables, with different goals: optimal design, optimal operation and optimal peak/off-peak. Their method is not specifically tailored to accommodate for transfer passenger arrivals, however as does accommodate for the variance in passenger demand their optimization methods are an interesting input for this research.

2.3. Dwell time

Dwell time in rail systems has been researched for many years. The dwell time of a (rail)vehicle includes the time it takes to open the doors, exchange the passengers at the station and again close the door. Already 1992 in research by Lin and Wilson (1992) a dwell time model was developed which could predict the dwell time of a light rail vehicle based on the number of passengers boarding and alighting and the level of crowding on board.

Especially in high frequency rail systems, where train arrivals can occur up to every 2 or 3 minutes, the dwell time of the vehicle becomes an important determinant for the capacity of the line (Harris, 2006). In general railway operators use a fixed time in the schedule for vehicles to dwell at a station. However, a fixed time is in reality often not the case. Especially in high frequency systems, a small deviation in dwell time of several seconds can already significantly affect the operation of the line (Luangboriboon, Seriani, & Fujiyama, 2020). Pardini-Susacasa (2020) also concluded that a lot of rescheduling models, used for disruption management and to be explained further in section 2.4, are too theoretical because they do not account for passenger interactions with the vehicle. This interaction can be seen twofold: the time it takes for passengers to alight and board during the dwell time of the vehicle is not accounted for in these models, but also the increased passenger demand at a station in case of a delayed vehicle, even further increasing the dwell time and thereby the delay. Therefore it's important to understand what factors are of influence on the dwell time. Christoforou, Chandakas, and Kaparias (2020) did an extensive analysis of factors that determine the dwell time of an urban light rail line in France. There was found that, besides the expected indicators, the number of passengers that alights and boards the vehicle and passenger volume on board the vehicle, the dwell time is significantly longer at stations close to points of interest and at stations offering a lot of connections. This last factor indicates that there is indeed a correlation between transfer passengers and the dwell time of a vehicle.

In Cats, West, and Eliasson (2016) a formula to calculate the dwell time of a metro vehicle is presented. It consists of the following components: passenger boarding flow, on-board flow and alighting flow. This describes the passenger exchange part of the dwell time. Additionally the following factors are of influence on the dwell time: technical features of the rolling stock, timetable, signaling, passenger distribution over the platform, number of passengers carrying luggage and driver behaviour (Cornet et al., 2019). All the components that make up the dwell time of a vehicle are depicted in Figure 2.1 Looking at the passenger exchange part of the dwell time, Puong, (2000) concludes that the number of passengers boarding and alighting linearly increases the dwell time. However, the onboard crowding level attributes to this dwell time on a nonlinear way. This was further researched by Luangboriboon et al. (2020), who conclude that with increasing on board passenger density the boarding and alighting rate also increases, until the onboard passenger density reaches 2.5-3 passengers per square meter. After this point, there is no clear direction of this rate increasing or decreasing, indicating that additional crowding doesn't necessarily lead to different boarding or alighting rates. The main important determinant in the process is thus the volume of passengers boarding and alighting. The arrival of transfer passenger flows can strongly influence this variable. Therefore these dwell time functions are very relevant in researching the correlation between transfer passenger flows and the dwell time of a vehicle.

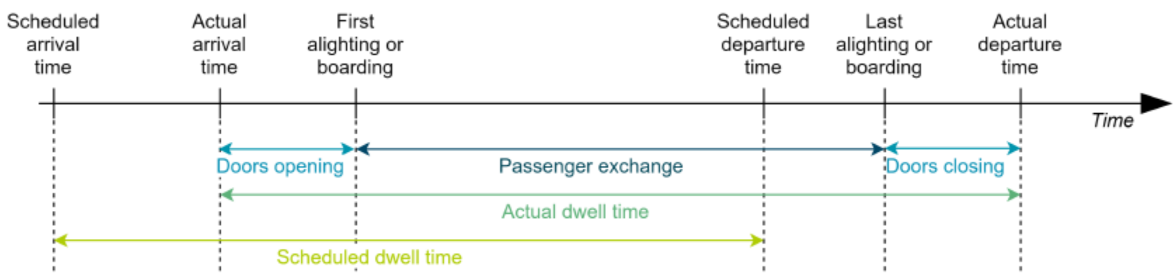


Figure 2.1: Illustration of dwell time components (Pardini-Susacasa, 2020) (Cornet et al., 2019)

By being able to more accurately predict the demand for metro services from passengers and especially transfer passengers and by being able to quantify the relation between these transfer passengers and the dwell time of a vehicle, these dwell time can be predicted more accurately in advance and real time, enabling options to apply real time rescheduling measures, prevent vehicle bunching and reduce the number of disturbances and delays.

2.4. Vehicle bunching

Guo et al. (2020) already researched how the timetable of a metro line can be optimized for passenger demand from intercity railways using a mathematical optimization model. It was found that passenger waiting time at the transfer station can be significantly reduced when taking as objective minimizing passenger waiting time at connecting stations. It is also pointed out that there is indeed a significant impact of these transfer passenger flows on the timetable of the metro line. However, in this paper the impact this has is not quantified as such and the possibility of delay propagation throughout the rest of the network is not considered, therefore also other possibilities to take into account this effect and minimize its impact will be explored.

Railway timetables are constructed in such a way that when operated exactly as planned, no conflicts arise. However, disturbances and even disruptions are always inevitable, causing deviations from the timetables, delays and vehicle bunching. Pardini-Susacasa (2020) investigated the effect of passenger demand, as being one of the important factors in passenger boarding and alighting rates, on the development of disturbances and delays throughout the network. There is concluded that passenger interaction with vehicles can have a significant impact on the development of disturbances throughout the network by causing *vehicle bunching*. This bunching effect is illustrated in Figure 2.2. It occurs when a vehicle, in the Figure vehicle B, gets delayed and has to pick up more passengers at the next station, leading to a longer dwell time. This vehicle then gets even further delayed. The vehicle behind, vehicle C in Figure 2.2, is relatively empty due to the delayed vehicle being close by. This vehicle then has shorter dwell times due to fewer passengers having arrived in the meantime, causing these vehicles to eventually drive in close proximity, 'bunching together', creating an uneven headway. This effect has been researched quite often in literature, especially for bus systems. However, practical applications and live experiments for as well bus systems (Berrebi, Óg Crudden, & Watkins, 2018) as rail systems (Altazin et al., 2020) remain limited.

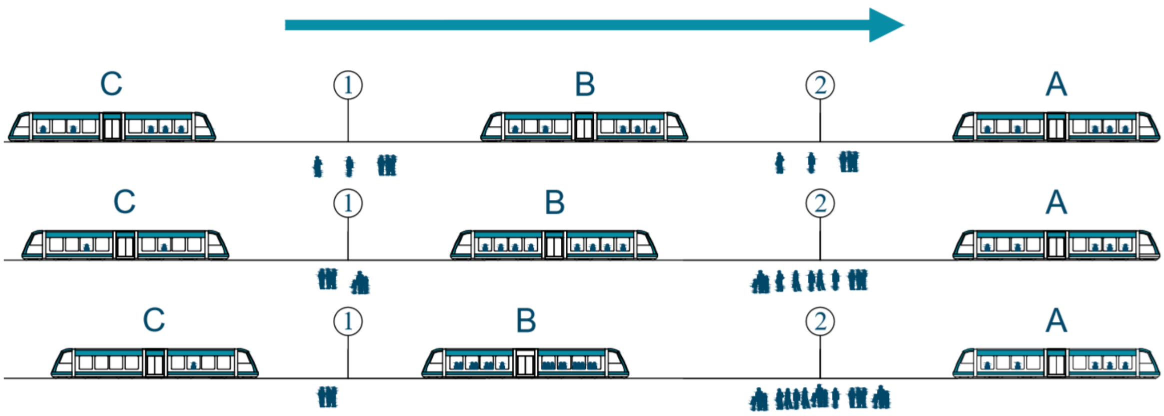


Figure 2.2: Illustration of bunching in a rail bounded line (Pardini-Susacasa, 2020)

This vehicle bunching problem, has already been researched for a long time, especially for bus lines (Fonzone, Schmöcker, & Liu, 2015). However, also other public transport modes have to deal with this problem. The bunching problem occurs when a disruption of a vehicle causes a delay and starts the negative feedback loop for accumulating passengers for the delayed vehicle, getting even more delayed and closer to the vehicle behind, which is relatively empty. Bunching is not necessarily always caused by a external delay, even an event as simple as a small peak or even dip in passenger demand can start the bunching effect (Fonzone et al., 2015).

2.5. Rescheduling measures

To minimise the impact of such disturbances, minimise delays and to prevent vehicle bunching, last minute rescheduling measures are used. There are a lot of measures that can be taken to reschedule a train. Several rescheduling measures that are often used and researched in literature are: increase the dwell time of a vehicle at a stop, increase or decrease vehicle speed between stations, dispatching a vehicle early, skipping a stop, change route, taking over another vehicle and short turning (Gkiotsalitis & Cats, 2021) .

In the past years real time rescheduling methods received a lot of attention in operations research. Fabian and Sánchez-Martínez (2017) found that to prevent bunching in railway lines, holding strategies aiming to even out head ways between vehicles are more effective than aiming for schedule adherence. However, achieving more even headways and thereby an increased service reliability not only requires the implementation of control strategies to achieve this. Currently most public transport operators contractually bound to on-time performance, with usually several 'measurement stops' along the route. With regularity based operations, these criteria disrupt the operations as the optimal regularity might not be the same as being on-time (Cats, 2014). Its therefore important in this research to identify the current policies and KPI's in place in the case study that will be researched. In the long term cultural shift towards regularity based operations is needed to enable public transport operators to adapt their agreements with authorities and update their business model (Cats, 2014).

Cacchiani et al. (2014) categorised several papers in this field into the following different categories: microscopic or macroscopic, disturbances and disruptions and focus on the trains or on the passengers. In this research there will be focused on disturbances in microscopic simulations, as its expected that transfer passenger flows will not cause disruptions but rather (small) disturbances. In order to be able to take into account passenger interactions with the vehicles, a microscopic approach is needed. As Pardini-Susacasa (2020) found that it is beneficial to optimize from a passenger objective, this also will be the case in this research.

Although rescheduling methods have been researched fairly frequently in recent years, the number of applications in real life still remains limited (Berrebi et al., 2018), (Cacchiani et al., 2014). Most metro dispatchers presently take rescheduling decisions manually based on experience and professional judgment, due to the lack of computational optimization models (Yin, Tang, Yang, Gao, & Ran, 2016). Though the number of applications remains limited, there are recent examples of successful implementations of real time rescheduling methods, for example in Paris (Altazin et al., 2020). With increasing computational power, the use of real-time rescheduling models therefore also has much more chance of succeeding in the future.

Another closely related field is the development of a framework to evaluate an metro timetable as a whole. Jiang, Hsu, Zhang, and Zou (2016) developed a modeling and solution approach to evaluate a public transport timetable based on big passenger data. Currently this method is only to evaluate the timetable statically, however the suggestion is also made to further develop this method for usage with the evaluation of actual operations, making it also an interesting application for real time rescheduling.

2.6. Scientific gap

In this section literature on research topics relevant to the journey of a passenger from a lower frequency heavy rail transportation mode to an metro higher frequency transportation mode has been presented. For each topic interesting findings relevant to this research were presented and several scientific gaps were identified.

The first gap that is identified is the impact of transfer passenger flows, in case of a difference in service frequency, on the development of delays and headway deviations in the higher frequency line. There are a lot of studies that concern travel time reliability and also studies that look at the behaviour of transfer passengers, however research into transfer passenger flows in the context of metro delays and headway deviations has not, to the best of the authors knowledge, been carried out yet. This research aims to fill this first scientific gap by analysing data of an high frequency metro line and connecting lower frequency heavy rail line and finding and quantifying the impact of transfer passengers between the two modes. The method for this analysis is further explained in 3.

With this improved knowledge this study aims to fill a second scientific gap: testing for rescheduling strategies with predicted influence of transfer passenger flows. This research combines knowledge on this field and model characteristics of a station on an high frequency metro line as well as a lower frequency heavy rail line which can be used to find recommended real time rescheduling strategies to minimise the impact of delays and headway diviations caused in the network by transfer passenger flows. For this an existing model is expanded, which is explained in 4.

In this study the aim is to make an unique combination of the three research topics discussed in this section. To the best of the authors knowledge, there has not been any research in which knowledge on transfer passengers flows, dwell time and rescheduling methods have been combined. It is useful to combine this knowledge because from a the view of a transfer passenger journey and the factors found in literature, logically it's very likely that transfer passenger flows are of influence on peaks in demand for metro vehicles, which then influences the dwell time of a vehicle, leading to unexpected delays, headway deviations and possibly vehicle bunching.

With the possible rescheduling strategies found in this study the aim is eventually to increase the service reliability and thereby also the efficiency of the system. With service reliability being one of the most important level-of-service determinants for both public transport users as well as for attracting car users, the are significant societal benefits (Cats, 2014).

3

Transfer Passenger Impact Analysis

The main research question of this research is defined as follows: *What impact do transfer passenger flows from lower frequency railway transportation mode have on disturbances in high frequency metro networks and which control and rescheduling methods are recommended to minimise these disturbances?* To find the answer to the main research question, first the four identified sub questions need to be answered. The research setup and the characteristics of the system researched are discussed in section 3.1. The first sub question is defined as follows: *Using smart card data, what correlations between transfer passengers from a lower frequency rail mode and disturbances in an higher frequency rail network can be found and how can this be quantified?* In the remainder of this chapter focuses on capturing the correlation between the arrival of transfer passengers from an intercity railway (hereafter referred to as rail) network to a metro network and the the impact this has on the development of delays and headway deviations in the metro network. This is done to quantify this correlation and determine to what extent passenger demand and disturbances to the metro network can be predicted based on rail arrivals to the transfer station. To determine what correlations are present and how they can be quantified, a data set from a case study is needed. The correlation of main interest is the number of transferring passengers from rail to metro and the demand, and thereby dwell time, for the next arriving metro vehicle(s). To research this correlation, smart card data is analysed from a station that accommodates a rail - metro transfer. In this station the rail connection should provide a lower frequency and higher capacity per vehicle than the metro, and a metro connection which should provide a higher frequency and lower capacity per vehicle than the rail connection. To obtain such smart card data for analysis, a case study with the specified characteristics is needed. In this study the metro network of Rotterdam is used. This case study is further explained in 5.1.

In this chapter, the method for obtaining and analysing the data used to research this correlation is explained. All the data described in this section is obtained in cooperation with a metro network operator, RET, and the national railway network operator NS. In section 3.2 the input data that is used and how it is processed is discussed. In section 3.3 is explained how the correlation analysis is performed, and what correlations were researched.

3.1. Problem Specification

In section 2.6 several scientific gaps that this research aims to fill are discussed. Based on these scientific gaps a problem specification is given in this section. The first gap that is identified is the impact of transfer passenger flows, in case of a difference in service frequency, on the reliability of the higher frequency line. The expectation is that passengers arriving from a lower frequency train service arrive in relatively large quantities, creating a higher demand for the next arriving metro vehicle, causing a longer dwell time and possibly delays. However, to what extent are these transfer passenger flows a contributing factor to an increase in dwell time and delay development? To quantify this a correlation analysis is performed, with as input passenger smart card data and vehicle data, and a quantified correlation between the arrival of transfer passengers and delays in the network as output. In this research there is focused on a system in which the high frequency system is a metro network which runs with a frequency of 18 metros per hour per direction on alternating lines and is connected to a train network which runs at a frequency of 8 trains per hour per direction on alternating lines, resulting in a 2.25 times higher frequency for the metro network than for the train network. For the analysis of transfer passenger flows the analysis performed in one single station with a transfer possibility between the two modes. There is only focused on the train to metro transfer, the other way around is not considered.

To assess the propagation of delays and vehicle bunching in the network, surrounding stations in the network need to be considered as well. Because the busiest section of the line is serviced by multiple lines, which then separate into different directions at certain stations, a decision is made to focus on the part of the network where the different lines are running on the same infrastructure. The stations that are covered on this part of the line will be considered, other stations disregarded. This is done because in this part of the network the chance of bunching vehicles is the highest and the impact of small delays is expected to be the largest.

For the next scientific gap, the testing of rescheduling methods with a modelling of transfer passenger flows using the obtained parameters from the correlation analysis is performed. For this purpose a simulation model that takes into account passenger-vehicle interactions developed by Pardini-Susacasa (2020) is used. This object oriented model simulates the metro network using data from the case study metro network and historical passenger and vehicle realisation data. The goal of this model is to test a set of rescheduling measures to see which combination would yield the most benefit for the passenger when taking into account possible disturbances caused by transfer passenger flows.

In this model the parameters obtained from the correlation analysis are used as input to obtain dwell time functions for each station simulated in the network, which are then used together with historical passenger numbers representative for the morning peak to yield a correct representation of dwell times at all stations. On the outcomes of this simulated real world model a rescheduling model is then applied which reschedules the timetable for the benefit of the passenger. This is done over several iterations, which results in an improved timetable in which the overall travel time of passengers is reduced. An overview of the input and expected output of the correlation analysis and the rescheduling model is presented in Figure 3.1. In this model the same selection of stations as for the correlation analysis is used for the testing of rescheduling measures, however the simulation is performed for the entire network. Metros will thus not be rescheduled outside the selected corridor, but will run their entire route in the simulation. This way conclusions drawn on the focus part of this study also take into account the remainder of the trip of a metro.

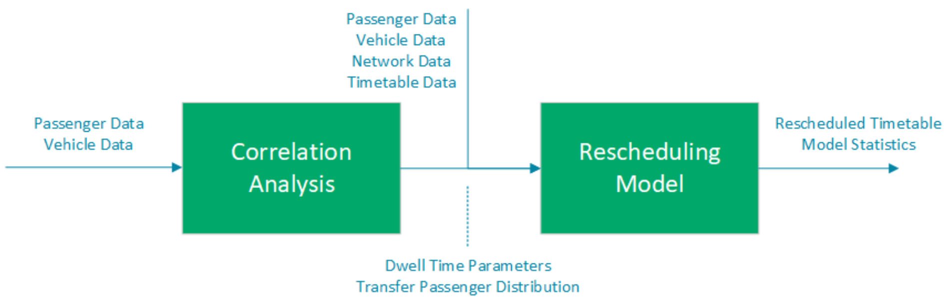


Figure 3.1: Input and Expected output of the correlation analyses and Rescheduling model

In this research the focus of determining the dwell time and delay development lies in the passenger demand component. Therefore no other disruptions and disturbances are considered in this simulation. This also includes peaks in demand on other stations than the transfer station: for the studied transfer station a detailed historical arrival pattern is used to determine passengers arriving at the station, for other stations simulated in the network an average number of arriving passengers per minute is taken for the entire morning peak, resulting in an even arrival pattern of passengers at other stations, but representative for the number of passengers for the respective station. Several experiments are performed with this simulation model are performed to obtain recommended rescheduling methods to deal with the peaks in passenger demand at the transfer station.

There are many more factors that could contribute to the dwell time of a vehicle or to delay development in the network. In Figure 3.2 an causal diagram is shown of what components can influence the dwell time and development of delays in the network. The items inside the green line marked model boundary are included in the considerations made in this study, the items outside the green box also can also impact the dwell time and delay development, but are not considered in this study.

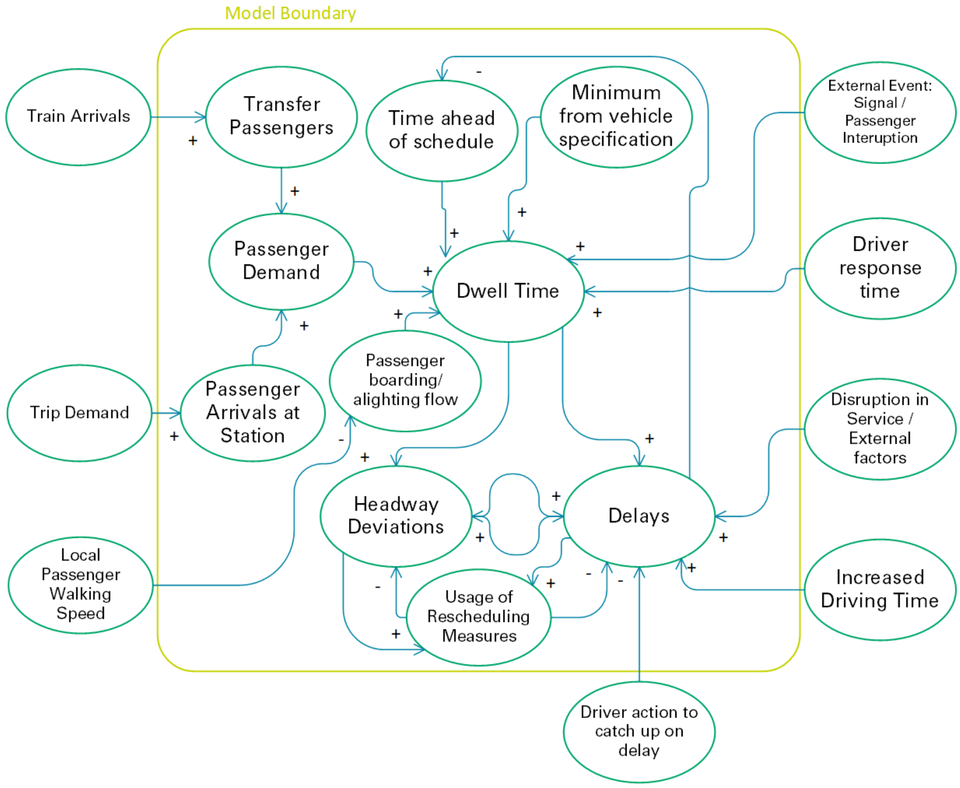


Figure 3.2: Input and Expected output of the correlation analyses and Rescheduling model

The modelling study thus makes use of historical data and optimizes the timetable in retrospect. Conclusions drawn from this model will point out what measures are best applicable in specific scenario's, but with the important assumption that the behaviour of passengers is already known upfront. Therefore the model is not usable real-time. In the remainder of this Chapter the data used as input is further explained as well as the method used to obtain the correlation parameters. In the next Chatper the setup of the simulation study is further elaborated on.

3.2. Input data

To obtain insight in the expected correlation between transfer passenger flows and delays or headway deviations to the next arriving metro vehicle(s), data is needed to quantify this. The input data that is used to study this and how it's processed is discussed in this section. For each data type is discussed what parameters are obtained and how they are processed.

3.2.1. Passenger data

The first step is to discover the share of transfer passengers from the national rail network to the metro in the total of boarding passengers at the station. Specifically what is important is to identify peaks in demand that are caused by these transfer passengers from rail to metro. For this smart card data (automatic fare collection data) is used from a system that requires a tap-in upon entering the station and a tap-out at the destination station in both systems. Additionally when switching from public transport carrier, i.e. switching from rail to metro or vice versa, a tap-in and tap-out are required. The total amount of tap-ins in the station is needed and which of these tap-ins came from the national railway. These

Table 3.1: Parameters obtained from the passenger data set

Parameter	Definition
$Date_{tap-in}$	Date of the tap-in
T_{tap-in}	Tap-in time for each tap-in HH:MM:SS
$Location_{tap-in}$	Location of the tap-in at the station, train platform or general entrance
Pax_{origin}	Passenger originating at the transfer station, 0 or 1.
$Pax_{transfer}$	Passenger transferring from rail to metro at the transfer station, 0 or 1
Pax_{total}	Sum of Pax_{origin} and Pax_{total}

tap-ins are anonymous timestamps of when a person tapped in at the station and contain the following information: date of tap-in ($Date_{tap-in}$), time of tap-in (T_{tap-in}) and tap-in location ($Location_{tap-in}$) in the station. Using the location of the tap-in at the station there can be derived if a metro passenger was originating at the station (Pax_{origin}) or that the passenger transferred from national rail ($Pax_{transfer}$), as transfer passengers have to tap in on the train platform itself. The total number of passengers boarding the metros (Pax_{total}) is thus made up of the sum of Pax_{origin} and $Pax_{transfer}$. The expectation is that these possible effects have the strongest presence during peak hours. It is therefore important that the obtained data contains sufficient peak hours for a valid analysis.

This data is processed in such a way that per minute the total number of tap-ins can be determined and which of these tap-ins came from the national railway. The parameters in this passenger data set and their definition can be found in Table 3.1.

3.2.2. Vehicle data

To be able to link data on transfer passengers to specific metro vehicles, vehicle data is needed. For this automatic vehicle location (AVL) data is used for the same period of time as the tap-in data. This data set includes the date of the departure ($Date_{departure}$), the scheduled and realised arrival times (STA, ATA) and departure times (STD, ATD) of all metros at the researched transfer station and at all other stations on the line operated. With this information the dwell time T_{dwell} of each metro vehicle can be calculated, as well as the arrival delay (T_{adelay}), departure delay (T_{ddelay}) and deviation from the planned headway ($\delta_{headway}$) of each metro vehicle at each station on the researched line. Additionally this data set includes the passenger load of each vehicle between every station (Pax_{Load}) and the number of passengers that boarded (Pax_b) and alighted (Pax_a) each vehicle. With this information also the total number of passengers exchanged at a station can be easily calculated (Pax_{ba}). These passenger load and exchange parameters are determined by metro operator, and they can therefore differ from the Pax_{total} from the previous section. The reason for this is that they are based on not only the tap-in data but a combination of tap-in data, tap-out data, AVL-data and metro occupation information (RET, 2020). However, in these passenger loads per vehicles no distinction can be made in whether the passengers that boarded a certain metro were transfer passengers. To do this the tap-in data is thus used. However, this tap-in data is only used to indicate metro vehicles that were possibly affected by transfer passenger flows and not to determine the passenger loads and exchange numbers, as the estimation of the metro operator is based on more parameters than only tap-in data and can thus be considered to be more accurate. A complete overview of all data that is obtained in the vehicle data set can be found in 3.2.

Next to vehicle data from the metro network also vehicle data from the rail network is obtained. In this data set the focus is on the arrivals of trains to the studied transfer station. This data set includes the date of the arrival ($Date_{arrival}$), the scheduled and realised arrival times of each train at the transfer station (STA, ATA), and the arrival delay (T_{adelay}) of each train. An overview of the parameters in this data set is given in Table 3.3.

3.2.3. Station characteristics

To estimate which tap-in corresponds to a vehicle that a passenger actually took, assumptions have to be made on the distribution of the walking times from a heavy rail train to the platform of the metro line. A distribution is determined based on the physical characteristics of the station together with the general walking characteristics of passengers as found by Bosina and Weidmann (2017). The average

Table 3.2: Data obtained from the metro vehicle data set (RET)

Parameter	Definition
$Date_{departure}$	Date of the departure
STD	Scheduled departure time
ATD	Actual departure time
STA	Scheduled arrival time
ATA	Actual arrival time
T_{dwell}	Dwell time of the vehicle
T_{adelay}	Arrival delay of the vehicle, |STA-ATA|, in seconds
T_{ddelay}	Departure delay of the vehicle, |STD-ATD|, in seconds
$\delta_{headway}$	Deviation from the planned headway at departure
Pax_{Load}	Number of passengers on board when the vehicle departs
Pax_b	Number of passengers boarding the vehicle
Pax_a	Number of passengers alighting the vehicle
Pax_{ba}	Total of passengers boarding and alighting the vehicle

Table 3.3: Parameters obtained from the rail vehicle data set (NS)

Parameter	Definition
$Date_{arrival}$	Date of the departure
STA	Scheduled arrival time
ATA	Actual arrival time
T_{adelay}	Arrival delay of the vehicle, |STA-ATA|, in seconds

walking speeds that are used in this research can be found in Table 3.4. The average walking distance is obtained by measuring the distance from tap-in location at the train platform to the metro platform.

Table 3.4: Reference walking speeds from (Bosina & Weidmann, 2017)

Facility	Walking Speed (m/s)
Regular (Netherlands)	1.43
Stairs	0.76

3.3. Correlation analysis

With this input data the analysis of correlations is performed. To find and quantify correlations between transfer passenger flows and metro vehicles several correlation analysis are performed. The goal is to find out what the impact of transfer passengers on the reliability of metro vehicles is. To do this, several steps are taken: first the correlation between peaks in passenger demand and the arrival of transfer passengers is analysed, in order to determine if peaks in passenger demand are indeed caused by the arrival of transfer passengers, and to what extent. Then is looked at to what extend this impacts the dwell time of the next arriving metro vehicle, and finally the impact of a varying dwell time on the headway and delays of metro vehicles is researched. For each expected correlation is tested if and to what extend this correlation is present. A schematic overview of the correlation analysis can be found in Figure 3.3. Each correlation is expected to have a positive correlation, i.e. an increase arriving transfer passengers will lead to an increase in total passenger demand. This is indicated with a '+' sign. For all correlations researched in this section the statistical processing software SPSS is used. Excel was used for pre-processing the data in the correct format.

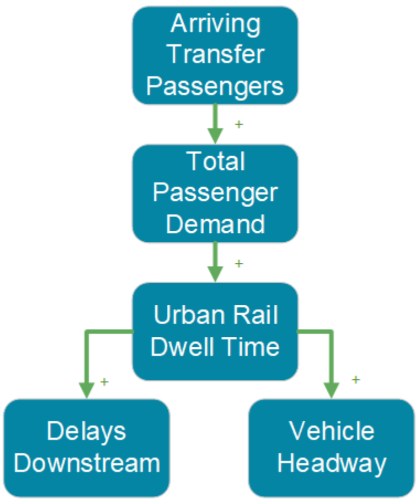


Figure 3.3: Schematic overview of the correlation analysis

3.3.1. Passenger demand - Number of transfer passengers

To determine to what extend the variance in the total passenger demand for the next arriving metro vehicle is explained by the number of transfer passengers, a linear regression analysis is performed. The goal of this analysis is to obtain a predicting parameter to predict the total passenger demand for the next metro(s) based on the number of transfer passengers. This is done using formula (3.1), in which the total number of passengers (Pax_{total}) is predicted using the number of transfer passengers ($Pax_{transfer}$), the correlation coefficient ($\beta_1^{Paxtotal}$), the corresponding constant ($\beta_0^{Paxtotal}$) and error term ϵ. The regression parameter $\beta_1^{Paxtotal}$ is estimated using formula (3.2), in which every data point in Pax_{total} and $Pax_{transfer}$ is compared to its corresponding mean $\overline{Pax_{total}}$) and $\overline{Pax_{transfer}}$ and divided by the number of cases n. The regression constant (3.3) is obtained using the obtained $\beta_1^{Paxtotal}$ and the means of $\overline{Pax_{transfer}}$ and $\overline{Pax_{total}}$). The R^2 is calculated to determine to what extend the variance in Pax_{total} is explained by $Pax_{transfer}$. This is done using formula using formula (3.4), in which the explained variance $(\hat{Pax_{total_i}} - \overline{Pax_{total}})^2$ is divided by the unexplained variance $\sum_{i=1}^{n}(Pax_{total_i} - \overline{Pax_{total}})^2$.

$$Pax_{total} = \beta_0^{Paxtotal} + \beta_1^{Paxtotal} Pax_{transfer} + \epsilon \tag{3.1}$$

$$\beta_1^{Paxtotal} = \frac{\sum_{i=1}^{n}(Pax_{total} - \overline{Pax_{total}})(Pax_{transfer} - \overline{Pax_{transfer}})/n}{\sum_{i=1}^{n}(Pax_{total} - \overline{Pax_{total}})^2/n} \tag{3.2}$$

$$\beta_0^{Paxtotal} = \overline{Pax_{total}} - \beta_1^{Paxtotal}\overline{Pax_{transfer}} \tag{3.3}$$

$$R^2_{Paxtotal} = \frac{\sum_{i=1}^{n}(\hat{Pax_{total_i}} - \overline{Pax_{total}})^2}{\sum_{i=1}^{n}(Pax_{total_i} - \overline{Pax_{total}})^2} \tag{3.4}$$

3.3.2. Passenger demand - Metro dwell time

When is determined to what extend peaks in passenger demand are caused by transfer passengers, the next step in the process is to look at what impact this has on the dwell time of the next arriving metro vehicle. As is already often determined in literature and explained in section 2.3, there is a correlation between the number of boarding and alighting passengers, passenger load and dwell time. However, the exact correlation between the number of boarding and alighting passengers and dwell time depends on a lot of different factors such as the number of doors in the vehicle, the station layout and demographics of the passengers. Therefore the correlation between passenger demand and the dwell time of the metro vehicle is also researched for this case study. This is done once again using a regression analysis, using the same formulas as in section 3.3.1. With formula (3.5) the goal is to predict the dwell time (T_{dwell}) of an metro vehicle based on the number of boarding (Pax_b) and alighting passengers (Pax_a) and in the passenger load (Pax_l). The formulas used to calculate the correlation coefficients are presented in (3.6), (3.7) and the R^2 is calculated in formula (3.8).

$$T_{Dwell} = \beta_c^{dwell} + \beta_b a^{dwell} Pax_{ba} + \epsilon \tag{3.5}$$

$$\beta_1^{dwell} = \frac{\sum_{i=1}^{n}(T_{dwell} - \overline{T_{dwell}})(Pax_{ba} - \overline{Pax_{ba}})/n}{\sum_{i=1}^{n}(T_{dwell} - \overline{Pax_{ba}})^2/n} \tag{3.6}$$

$$\beta_0^{dwell} = \overline{T_{dwell}} - \beta_1^{dwell}\overline{Pax_{ba}} \tag{3.7}$$

$$R^2_{dwell} = \frac{\sum_{i=1}^{n}(\hat{T_{dwell_i}} - \overline{T_{dwell}})^2}{\sum_{i=1}^{n}(T_{dwell_i} - \overline{T_{dwell}})^2} \tag{3.8}$$

This regression analysis in (3.5) is in the first place done for all cases, but also several subsets of the data are explored. This is done because when considering all cases in this regression analysis there is a high chance of picking up a lot of 'noise' in determining the correlation. For example metros that arrive early to a station can have a longer dwell time to sync with the schedule again, or late at night a passenger holding the door for another passenger causing also causing the metro to have a longer dwell time. These metros are then registered with a longer dwell time which was not caused by the number of passengers boarding and alighting. By exploring subsets of the data there is aimed to obtain a more pure effect of passenger demand on the dwell time of a metro.

The first subset that is explored is, that as the expectation is that the impact of transfer passengers is more strongly visible during morning peak hours, an analysis with only the morning peak hours included. This includes metro vehicles that departed from Rotterdam Blaak between 6.00am - 10.00am. The second subset that is explored is one with metros that are specifically affected by transfer passenger flows. The goal of exploring this subset is to find out whether the impact of passenger demand on the dwell time differs in case of metros affected by transfer passenger flows as opposed to other metros. This is done for different threshold values that classify a train as 'affected by transfer passengers', ranging from 20 transfer passengers to up to more than 60. This classification is done based on tap-in data, which can differ from the actual number of passengers boarding a metro. However, the expectation is that, as most passengers will board the next arriving metro, that it is a good indicator. The third subset that is explored is one which only includes metro vehicles that were already delayed upon arrival in Rotterdam Blaak. This to exclude metro vehicles that arrived early and therefore had a longer dwell time at the station. For all subsets parameters are obtained and compared to see which yields the best results and the highest explanation R^2.

Next to the regression analysis it is tested whether the dwell time of metro vehicles 'affected by transfer passengers' significantly differs from other departures of metro vehicles during the day, and to what extend. This is also done for different threshold values of the number of transfer passengers and is done through a Student's T-test. In this Student's T-test the null hypotheses (H_0) is that there is no significant difference between the dwell time of an metro vehicle affected by transfer passengers and other metro vehicles stopping at the transfer station. The alternative hypotheses (H_1) is that there is a significant difference. The Student's T-test is performed assuming in-dependant samples, because the arrivals marked as 'effected by transfer passengers' are different arriving metros then the other metros, i.e. the same arrival is not measured twice. The formula for the Student's T-test is presented in figure (3.9), in which the test value t is calculated by dividing the averages of the dwell time groups compared, in this case denoted with T_{dwell1} for the first group and T_{dwell2} for the second group, by the standard deviation of the difference $s_{\overline{T_{dwell1}}-\overline{T_{dwell2}}}$. This standard devation of the difference is calculated in formula (3.10) using the estimators of the variance for both groups s_{dwell1} and s_{dwell2}.

$$t = \frac{\overline{T_{dwell1}} - \overline{T_{dwell2}}}{s_{\overline{T_{dwell1}}-\overline{T_{dwell2}}}} \tag{3.9}$$

$$s_{\overline{T_{dwell1}}-\overline{T_{dwell2}}} = \sqrt{\frac{s^2_{dwell1}}{n_{dwell1}} + \frac{s^2_{dwell2}}{n_{dwell2}}} \tag{3.10}$$

3.3.3. Metro dwell time - Delays downstream

The third step in determining the correlation between transfer passenger flows and the reliability of metro vehicles is to analyse the correlation between the dwell time of metro vehicles at the transfer station and delays of that same metro vehicle downstream, either at the next station or further down the line. The expectation is that vehicles which experience a longer dwell time at the transfer station will eventually be more vulnerable to having delays further down the line. To see if this effect is also present in the data, firstly the average delay of the metro line is plotted to see if there is an increase in delay visible after the case station in which passengers transfer. Thereafter once again a regression analysis is performed, in which the correlation between the dwell time and delay of the metro vehicle is tested for several stations along the line. The goal is to predict the delay at station i ($T_{delay}^{station_i}$) that will occur based on the dwell time (T_{dwell}) of the vehicle at the transfer station. Several stations from the main transfer station until the final station of the line are used for this analysis, to also determine to what extand delays propagate through the network. Once again this is done with the same formulas as in the previous sections. The formula used for the prediction is presented in (3.11). The estimation of the parameters of this formula is done in formulas (3.12), (3.13) and the correlation coefficient is calculated in (3.18).

$$T_{Delay}^{Station_i} = \beta_0^{delay} + \beta_1^{delay} T_{dwell} + \epsilon \tag{3.11}$$

$$\beta_1^{delay} = \frac{\sum_{i=1}^{n}(T_{delay}^{Station_i} - \overline{T_{delay}^{Station_i}})(T_{dwell} - \overline{T_{dwell}})/n}{\sum_{i=1}^{n}(T_{delay}^{Station_i} - \overline{T_{dwell}})^2/n} \tag{3.12}$$

$$\beta_0^{delay} = \overline{T_{delay}^{Station_i}} - \beta_1^{delay}\overline{T_{dwell}} \tag{3.13}$$

$$R_{delay}^2 = \frac{\sum_{i=1}^{n}(\hat{T}_{delay_i}^{Station_i} - \overline{T_{delay}^{Station_i}})^2}{\sum_{i=1}^{n}(T_{delay_i}^{Station_i} - \overline{T_{delay}^{Station_i}})^2} \tag{3.14}$$

An variant on this analyse that is also explored, is not to correlate the dwell time of the metro to the delay, but rather compare the delay of a metro vehicle at the transfer station to the delay downstream. In this case instead of T_{dwell} the delay at the transfer station $T_{delay}^{station_{transfer}}$ is used as predictor. This analysis is done to determine to what extent vehicle already delayed at the transfer station is more likely to suffer from an (increased) delay further down the line.

Additional to only having the dwell time at the transfer station as predicting variable for the delays downstream, there is also looked at how the dwell time relates to other factors that can contribute to a possible delay of the vehicle. The factors that are also considered and added to the correlation analysis are:

- Driving time between stations
- Passenger volume boarding and alighting at the station on which the delay analysis is performed
- Crowding in the vehicle

3.3.4. Metro dwell time - Metro headway

Finally the last step of this correlation analysis is to test to what extent transfer passenger flows impact the headway of the metro line. The goal of this analysis is to determine to what extent the dwell time of a metro headway can be used to predict deviations in headway further down the line. Deviation from headway is measured in deviation from the planned headway and not necessarily towards an even headway. For headway deviation there is also first looked at several stations on the line and the average headway deviation a metro has. The next step is to once again perform a regression analysis between the dwell time (T_{dwell}) and the deviation a metro has from the scheduled headway (δ_{hw}). The same regression analysis as in the previous sections is used. The formula for this regression analysis is given in (3.15). The formulas for the parameter estimation are presented in (3.16) and (3.17). To what extent the deviation in headway can be predicted by the dwell time is determined by calculating the R_{hw}^2 in (3.18). This is done for several 'measure points', in the form of stations further down the line, as well as an averaged headway deviation for the remainder of the journey, from the transfer station to the end of the line, correlated to the dwell time this vehicle has at the station connecting to the national railway network.

$$\delta_{hw} = \beta_0^{hw} + \beta_1^{hw} T_{dwell} + \epsilon \tag{3.15}$$

$$\beta_1^{hw} = \frac{\sum_{i=1}^{n}(\delta_{hw} - \overline{\delta_{hw}})(T_{dwell} - \overline{T_{dwell}})/n}{\sum_{i=1}^{n}(\delta_{hw} - \overline{T_{dwell}})^2/n} \tag{3.16}$$

$$\beta_0^{hw} = \overline{\delta_{hw}} - \beta_1^{hw}\overline{T_{dwell}} \tag{3.17}$$

$$R_{hw}^2 = \frac{\sum_{i=1}^{n}(\hat{\delta_{hw_i}} - \overline{\delta_{hw}})^2}{\sum_{i=1}^{n}(\delta_{hw_i} - \overline{\delta_{hw}})^2} \tag{3.18}$$

3.4. Station Specific Parameters

The correlation analyses described in the previous sections only concern the correlations at the researched transfer station. To accurately model the stations around the researched transfer station and to get an accurate picture of delay development over the line, for each station station specific parameters are needed. For each station the dwell time of a specific metro vehicle should be calculated based on the number of boarding and alighting passengers and the passenger load on board of a vehicle. For these calculations thus the following parameters are needed: the estimated passenger demand at a station and dwell time parameters for each station.

3.4.1. Estimated Passenger Demand

As described in section 3.2 for the researched transfer station detailed check-in information is available and a very detailed passenger arrival distribution can be constructed. This is also necessary to accurately mimic train arrivals to the station. For the researched transfer station a detailed arrival distribution with number of arriving passengers per minute is made based on the check-in data for this station. However, for the other stations in the network this detailed check-in information is not available for this research. Therefore the average number of arriving passengers during morning-peak is calculated based on the number of boarding passengers at each station obtained from the vehicle data. To obtain the average number of passengers arriving at a station per minute, the number of boarding passengers in the busiest section of the morning rush hour, in the Netherlands considered to be between 7.30am and 8.30am (NS, 2017), is used.

The next step is then to determine the destination of these passengers. This is done based on the destination split as obtained by Pardini-Susacasa (2020). However, as this destination split is based on data from 2018, this destination split will be update with 2019 data based on the number of alighting passengers per station. This is done by calculating the share of alighting passengers for each station and in this way determine the split of passengers based on the split of alighting passengers combined with the historical destination split to obtain an updated destination split per station.

3.4.2. Dwell times

With the passenger numbers per station in place the next step is to obtain correct dwell time parameters for each station. For this an approach adapted from Pardini-Susacasa (2020) is used. The dwell time of a vehicle is dependant on multiple factors, as described in section 2.3. From this section can be concluded that the factors that are important in estimating the dwell time of a vehicle are: minimum dwell time of a vehicle based on technical factors (opening and closing of the doors and the minimal passenger exchange time), additional time for each additional boarding or alighting passenger and the speed of this passenger exchange based on the crowding level of the vehicle. From the dataset all these variables can be obtained. For each station the following parameters will be obtained using a regression analysis: A dwell time constant (the minimal dwell time of a vehicle), a factor for each boarding and alighting passenger and a factor for the load of a metro vehicle. The formula to calculate the dwell time based on these parameters is presented in formula 3.19.

$$T_{Dwell} = \beta_c^{dwell} + \beta_b^{dwell} Pax_b + \beta_a^{dwell} Pax_a + \beta_l^{dwell} Pax_l + \epsilon \tag{3.19}$$

With the quantification's obtained with this correlation analysis, the next step of this research is to update an existing simulation framework with these parameters to get an accurate simulation of these effects, enabling to test rescheduling measures for different scenarios in the context of peak demands caused by transfer passengers.

4

Model Development and Rescheduling Methods

To answer the remaining research questions, an existing simulation optimization framework is used in which parts of a metro network are modelled with a module which accounts for passenger vehicle interactions during operation. This framework is updated with the quantified correlation between transfer passengers from rail and the reliability of the metro network from chapter 3. With this updated framework rescheduling measures can be tested to cope with these transfer passenger flows. The simulation optimization framework that is used is developed by Pardini-Susacasa (2020). To understand how the framework developed by Pardini-Susacasa (2020) can be adapted for usage in this research, the basis of the framework developed in her research is explained first in section 4.1. In section 4.2 is explained what adaptations to this existing framework are made for usage in this research. In section 4.3 KPI's for the model are defined and in this section is explained how the verification of the model is performed. Finally in section 4.4 the scenarios that are planned to be ran with the model are explained an there is concluded how this framework will be used in this research. The explanation of this framework used is a brief recap of the framework. More information and underlying assumptions can be found in Pardini-Susacasa (2020).

4.1. Simulation Based Traffic Management for Metro Networks (SBTM-MN) framework

The findings from the previous chapter, chapter 3, are used to update the Simulation-Based Traffic Management for Metro Networks (SBTM-MN) developed by Pardini-Susacasa (2020). To understand how this is done and what results can be obtained by adapting this framework, first the basics of this framework are explained. The SBTM-MN framework is depicted in Figure 4.1 and is used to simulate a metro network with the goal to reduce the impact of disturbances in the network while accounting for the dynamic impact of passenger demand on the operation of metros. The framework consists of a Transport Simulation Model (TSM), Train Rescheduling Model (TRM), and a Transport Simulation Model of the Real World (TSM-RW). The SBTM-MN uses metro lines D and E of the metronetwork of Rotterdam as a case study for its simulation.

A simulation iteration is started with the TSM-RW which simulates the metro network for a given time horizon with Real-World data. The TSM-RW then feeds information such as train and station occupation and realised train events to the TSM. The TSM predicts passenger demand and distribution over the network and simulates train movements for a given time horizon. This is then used as input for the TRM. The TRM interacts iteratively with the TSM to reschedule the timetable for the benefit of the passengers. The TRM computes a rescheduled timetable for the given input of passenger demand and aims to minimize passenger journey times. It comes up with a tentative solution that is evaluated throughout a run in the simulation and is considered to be a linear programming problem (Pardini-Susacasa, 2020). This process is performed iteratively until the timetable no longer improves or starts

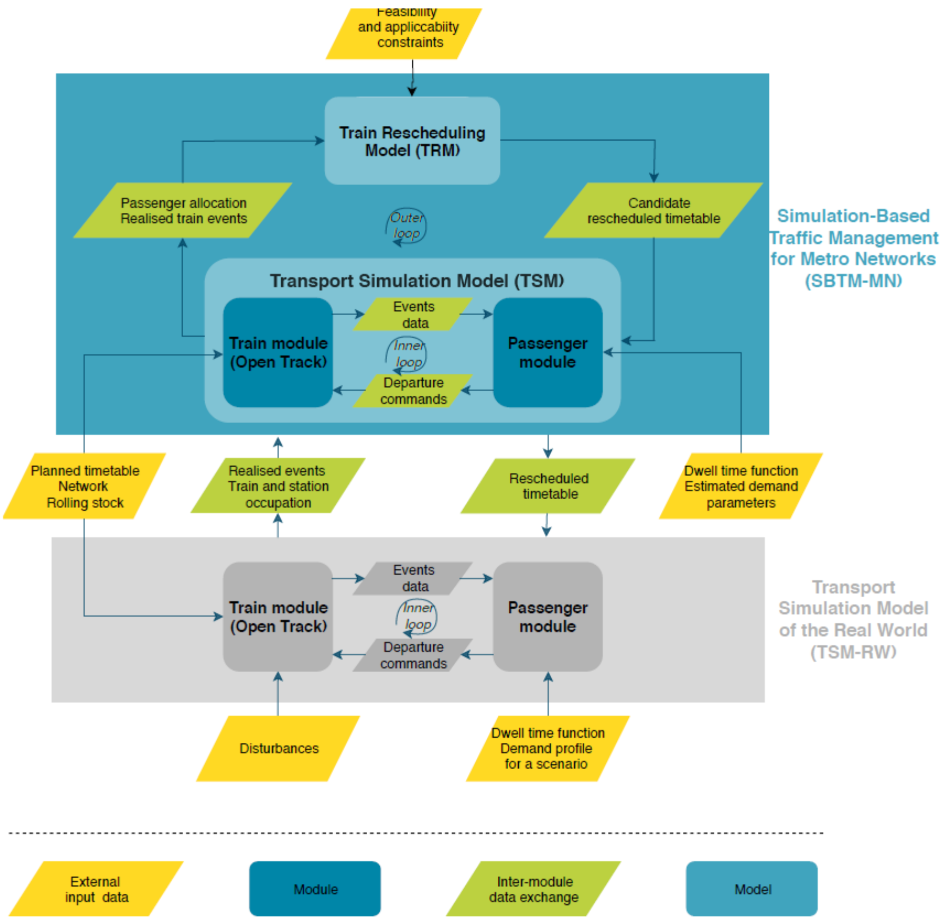


Figure 4.1: SBTM-MN Framework (Pardini-Susacasa, 2020)

to deteriorate. The best performing solution is then selected. In the next sections there is further elaborated on the functioning of each model element.

4.1.1. Transport Simulation Model of the Real World (TSM-RW)

The first part of the framework is the Transport Simulation Model of the Real World (TSM-RW). The TSM-RW simulates real world operations such as train movements, passenger rides and disturbances based on the actual conditions in the network. The TSM-RW triggers the SBTM-MN on different points in time and feeds the SBTM-MN with data from the simulation, such as realised events and occupation of train and stations.

Where the TSM works with obtained arrival rates which can be altered for different scenario runs, the TSM-RW works with actual historical smart card data. The TSM-RW thus aims to mimic the actual situation in the network as realistically as possible, whereas the TSM is used to test for different scenarios.

4.1.2. Transport Simulation Model (TSM)

The TSM consists of a train module and a passenger module. The train module is simulated in OpenTrack, a railway simulation tool developed by Hürlimann (2002) and is able to simulate different types of railway networks and run tests under different circumstances and with different parameters, enabling the testing of different scenarios and rescheduling measures. An example of the OpenTrack environment is depicted in Figure 4.2. The passenger module is used to model the interaction of passengers with the vehicle, which is not accounted for in OpenTrack. This passenger module estimates passenger demand based on station specific arrival rates and a destination split derived from historical data as well as real-time data from the modelled real world, which is provided by the TSM-RW explained in section 4.1.1. The station specific arrival rates are obtained through boarding passenger numbers for each station, and the destination split is based on historical chipcard data combined with alighting passenger numbers. The passenger module computes boarding and alighting rates for passengers at each stop, as well as the train load after departure, and keeps track of passenger movements. Each time a train arrival occurs in OpenTrack the passenger module is notified. The passenger module then calculates the dwell time based on the obtained passenger numbers and calculates the departure time of the train, and notifies the train module when a metro can depart again based on the calculated dwell time. This process is repeated until the section of the timetable that has to be optimized is simulated in the TSM. Once this process is completed the results are exported to the TRM.

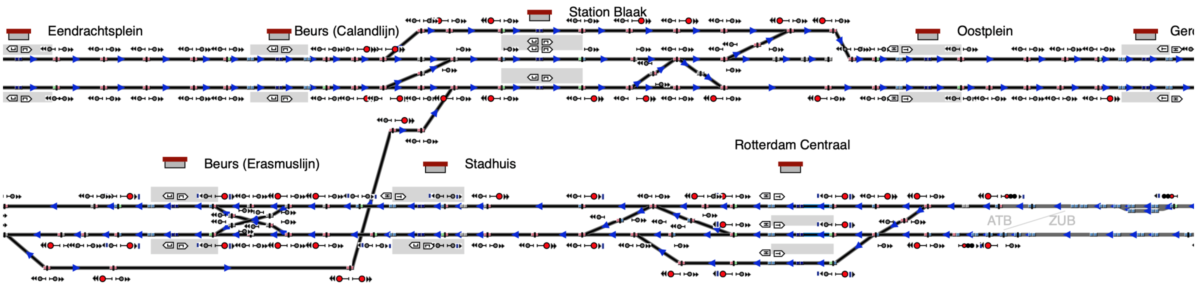


Figure 4.2: OpenTrack environment

4.1.3. Train Rescheduling Model (TRM)

There are several measures that can be taken to reschedule the timetable. The rescheduling measures that are incorporated in the SBTM-MN are the following:

- Increasing the dwell time of a train at the station
- Increasing or decreasing the speed of a train in a segment between two stations
- Dispatching a vehicle earlier or later than scheduled

Mathematical formulation

Timetable rescheduling in for railway networks is typically a multi-objective problem (Binder, Maknoon, & Bierlaire, 2016). The objective function of the TRM aims to minimize the waiting time for all passengers (W_t), the in vehicle time of all passengers (Ivt) , the deviation from the departure times of all metros at all stations ($Y_{s,m}$) and the deviation of arrival time of metro vehicles at the terminal (X_m). The weights that can be adjusted are to minimize for: passenger waiting time (β_w), minimize passenger in-vehicle time (β_i), the total deviation from the timetable (β_a) and to delays at the terminal station (β_t). All these factors are weighted accordingly to stress the importance of specific terms. These weights can be changed to tweak the objective, as they weight the different objectives in the objective function. In Table 4.1 all the parameters, variables and sets used in the TRM are summarized.

The mathematical formulation of the TRM is defined as follows:

Objective function (Pardini-Susacasa, 2020):

$$min \qquad \beta_w * Wt + \beta_i * Ivt + \beta_a * \sum_{m \in M} \sum_{s \in S^m} Y_{s,m} + \beta_t * \sum_{m \in M} X_m \tag{4.1}$$

Subject to (Pardini-Susacasa, 2020):

$$t_{s,m}^{dep} - t_{s,m}^{arr} \geq e_s^{min} \qquad \forall s \in S^m, m \in M \tag{4.2}$$

$$t_{s+1,m}^{arr} - t_{s,m}^{dep} \geq q_{s,s+1}^{min} \qquad \forall s \in S^m, m \in M \tag{4.3}$$

$$t_{s,m+1}^{dep} - t_{s,m}^{arr} \geq h_s^{out} \qquad \forall m \in M^{-,s}, s \in S \tag{4.4}$$

$$t_{s,m+1}^{dep} - t_{s,m}^{arr} \geq h_s^{in} \qquad \forall m \in M^{+,s}, s \in S \tag{4.5}$$

$$t_{s,n}^{dep} - t_{s,m}^{arr} \geq c_{m,n,s}^{min} \qquad \forall m, n, s \in V \tag{4.6}$$

$$t_{l,m}^{arr} - t_m^{arrs} \leq x_m \qquad \forall m \in M \tag{4.7}$$

$$t_m^{arrs} - t_{l,m}^{arr} \leq x_m \qquad \forall m \in M \tag{4.8}$$

$$t_{s,m}^{deps} - t_{s,m}^{dep} \leq Y_{s,m} \qquad \forall m \in M, s \in S^m \tag{4.9}$$

$$t_{s,m}^{dep} - t_{s,m}^{deps} \leq Y_{s,m} \qquad \forall m \in M, s \in S^m \tag{4.10}$$

$$t_{s,m}^{dep} - t_{s,m}^{depo} \leq u \qquad \forall S \in S, m \in M \tag{4.11}$$

$$t_{s,m}^{depo} - t_{s,m}^{dep} \leq u \qquad \forall S \in S, m \in M \tag{4.12}$$

In which Formula 4.1 is the objective function. This objective function minimizes the weighted waiting time for all passengers (W_t), In-vehicle time for all passengers (Ivt), Deviation from departure time at all stations ($Y_{s,m}$) and Deviation from schedule at the terminal station (X_m). The corresponding weights are represented by their corresponding β.

The waiting and in-vehicle time is calculated using passenger data from the TSM. The waiting time can be calculated as the average number of passengers over time waiting at a station, multiplied by the time elapsed between arrivals. The waiting time is calculated using Formula 4.13 (Pardini-Susacasa, 2020).

$$W_t = \sum_{s \in S}((t_{s,0}^{arr} - t_0) * \frac{(w_{s,0} + \hat{w}_s)}{2}) + \sum_{s \in S}\sum_{m \in M^s}((t_{s,m}^{arr} - t_{s,m-1}^{arr} * \frac{(w_{s,m} + r_{s,m-1})}{2}) \tag{4.13}$$

Also the In Vehicle Time is calculated using data from the TRM. Using the capacity of a metro vehicle, with the load for each metro there can be determined whether a passenger is standing or not. Assuming that a passenger perceives in-vehcile time more negative when standing, the in-vehicle time can be calculated using Formula 4.14 (Pardini-Susacasa, 2020).

$$Ivt = \sum_{m \in M}\sum s \in S^m(l_{s,m}^{sit} * \gamma_{sit} + l_{s,m}^{stand} * \gamma_{stand}) * (t_{s+1,m}^{arr} - t_{s,m}^{arr}) \tag{4.14}$$

The objective function is subject to the following constraints: constraint 4.2 ensures that the time spent by train at a station should be greater than or equal to the minimum dwell time. Constraint 4.3 ensures that the travel time between two stations cannot be smaller than the minimum driving time, while constraints 4.4 and 4.5 ensure that the headway between two trains cannot be smaller than the minimum safety headway. Constraint 4.6 is used for the minimum connection time between two consecutive train services, service can only depart if inbound train has arrived. Constraints 4.7, 4.8, 4.9 and 4.10 are used for the linearization of schedule adherence term in objective function. Finally constraints 4.11 and 4.12 ensure a limitation of the step size between the current and previous iteration.

From the results of the research performed by Pardini-Susacasa (2020) can be concluded that there is a significant difference in the development of delays when considering the modelled passenger-train interactions. Therefore this model is very well suited to analyse the effect of transfer passenger flows, as this is a passenger-train interaction effect, while not neglecting other passenger train effects on other parts of the line as well. However, to be able to research the effect of transfer passenger flows, some required adaptations need to be performed, which are explained in section 4.2. However, to get a clear insight into what possibilities there are to adapt and extent the framework, first the assumptions and limitations of the model are discussed in the next section.

Table 4.1: Variables, sets and parameters of the TRM (Pardini-Susacasa, 2020)

Parameter	Explanation
Indices and Sets	
S	Set of stations in the network
s	Current station in set stations s ∈ S
M	Set of vehicles, with M^+ for inbound trains and M^- for outbound trains
m	Single metro in set of metros m ∈ M
S^m	Set of stations to be served by metro m
M^s	Set of metros that serve station s
V	Set of trains pairs m,n that have a connection at station s
Decision Variables	
$t_{s,m}^{arr}$	Time of arrival of vehicle m at station s
$t_{s,m}^{dep}$	Time of departure of vehicle m from station s
X_m	Extra variable to linearize absolute deviations from scheduled arrivals
at terminal stations	
Parameters obtained from the simulation	
$l_{s,m}$	Passenger occupation in vehicle m at the moment of departure from station s
$r_{s,m}$	Passengers left behind by vehiclem at station s
$w_{s,m}$	Passengers waiting at station s when vehicle m arrives
w_s	Passengers waiting at a station s at the time in which the optimization is triggered
t_0	Time in which the optimization is triggered
e_s^{min}	Minimal dwell time at station s. This is the maximumbetween the originally scheduled dwell time and the time needed for passenger exchange in the last iteration.
$t_{s,m}^{depo}$	Realised departure time of trainm from station s in the last simulation
t_m^{arrs}	Originally scheduled time of arrival of trainm at its destination station
$t_{s,m}^{deps}$	Originally scheduled time of departure of trainm from station s
General Parameters	
γ_{sit}	Crowding multiplier for sitting passengers
γ_{stand}	Crowding multiplier for standing passengers
β_w	Cost coefficientmultiplier for waiting time
β_i	Cost coefficientmultiplier for in vehicle time
β_o	Cost coefficientmultiplier for schedule deviation at the terminal station
$q_{s,h}^{min}$	Minimal running time for the stretch between two consecutive stations s and h
h_s^{out}	Required headway between two consecutive outbound trains at station s
h_s^{in}	Required headway between two consecutive inbound trains at station s
u	Allowed margin of difference between iterations
k_m	Sitting capacity of train m
$c_{m,n,s}^{min}$	Minimal connection time between trainsm and n at station s

4.1.4. Assumptions and Limitations

There are several assumptions and limitations in the presented SBTM-MN framework that should be considered when using it for simulations. For each assumption or limitation there is also explained what impact this can have on the results obtained from this model.

- It is assumed that an arriving passenger at the platform boards the next possible metro vehicle towards its destination. Passenger numbers of lines that are not considered in this research are added as boarding and alighting passengers at their corresponding transfer station. No conclusions can thus be drawn on the impact for transfer passengers on parts of the metro network that are not modelled.

- Only passengers that are already at the platform once the metro arrives are considered to be able to board said metro. Passengers arriving while the metro is still at the platform are assumed not to be able to board that metro, but will rather board the next metro. This is an important consideration when working with peak loads in the system and can deviate from reality when it is the case that a lot of newly arriving passengers are aiming to board a metro that is already at the platform.

- No maximum vehicle capacity included in the model. A careful consideration is made to what extent this results in problems when interpreting the results of the model. The most important consideration is when applied to the case study: how often does it occur that the maximum vehicle capacity is exceeded in practice? From the data set there can be concluded that this is the case for 0.01% of the cases, which means it thus doesn't form a big problem. However, there are also other considerations to be taken into account: when determining the type of experiments to be carried out there should be taken into account that when working with peak demands there should be looked out for exceeding the maximum capacity of the vehicle. Would this occur too often, this might affect the reliability of the results of the experiments carried out. What impact this consideration has on the case study of this research, is explained in section 5.1.

- The TSM uses single arrival rates to estimate passenger demands. These arrival rates are only applicable to a certain time of day, as arrival rates of passengers change over the course of the day. Therefore the TSM can only be ran for a very specific time frame.

4.2. Framework adaptations and extensions

In this section the adaptations extensions that are made on the existing framework are discussed. There are several adaptations to the framework considered, not all of the extensions that are discussed in this section are eventually implemented. For each consideration an explanation is given why an extension is made or not. For the parts that are extended there is explained for each part what is added and how this is done.

4.2.1. On TSM-RW

As explained currently passenger arrivals are simulated using passenger chipcard data. This already yields a pretty accurate picture of passenger arrivals throughout the day and peak demand is already accounted for in the model. The TSM-RW is for this research updated with chipcard data from the relevant stations for this research.

4.2.2. On TSM

The passenger module is updated with parameters found from the correlation analysis in chapter 3. This is accounted for in general in the TSW-RW because of the usage of smart card data, but is not accounted for in the TSM which uses a single average of arriving passengers per minute for the morning peak. Additionally the case study used in the research by Pardini-Susacasa (2020) considers lines D and E of the metro network of Rotterdam which, apart from Rotterdam Centraal, doesn't contain major intermediate transfer stations to the national train network. Therefore in this research there is looked at lines A, B and C which do contain intermediate transfer stations to the national train network. The TSM thus is also adapted to correctly work with these lines, and all the station specific parameters for the stations one line A, B and C are added to the TSM. Further explanation on the case study can be found in section 5.1. The aim of this research is to contribute to the framework with the ability to link passengers to these train arrivals and reschedule for the impact of a train arrival and the transfer passenger flow this will create. For this goal impact parameters of transfer passenger flows were obtained in chapter 3. With these parameters the flow of arriving passengers can be modelled more accurately and can also be coupled to train arrivals in the network. Looking at the framework, specifically the demand profiles and estimated demand parameters that provide the input to the passenger module of the TSM are updated. Additionally for the researched transfer station a detailed arrival rate per minute is obtained to be able to model the flow of arriving transfer passengers with high accuracy.

Also adaptations to the train module of the TSM are made: these are adaptations to the simulation model in OpenTrack to ensure that the part of the network that is studied in this research correctly works with the passenger module. The part of the network that was already modelled with the passenger module is the part of metro line E from Slinge to Rotterdam Centraal (Pardini-Susacasa, 2020). In this research there is made use of a different metro line, explained in section 5.1. No adaptations are made to the train model and the way trains are simulated in the network for this research.

4.2.3. On TRM

As the TSM, the TRM is also adapted to work with the metro lines that this study uses. Because the focus of this study lies in the busiest sections of the lines, further explained in section 5.1, the TRM is adapted in such a way that not the entire line is rescheduled, but that rescheduling measures are only applicable to the section of the line where all metro lines are running over the same infrastructure, the outer branches of the metro network are excluded. This is done to limit the 'noise' generated by the model and allows for a more detailed study on the section of the line where the transfer station of interest lies in. There are additional possibilities on top of the existing rescheduling measures in the model, that are not yet incorporated in the model, as explained in section 2.4. There are currently 4 rescheduling measures incorporated in the TRM as explained in section 4.1.3. In this research the same rescheduling measures are also applied. However, there are more rescheduling measures that could be applicable. Rescheduling measures that are not incorporated in the framework include: Stop skipping, changing the route of the vehicle, overtaking another vehicle, rolling stock reservation and short turning. For this study no additional rescheduling measures are added to the model, for some rescheduling measures a consideration is given below.

Changing route and Overtaking

Another rescheduling measure that is possible is to change the route of a metro or let a metro take over another metro. However, considering the metro network of the case study, changing the route of vehicle is possible to a very limited extent and overtaking another vehicle is also very difficult and not very relevant considering the metro infrastructure. Therefore this will not be implemented as a possible rescheduling measure in the model.

Rolling stock reservation

Another rescheduling measure that could be used is rolling stock reservation. With this measure a part of the metro vehicle would be closed to passengers up until a certain stop, for example the stop in which the peak demand would occur. The idea is that passengers can easily enter the empty vehicle at the station where a peak demand occurs, such that the peak in demand doesn't cause additional dwell time. To check whether this measure would be feasible for implementation two checks are performed based on case study data: (1) is it possible to reserve one metro part up until the transfer station with peak demand without exceeding the capacity provided by only vehicle earlier on the line? (2) What is the difference in contribution to the dwell time of boarding and alighting passengers and how does this relate to crowding? Currently this rescheduling measure is mainly used in metro networks that are dealing with a very high level of crowding and a lot of cases of denied boarding, in which this measure is applied to balance the number of waiting passengers between stations. Since the metro network of the case study is not dealing with a lot of cases of denied boarding and the benefit of mainly having passengers boarding in one empty part of the vehicle would need further research, there is chosen not to implement this measure for this research.

Short turning

When short turning a metro the route is ended earlier than a final stop, to have the vehicle turning around at an earlier station and prevent knock-on delays as a connecting service a vehicle would perform also gets delayed if a vehicle suffers from a too large delay. This rescheduling measure is especially interesting of a network is dealing with a lot of knock-on delays. However, there should be possibilities to make this turn-around and end a route early. As there is no evidence in the data that the metro network of the case study deals with a lot of knock-on delays and the options for short turning a metro on the metro network of the case study are very limited, therefore short turning a metro is also not considered as a rescheduling measure.

Stop skipping

Last implementing stop skipping as a rescheduling measure is considered. In case of a vehicle being delayed, a scheduled can be skipped to catch up on the delay. This does come at a price, however as it has relatively large implications on passengers at both the stop and in-vehicle. Currently it is not a common rescheduling measure in the network of the case study. Also as the stop-skipping problem brings a great deal of additional complexity to the model (Gkiotsalitis & Cats, 2021), there is chosen to not add this rescheduling measure to the model for this study.

Concluded can be that none of these rescheduling measures are considered relevant enough to be added to the simulation framework for this study, however they could provide input for future research, which is further elaborated on in section 6.4.

4.3. Validation and KPI's

The validation of the models used in this study can be seen twofold: first the outcomes of the TSM and the TSM-RW are validated against historical data to ensure a correct representation of metro vehicle behaviour in the model, especially on the line segment of interest around the researched transfer station. Second the timetable resulting from the TRM should be validated in terms of performance and improvement compared to the existing timetable.

To measure the performance of the different models and to check their validity they need to be compared to historical data and to each other. To make this comparison, Key Performance Indicators (KPI's) are needed to asses the performance of the different models. These KPI's are also selected based on the available data from the case study to be able to make the comparison with the real world scenarios. The KPI's are defined as follows: As the passenger vehicle interaction is one of the main contributing factors of the SBTM-MN framework and play an important role in the definition of the transfer passenger problem, it is very important that the **passenger numbers** are correctly represented in the model. Therefore the realised passenger numbers will be validated against the passenger numbers generated by the model. For this the number of boarding passengers per vehicle will be used.

With the correct passenger numbers in place in the model the next step is to have a correct representation of the **dwell times** of the metro vehicles corresponding to the passenger numbers. The dwell time from the actual data is determined by taking the time between the actual arrival time and actual departure time at the station. The dwell times per station generated by the model are compared to the dwell times from the actual data.

The next validation step is to see whether with the correct passenger numbers and the correct dwell times in place, if **delays** propagate through the model in the same way as in the actual situation. Therefore the generated delays per station by the model are compared to the actual delays in the system per station. This way conclusions on delay propagation in the different test scenarios can be validated.

These KPI's will be used to validate the model in terms of correct representation of the network. However, there are also additional important KPI's to assess the performance of a public transport network. Not only is schedule adherence (delays) important, especially in high frequency systems it's also very common to look at regularity or deviation headways (van Oort, 2019). This is measured as the scheduled headway minus the actual headway divided by the scheduled headway.

More recently there are also more passenger oriented KPI's for public transport networks coming up. Rather than measuring the punctuality of a train, the delay of individual passengers is calculated based on chip card data (Cacchiani et al., 2014). Also in the SBTM-MN the optimization can be performed with this passenger objective rather than the vehicle perspective, with as KPI's **passenger waiting time** and **passenger in vehicle time**. Therefore these KPI's are also in this research used to assess the performance of schedules created with the SBTM-MN framework, with also vehicle delay in mind.

4.4. Scenarios and Outcomes

With the updated model and clear view of the rescheduling strategies to be used, the model can be set up for usage and running experiments. The focus of the experiments will lie in rescheduling for the implemented effect of peaks in demand due to transfer passenger flows. A combination of historic train arrivals and theoretical train arrivals is used to test different scenarios. The goal is to predict peaks in passenger demand based on train arrivals, and to take the appropriate action to deal with these peaks in passenger demand. Several scenarios are considered, their setup is as follows:

1. **Base scenario:** In the first scenario is explored how the timetable as is can be improved. This is done for various passenger arrival distributions at the transfer station, simulating day to day delays and disturbances in the network. These runs are then compared to see what the impact of different transfer passenger arrival rates is on the optimal rescheduled timetable. Also the distribution of the passengers numbers over these different train arrivals will be varied, however the total number of passengers will be kept in the same magnitude for this scenario. The outcomes

of this scenario is used to conclude what rescheduling measures can be used under current circumstances to improve the timetable.

2. **Increasing the number of transfer passengers:** The second scenario is also used to test to what extent other rescheduling decisions are taken by the TRM when the distribution of transfer passengers at the transfer station change. In this scenario the number of passengers arriving at the transfer station is raised by 20 %. This percentage is chosen as average growth scenario from the next scenario, in which overall passenger growth is tested.
3. **Increasing passenger numbers:** In the third scenario the overall passenger numbers in the system are increased. This scenario is used to discover to what extent increasing passenger numbers over the coming years will have an increasing impact on the daily operation of the metro. Passenger numbers for rail are expected to increase in the coming years (Puylaert, 2019), creating an even higher (peak) demand for the metro, more transfer passengers and a higher occupancy in the metro. The question is; to what extent can this lead to problems and to what extent should measures be taken to prevent possible negative consequences in the future? Several growth scenario's are considered. For example, Prorail estimates growth percentages of 30 to 40 percent in the coming years (Prorail, 2019). However, as these growth percentages are highly subject to change, especially with the change of travel behaviour during the Covid-19 pandemic, several different growth scenarios are considered in this scenario: 10%, 20% and 30%. With these different percentages a picture can be created on how the network will develop over time given the different growth scenarios.
4. **Higher frequency of Train Services:** The fourth scenario is used to test what the impact is of a higher frequency on the train side. The assumption is that there has to be a difference in frequency in the case study in order to perform the described research, but what happens is this frequency is bound to change? In the case study there are plans to change the frequency of the train service from every 15 minutes to every 10 minutes, which are also the frequencies that are tested in this scenario.

As can be concluded from the objective function described in section 4.1.3, the TRM can optimize for different objectives. Because of the limited time and resources available for this Thesis a choice has to be made which objectives are applied for this Thesis. A balance has to be found between optimizing the timetable for the benefit of the passenger while looking out for the adherence to the schedule. In the research by Pardini-Susacasa (2020) many possible combinations of objective weights are already tested. From her research can be concluded that the first weight two sets W_1 and W_2 presented in Table 4.2 yield the best performing solutions in terms of percentages total weighted improvement when optimizing for the passenger objective while still looking out for delay development in the network. Weight set W_1 focuses on lowering the impact on passengers without worsening train delays. Weight set W_2 does roughly the same, but in this case the weight of in-vehicle time is raised to better account for actual travel time of passengers, as the in-vehicle time component is the largest component in the travel time journey. This is thus a trade-off between actual travel time and perceived travel time, as waiting time is perceived longer by passengers than in-vehicle time (dell'Olio, Ibeas, & Cecin, 2011). Because the interest of this research also lies in improving the service reliability of metro networks, also the performance of W_3 is tested in which there is only optimized for schedule adherence. Using the base scenario there is tested which of these three objective combinations yields the highest improvement, this set objectives will then be used to run the other scenarios.

Table 4.2: Objective Weights Used

	Waiting Time β_w	In-Vehicle Time β_i	Train delays at all stations β_a	Train delays at terminal β_t
W_1	1	2/3	1/3	0
W_2	2/3	1	1/3	0
W_3	0	0	1	0

The number of combinations used to obtained results for this study are a limitation for this study. As not all combinations are explored, there is a possibility that there are better combinations of weights possible to obtain a more suitable timetable. However with the current set of weight sets chosen the Timetable will be rescheduled for the benefit of the passenger using W_1 and W_2, yielding a balanced solution. The comparison with W_3 is made to see what happens when only optimizing for the timetable objective, and a consideration can be made on how desirable this would be.

With a clear view of the modelling study and the planned experiments, the case study will be introduced in the next Chapter. The described correlation analyses from the previous Chapter as well as the modelling study described in this Chapter will be applied to the case study. The results of this study will also be presented in the next Chapter.

5

Case Study and Results

In this section the developed method in chapters 3 and 4 will be applied to the case study. A more detailed explanation of the case study will be given in section 5.1. Several experiments and scenarios were already established in 4.4. In section 5.2 is explained how these experiments are applied to the case study. The results of the correlation analysis explained in Chapter 3 are presented in section 5.3. The results of the model validation of the adapted SBTM-MN framework explained in Chapter 4 are presented in section 5.4. Finally the results of this model are presented in section 5.5.

5.1. Case study overview

The metro network of Rotterdam, depicted in Figure 5.1, consists of 5 lines in total. Three lines mainly in the east-west direction, and two lines mainly in the north-south direction. There are several transfer stations in the network, some offer only a metro-metro transfer, others also offer connections to national train services, trams or busses. The metro network of Rotterdam contains four major transfer stations to the national rail services.

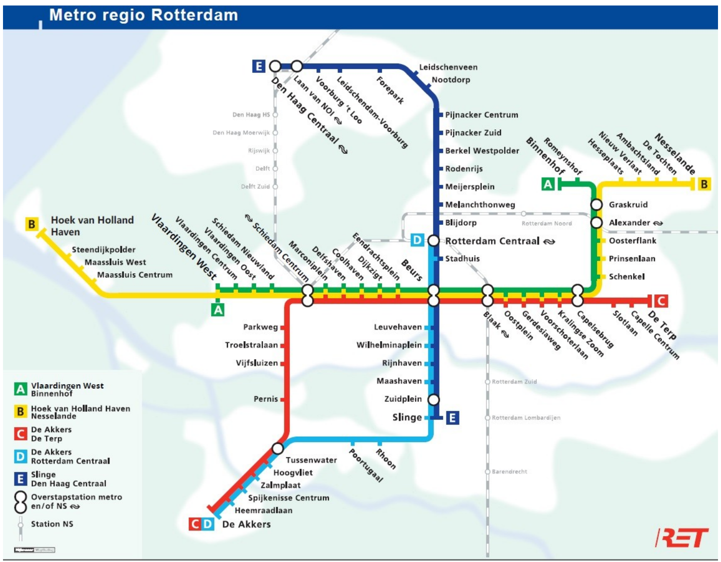


Figure 5.1: Metro network of Rotterdam

In *Rotterdam Alexander, Rotterdam Blaak* and *Schiedam Centrum* it is expected that the flow of transfer passengers is substantial enough to have an impact on the reliability of the metro line. These stations have direct connections to intercity trains on various routes in the national railway network. *Rotterdam Centraal* also being a major transfer station in the metro network is in this case disregarded, because train arrivals are frequent in such a way that it is expected that no clear correlation to a train arrival and demand for a metro line can be determined.

Since the aim is to find the pure effect of transfer passengers on a single transfer station, the focus lies in quantifying the correlation in one selected station in the network, *Rotterdam Blaak*. This station is selected based on several criteria; Rotterdam Blaak has the highest passenger number of the three considered transfer stations in which the effect is expected to be present, as presented in Table 5.1. Of the three considered transfer stations stations, Rotterdam Blaak is also the closest to the city center and it is therefore expected that passenger loads are highest in this section of the lines. Additionally the effect is expected to be present strongly in this station based on experiences from the RET.

Table 5.1: Passenger numbers for Blaak, Alexander and Schiedam in November 2019 (RET)

Station	**Total number of passengers in November 2019**
Rotterdam Blaak	802632
Rotterdam Alexander	411571
Schiedam Centrum	696562

With the transfer station of interest selected, the study area around Rotterdam Blaak has to be determined. If the studied area around Rotterdam Blaak is picked to large, there might be a risk that the performed correlation analyses might contain too much noise and the rescheduling model reschedule for too much other effects present in the network. However, if the study area is chosen too small, possible rescheduling measures might not be as effective and possible correlations downstream cannot be found. As a balanced choice the study area around Rotterdam Blaak is chosen to be the part where lines A, B and C are running on the same infrastructure. These stations are also considered to be the busiest stations on the line in terms of passenger numbers. The studied area therefore focuses on the section of lines A, B and C between Schiedam Centrum and Capelsebrug. This section of the line is depicted in Figure 5.2.

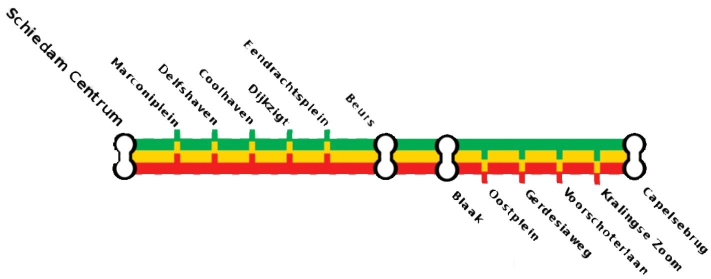


Figure 5.2: Study area of this research

As mentioned Rotterdam Blaak is served by metro lines A, B and C, as presented in Table 5.2. During peak hours a total of 18 metros per direction arrives at Rotterdam Blaak, resulting in an average headway of $3\frac{1}{3}$ minutes. In practice the scheduled headway lies between two and four minutes during peak hours.

Table 5.2: Metrolines serving Rotterdam Blaak

Line	**Peak Frequency**	**Off-peak Frequency**
A	6x per hour	4x per hour
B	6x per hour	4x per hour
C	6x per hour	4x per hour

The station is also served by Sprinter and Intercity lines operated by NS. The lines and their frequency are presented in Table 5.3. During peak hours a total of 8 trains per hour per direction arrives at Rotterdam Blaak, resulting in an average headway of 7.5 minutes. In practice this headway lies between 5 and 10 minutes during rush hour.

Table 5.3: Train lines serving Rotterdam Blaak

Line	Peak Frequency	Off-peak Frequency
Intercity (IC): Amsterdam/Lelystad - Dordrecht/Vlissingen	4x per hour	2x per hour
Sprinter (SPR): Den Haag Centraal - Dordrecht	4x per hour	2x per hour

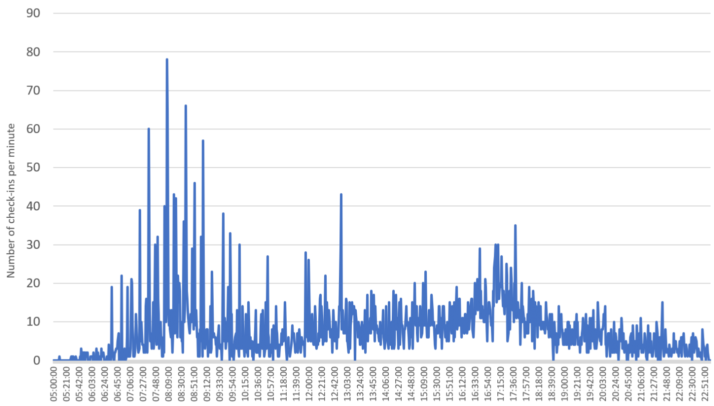


Figure 5.3: Boarding Passenger Pattern at Rotterdam Blaak

Because the expectation is that the impact of transfer passengers on the reliability of the metro network is the highest when the passenger volumes in as well transfer passengers as the number of passengers already in the system, there is looked at the demand throughout the day. The passenger demand for Blaak is the highest in the morning peak, as can be seen in Figure 5.3. Therefore in performing the correlation analysis, the focus is mostly on the morning peak hours from 6am to 10am.

As explained in chapter 3 several data sets are used to perform the correlation analysis described in this chapter. This data is obtained in cooperation with RET and NS. In the selection of the data needed several considerations were taken into account. Because of the strong change in travel behaviour during the current Covid-19 crisis, data from before the Covid-19 pandemic is used. This is considered to be more representative for regular operation conditions and expected operating conditions in the future. Also a representative time of the year has to be taken into account. In this case data from November 2019 is used. In this time of the year there are no major holidays in the Netherlands and there are usually relatively few people on holidays as compared to other months of the year. For the data-set this means that its expected that the usage of public transport is high during the period of measuring, resulting in that the at conditions in which the maximum demand on the system is present.

5.2. Case study exploration

The methods described in chapters 3 and 4 will be applied for the case study of Rotterdam, with specifically station Rotterdam Blaak as the transfer station of main interest in the case study. The correlations described in section 3.3 are researched for the case study. The results of this correlation analysis are used as input for the next phase of the application in this case study; coupling the correlations to the SBTM-MN. With this updated model experiments are performed to test rescheduling methods for this case study.

To check whether the chosen study area is suitable for this research, several time-distance diagrams of lines A, B and C of the metro network are constructed to see if there are more metros bunching on this part of the line. This is done for the direction east, as during the morning peak most transfer passengers arriving at Rotterdam Blaak will travel towards the city center. One of these diagrams is presented in the figure in 5.4. In this figures the light grey colored paths represent the planned timetable. The blue colored lines represent a metro running 'on schedule', in this case measured in deviation from scheduled headway of less than 70%. The red dots represent a metro that has a deviation from the scheduled headway compared to to the following vehicle of more than 70% and is therefore considered to be delayed and the vehicle and is the vehicle that is considered to be bunched. More time-distance diagrams can be found in Appendix B. From this example figure can already be concluded that indeed the part between Capelsebrug and Schiedam Centrum is dealing with the most cases of vehicle bunching. Also several cases are visible in which bunching of two metro vehicles starts after a stop in Rotterdam Blaak, possibly caused by longer dwell times at Rotterdam Blaak. When looking at the total of the Figures in Appendix B concluded can be that

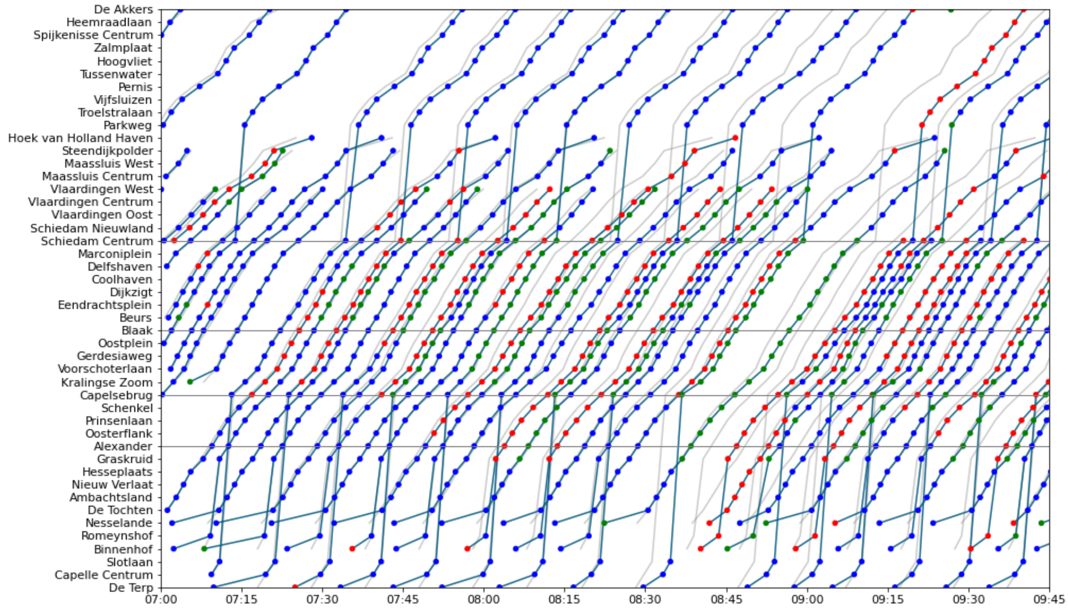


Figure 5.4: Time Distance Diagrams of Metro lines A, B and C direction east from the morning peak of Thursday November 28th, 2019h

5.2.1. Scenario applicability

Four scenarios for experiments to be applied to the case study were explained in section 4.4. Several final case study relevant considerations have to be made before setting up the model for the case study. The first (base) scenario is tested with different arrival at the transfer station Rotterdam Blaak to test the difference in rescheduling measures suggested by the TRM for different arrival rates. From the data set of the case study several days of sample data have to be selected to run these different scenarios with. Four weekdays are selected from the data set, which include the day with the highest number of passengers and three days with an average number of transfer passengers. The day with the highest number of transfer passengers in the data set is Tuesday November 19th, 2019. The other days selected are Monday November 4th, 2019, Thursday November 7th, 2019 and Thursday November 14th, 2019.

5.3. Results transfer impact analysis

To determine to what extent transfer passenger flows at station Rotterdam Blaak are correlated to disturbances in the metro network, several correlation analysis are performed. How this analysis is performed, is explained in section 3.3. A total of four correlation analyses are performed according to the expected correlations presented in figure 3.3. For each correlation analysis the results are presented in this section.

5.3.1. Passenger demand - Number of transfer passengers

In figure 5.5 the passenger demand per minute, based on check-in data of station Rotterdam Blaak, is plotted in blue. In green the share of transfer passengers in this total demand is plotted. This is done for the period of one morning peak from 6am to 10am. In this figure can be seen that almost all high peaks in passenger demand are caused by the arrival of a train at the station. This is supported by the results of the correlation analysis performed over all business days in the data set. These results are presented in Table 5.4. The goodness of fit is estimated through the adjusted R^2. Here can be concluded that during the day the variance in overall passenger demand can be explained for 64% by transfer passengers, and during the morning peak this increases to 94%. The estimated parameters for β_1 is a logical result, lying around 1 meaning that for every passenger that transfers from the train, demand for the next metro also raises with 1, indicating a largely 1:1 relation. β_0 in this case would then represent the base number of check-ins per minute. When thus having a good insight in the arrival of trains to the station peaks in passenger demand can easily be predicted.

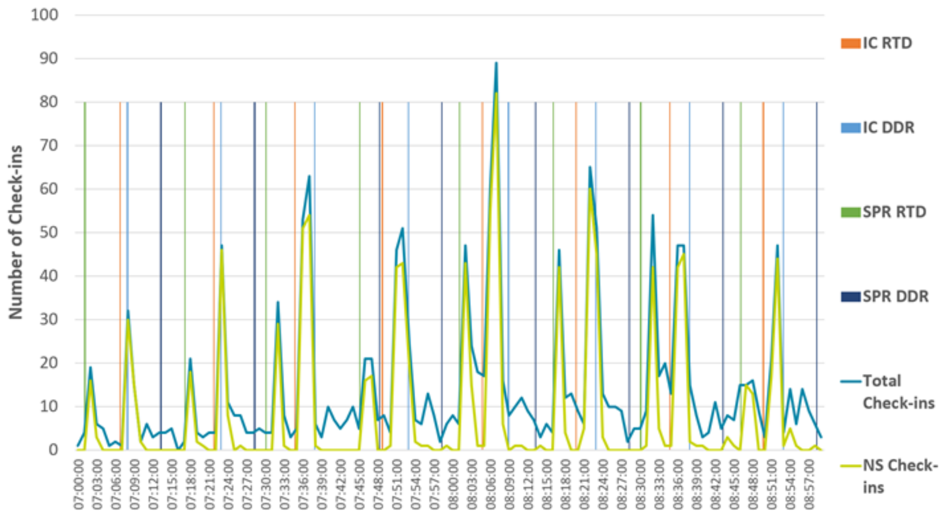


Figure 5.5: Total passenger demand - Number of transfer passengers at Rotterdam Blaak, with train arrivals

Table 5.4: Results regression analysis Total Passenger demand - Number of transfer passengers

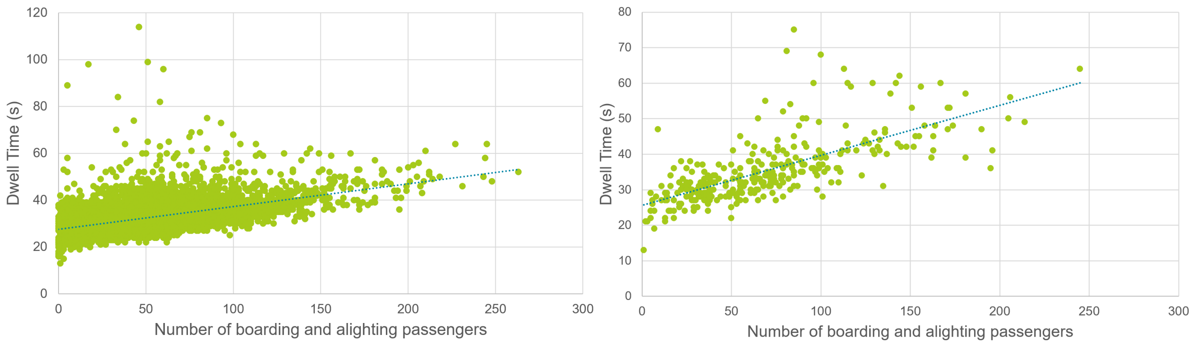
Cases Selected	Parameter	Value	Parameter	Value	Parameter	Value
Entire Day	R^2_{day}	0.638	β_{0day}	6.790	β_{1day}	0.976
Morning Peak (am)	R^2_{am}	0.935	β_{0am}	4.479	β_{1am}	1.019

Now that is known that the peaks in passenger demand at Rotterdam Blaak are strongly correlated to the arrival of trains to the network, a next question arises; is this the case for each train or do the trains also differ in impact? To see if this is the case, train arrival times are also plotted against the arrival of transfer passengers at Rotterdam Blaak in figure 5.5. Here can be concluded that the highest peaks are mainly caused by the IC in the direction of Rotterdam, depicted in orange. The IC in the direction of Dordrecht, depicted in blue, often coincides with the arrival of the IC in the direction of Rotterdam, making it somewhat harder to tell which train has which impact. However, as can be seen a couple of times in the figure the IC in the direction of Dordrecht also sometimes falls behind the peak, indicating that the IC in the direction of Rotterdam is mainly responsible for the peak in passenger demand. After that the highest peaks are caused by the SPR in the direction of Rotterdam, depicted in green. Trains in the direction of Dordrecht thus play a much less significant role in peaks in passenger demand than the trains in the direction of Rotterdam. This is logical as it is likely that passengers having a destination in Rotterdam already left the train at Rotterdam Centraal, whereas the for passengers coming from Dordrecht the most direct connection would be via Rotterdam Blaak. Also there is a difference in number of transferring passengers between an Inter City and a Sprinter train.

There can be concluded that there is indeed a strong correlation between peaks in passenger demand and the arrival of trains at trains at Rotterdam Blaak. The impact differs per train arrival and mainly depends on the direction of the train and secondly the type of train. There is now a clear picture of the passenger demand pattern at Rotterdam during the morning peak, which will be used as input for the simulation framework used in this study. With this correlation in mind the next step is analyzed: does this increased passenger demand also influence the dwell time of the next arriving metro vehicle?

5.3.2. Passenger demand - Metro dwell time

The next regression analysis that is performed is between passenger demand and the dwell time of the metro. The expectation is that an increase in passenger demand will also lead to an increase in dwell time, as a higher volume of passengers will also take a longer time to board. A visualisation of this analysis can be found in Figure 5.6a. The result of this analysis is that 0.253 of the variance in dwell time can be explained by the number of boarding passengers. However, as this analysis included all cases there are also plenty of cases in which other factors could have had a strong influence of the dwell time of the vehicle, for example if the service was early and increased dwell time up to the scheduled departure time or a passenger holding the door for somebody late at night. To filter out some of this noise, the analysis is also performed for services that were already delayed. This is depicted in Figure 5.6b. In this case the R^2 increases to 0.488.



(a) All cases

(b) Delayed vehicles

Figure 5.6: Passenger demand - Metro dwell time.

The interest of this research lies specifically in the impact of these passenger numbers in crowding conditions. As the expectation is that the number of passengers boarding and alighting the vehicle has a stronger impact on the reliability in already crowded conditions, this analysis is also performed with data from morning peak hours only. This analysis is depicted in Figure 5.7. In this analysis also the metros for which over 50 passengers from the national rail network have checked in since the previous metro arrival are marked as *affected by transfer passengers*. Here there can be seen that these metros are mainly on the high end in terms of dwell time and passenger numbers. In this case the R^2 found is 0.450.

In Table 5.5 the obtained parameters from the second correlation analysis are presented. The β_0 parameters in this correlation represent the base dwell time of a metro vehicle, which is slightly higher when looking at the average over all day compared to only the morning peak and delayed cases. This is logical since these trains are more likely to also dwell for schedule adherence as most of these trains are on time. The β_1 parameter represents the contribution of each additional passenger to the dwell time of a metro vehicle. For both the all day and morning peak cases this is quite similar, however the contribution seems to be higher in case of a delayed train. A possible explanation could be crowding levels in an already delayed train contributing to a longer dwell time.

Concluded can be that the effect of the number of boarding passengers has a substantial effect on the dwell time of metro vehicles, which becomes especially visible if there is aimed to filter out as much other effects as possible, which is the case for metros during the morning peak or in case of delayed metros. This completes the second link in the question if transfer passenger flows can cause delays in the metro network; peaks in passenger demand can indeed cause metro vehicles to have a larger dwell time. In the next correlation analysis there is researched if this increase in dwell time is substantial enough to impact the metro timetable and cause delays.

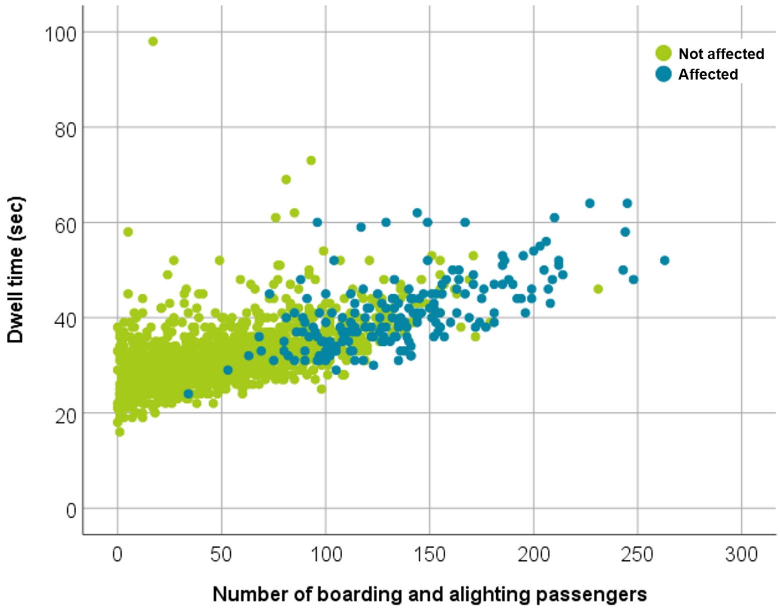


Figure 5.7: Dwell time - Number of boarding passengers at Rotterdam Blaak, with metros affected by transfer passengers highlighted

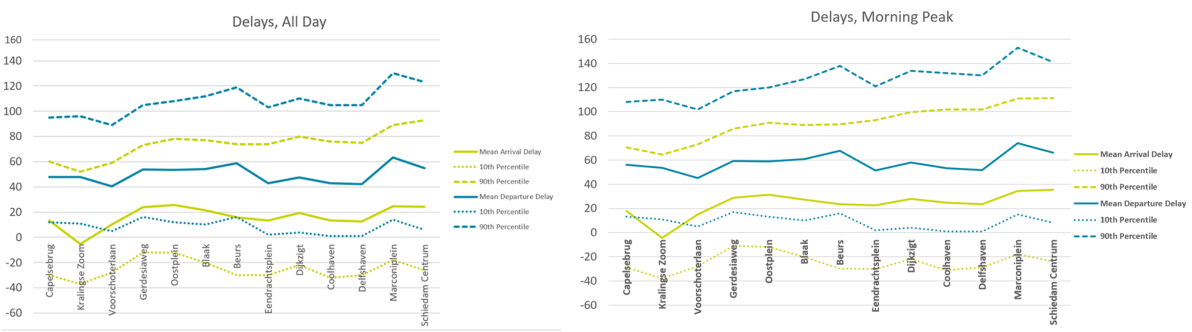
Table 5.5: Results regression analysis Passenger demand - Dwell Time

Cases Selected	Parameter	Value	Parameter	Value	Parameter	Value
Entire Day	R^2_{day}	0.253	β_{0day}	27.534	β_{1day}	0.097
Delayed metros only	$R^2_{delayed}$	0.488	$\beta_{0delayed}$	25.615	$\beta_{1delayed}$	0.141
Morning peak only (am)	R^2_{am}	0.450	β_{0am}	26.597	β_{1am}	0.102

5.3.3. Metro dwell time Blaak - Delay

To analyze the correlation between the dwell time at station Rotterdam Blaak, there first needs to be a clear picture of the development of delays in general across the studied part of the line. Therefore the average delay on the line is plotted in Figure 5.8a for the entire day as well as in Figure 5.8b for the morning peak only in the east direction. This figure indicates where usually metros suffer from an increase in delay or have a chance to catch up on some delay. For example there can be seen that usually around Kralingse Zoom there is some extra time from the previous station to catch up on delays, but that to the next station Voorschoterlaan delay usually increases for as well the average, 10th-percentile and 90th-percentile. An interesting observation from these graphs is that, for trains that are already delayed at the start of this section of the line, the 90th-percentile trains, there is no chance of catching up these delays and they only increase.

To determine what role the dwell time and thereby the passenger demand at Rotterdam Blaak plays in the development of delays on the line, a regression analysis between the dwell time and the departure delay at the next station, Beurs, is performed. The results of this analysis can be found in Figure 5.9 and Table 5.6. For the overall data set the explained variance with 0.075 is low. However, considering the subset of metros that is affected by transfer passengers, the explained variance is already higher with 0.174. This indicates that there are many contributing factors that can delay a metro, but that the dwell time at Blaak is a contributing factor in the delay development over the line, and that there is indeed a clear indication that metros affected by transfer passengers suffer from a longer dwell time and thereby also a higher delay.



(a) All cases (b) Morning peak

Figure 5.8: Delay distribution over the line between Capelsebrug and Schiedam Centrum

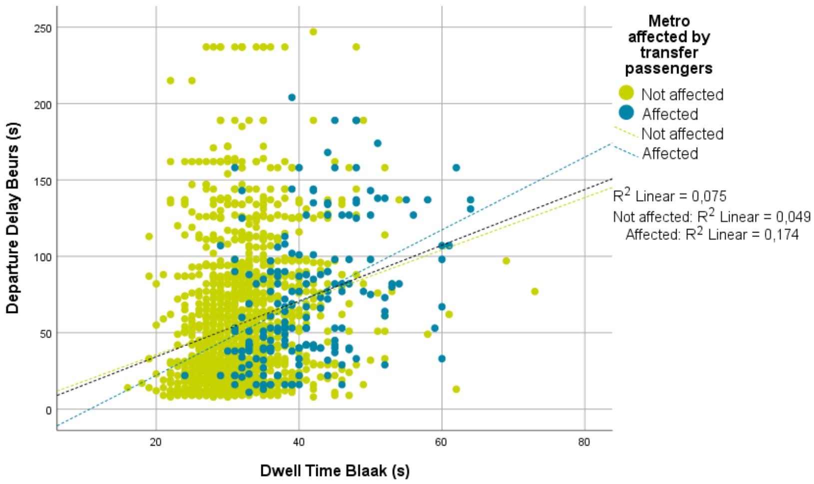


Figure 5.9: Dwell time - Delay

Table 5.6: Results regression analysis Dwell Time Blaak - Beurs Departure Delay

Cases selected	Parameter	Value	Parameter	Value	Parameter	Value
All Cases	R^2_{all}	0.075	β_{0all}	-2.201	β_{1all}	1.825
Affected by transfer passengers	$R^2_{affected}$	0.174	$\beta_{0affected}$	-25.475	$\beta_{1affected}$	2.380

When looking at the average departure delay at the next stop, Beurs, of metro vehicles during the morning peak, there can be found that this average departure delay of metro vehicles affected by transfer passengers significantly differs from the other metro vehicles during the morning peak. The outcomes of this test can be found in Table 5.7. From the results of this test can be concluded that there is indeed an impact on the delay when a metro has to pick up a substantial load of transfer passengers. However, as the explained variance from the regression analysis remains limited, to what extent it has an impact can differ strongly. The dwell time at the transfer station, Rotterdam Blaak, can thus be a contributing factor in the development of delays over the line, but there is no clear indication that a large increase in delay is systematically caused by longer dwell times at Blaak.

Table 5.7: Average Departure Delays at Beurs for metro's that are or aren't affected by transfer passengers

Affected by transfer passengers	Average Departure Delay Beurs (s)	Standard Error
No	55.31	1.17
Yes	72.41	3.18

5.3.4. Metro dwell time Blaak - Metro Headway

The last regression analysis that is performed is correlating the dwell time at Blaak to headway deviations along the line. Also in the case of headway deviation there is first looked at how the headway deviation develops over the course of the line, depicted in Figure 5.10. From this figure can be concluded that the average headway deviation is very steady throughout the course of the line, only in the case of the 90-th percentile the the headway deviation increases over the course of the line. When correlating the dwell time at Blaak at the headway deviation at the next station however a very low R^2 of 0.02 is found, concluding that no useful parameters can be obtained for this correlation. The same analysis was also done for other stations on the line, but no clear correlation was found. Concluding that the dwell time at Blaak only is a significant enough contributor to cause headway deviations, however it can still be a contributing factor in causing headway deviations.

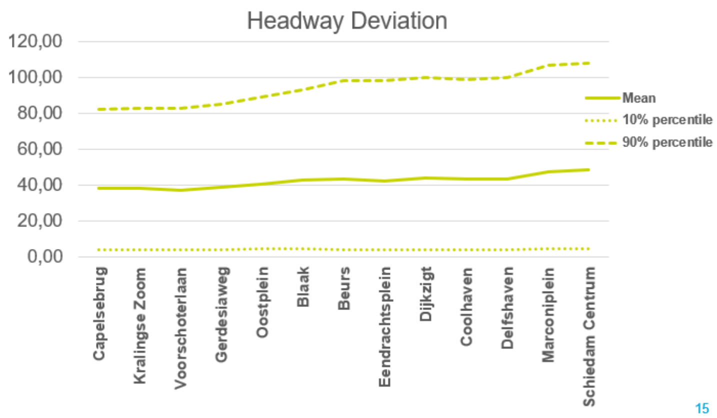


Figure 5.10: Development of Headway Deviation over the line

5.3.5. Obtained Parameters

The parameters obtained from the correlation analysis are used to update the SBTM-MN framework to make it suitable for usage in this study. For each station in the part of the network studied a regression analysis was performed to determine the parameters to calculate the dwell time of a vehicle based on the number of boarding passengers, number of alighting passengers and passenger load. This is done for each station separately to capture station specific effects in the model. The results of these regression analyses are presented in Table 5.8. Note that there is no separate constant estimated for each station. The constant was systematically over-estimated and therefore yielded too large dwell times, therefore a fixed minimum dwell time of 20s was assumed.

Table 5.8: Station specific parameters

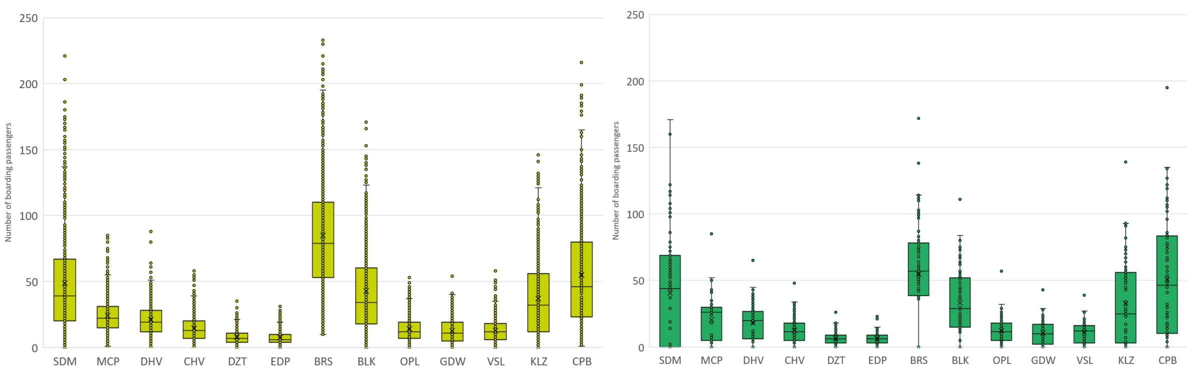
Station	Boarding	Alighting	Load
CPB	0,086	0,203	0,04
KLZ	0,118	0,131	0,041
VSL	0,196	0,148	0,019
GDW	0,193	0,315	0,017
OPL	0,213	0,157	0,02
BLK	0,118	0,103	0,039
BRS	0,131	0,06	0,064
EDP	0,11	0,117	0,012
DZT	0,113	0,067	0,04
CHV	0,09	0,059	0,033
DHV	0,148	0,099	0,033
MCP	0,21	0,181	0,042
SDM	0,069	0,093	0,046

5.4. Validation of the adapted SBTM-MN framework

To determine if the adapted model used in this research yields accurate results can be used to make predictions, it is validated on several aspects by comparing the model results with the actual values of parameters from the dataset. This is done by using the KPI's defined in section 4.3. For the readability of several Figures in this section, acronyms are used to indicate station names. Their corresponding full name can be found in C

Passenger Numbers

To ensure that the passenger numbers generated by the model are in the same magnitude as the actual boarding passenger numbers in the system, the number of boarding passengers is compared to the actual data. This is with passenger numbers between 7.30am and 9am, the same time for which the TSM is ran. The total number of passengers boarding a metro in the system is according to actual data on average on which two box plots of several days of data and several runs of the model are generated, presented in figures 5.11a and 5.11b. The average number of boarding passengers on this part of the line as obtained from the data is **29,47** and the average generated by the model is **24,5**. As can be concluded from these figures is that the passenger numbers follow a very similar distribution and similar averages and medians indicating that the correct passenger numbers are generated by the model. However there can be noted that the variation in the actual data is larger then in the generated data. This can be explained by the fact that the model generates the arrivals rather deterministic: a single arrival rate is used for the morning peak which causes the averages to be on point but will prevent outliers from occurring.

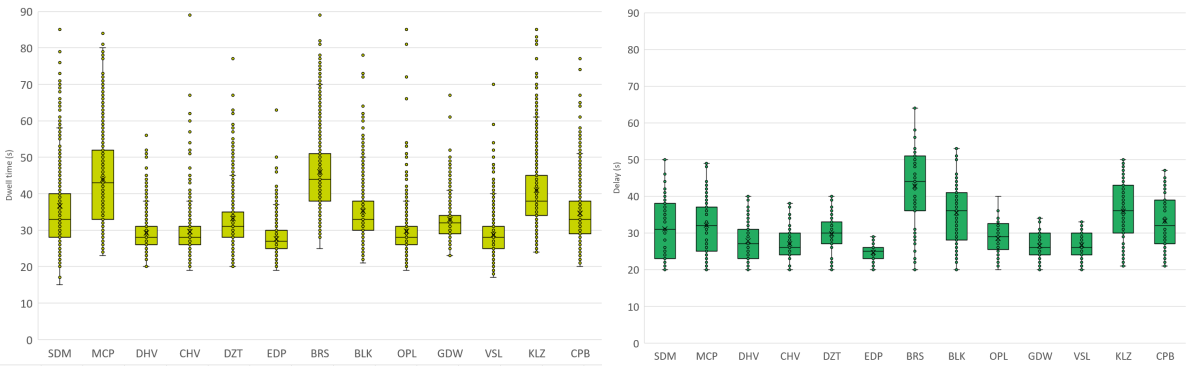


(a) RET Data (b) Generated by the model

Figure 5.11: Number of boarding passengers per station

Dwell times

With the model generating a similar pattern of passengers over the line as can be seen in the actual data the next step is to ensure that the dwell times of the metro vehicles are similar over the line as generated by the model. As briefly mentioned in section 5.3.5 the estimated station specific minimum dwell times were found to be too high in running the model validation. Upon this action was undertaken to limit the minimum dwell time to 20 seconds. The actual dwell times and the dwell times that are generated by the model are depicted in figures 5.12a and 5.12b. The overall average dwell time obtained from RET data for this section of the line is **30,92s**, the average dwell time generated by the model is **30,93s**, indicating a very accurate representation of the dwell time in General. From the figures can also be concluded once again that there is a very similar distribution of dwell times as generated by the model compared to the actual data, with a more limited number of outliers to be found in the generated data. The dwell time at Marconiplein however seems to be higher in the actual data set than in the generated data set. This could be explained by the fact that the dwell time at Marconiplein is relatively high compared to the passenger numbers in the actual data set and is therefore not picked up by the model. Other factors than passenger numbers may increase the dwell time. Because the dwell times at the other stations yield a very accurate picture and Marconiplein is near the end of the studied line, no action is taken to change the behaviour here.



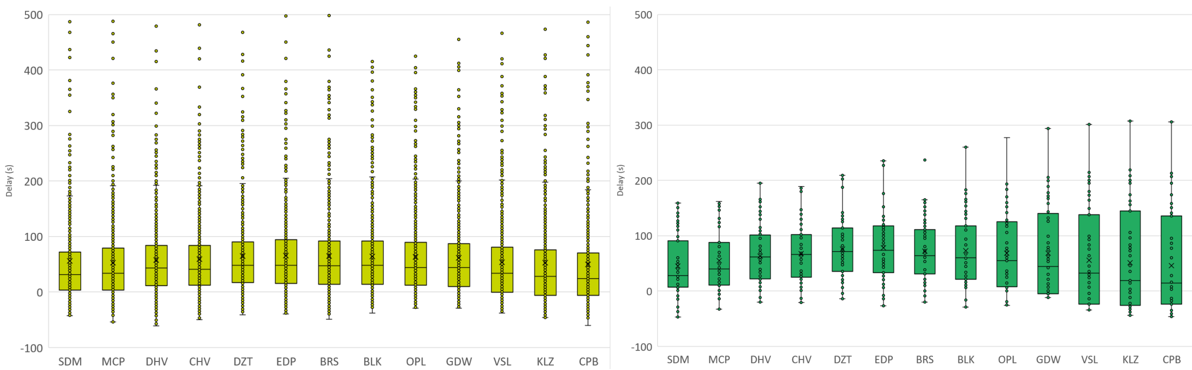
(a) RET Data

(b) Generated by the model

Figure 5.12: Dwell times per station, in seconds

Delay

With the correct dwell times in place, the next validation step is to see how delays in the model develop over the line. The results for this validation are presented in figures 5.13a and 5.13b. The overall average delay as obtained from the RET data for this section of the line is **58,82s** and the average delay generated by the model is **54,20s** Here a somewhat different distribution can be seen when comparing the model data to the actual data. The average delays generated by the model follow a quite similar pattern compared to the actual data, but the distribution of the delays is larger for the stations Gerdesiaweg through Capelsebrug compared to actual data. It should be noted that these plots are non-directional and therefore present the the distribution of delays for the station in both directions.

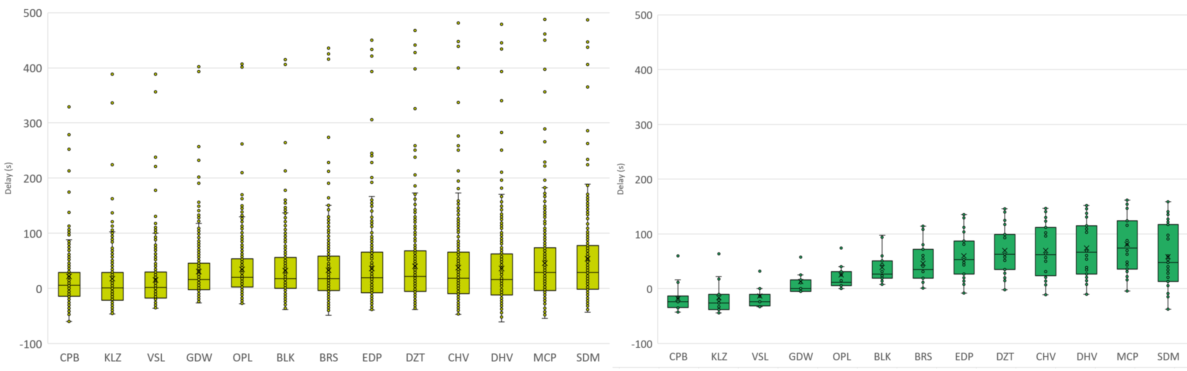


(a) RET Data

(b) Generated by the model

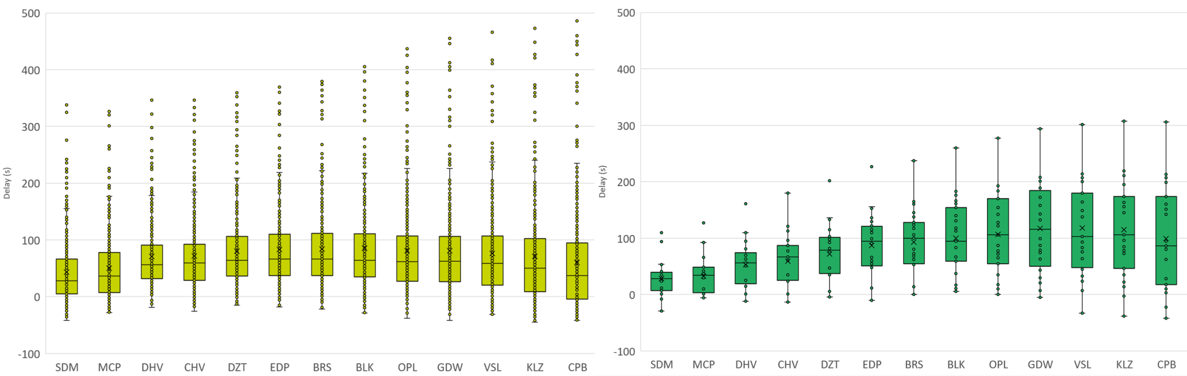
Figure 5.13: Arrival delays per station for both directions, in seconds

To get a better picture of what is happening in the model, also the delay distribution for the directions are plotted separately. In figures 5.14a and 5.14b the delay development over the line for the eastern direction are plotted. For readability, the station order in the plots is changed into the driving direction from left to right. Similar to the behaviour seen in section 5.3.3, from the actual data can also be concluded that the distribution of the delay increases as the metros move along the line. This similar behaviour is also simulated by the model, however it seems the effect is somewhat stronger than can be observed in the data. A possible explanation for this is that during the entire simulation period there is worked with a single arrival rate for the busiest section of the morning peak. This could lead to an over-estimation of the number of arriving passengers towards the end of the simulation period, preventing metro vehicles to catch up on their delay. However, as the overall average delay and the average delay per station are in the correct order of magnitude, the model can be interpreted correctly with the notion of the distribution of the delay in place.



(a) RET Data (b) Generated by the model

Figure 5.14: Arrival delays per station in eastern direction only, in seconds



(a) RET Data (b) Generated by the model

Figure 5.15: Arrival delays per station in western direction only, in seconds

5.5. Results of simulations with SBTM-MN framework

In this section the results obtained from the simulation framework presented in Chapter 4 are presented. The model is ran for the different scenarios described in section 4.4. These simulations include a mix of model runs with the SBTM-MN framework. These scenarios include:

1. Base Scenario (Section 5.5.1)
2. Increased Number of Transfer Passengers (Section 5.5.2)
3. Increased Passenger Numbers (Section 5.5.3)
4. Altered Train Frequency (Section 5.5.4)

For each of these scenarios their results are presented and discussed in their respective subsections.

5.5.1. Base Scenario

In this section the results of the optimizations with the TRM for the base scenario are presented. The optimization is ran for the studied section as defined in section 5.1. The optimization is ran with the weights defined in Section 4.4 and also several different arrival patterns at Rotterdam Blaak from different days in the data set; 4, 7, 14 and 19 November 2019. The best performing solution is presented in Table 5.9, which is obtained using weight set W_2 and arrival data from November 4th. The results of other iterations can be found in Appendix D. Because of the limited time and resources for this Thesis and to make fair comparisons between scenarios, the remaining scenarios will all be ran with weight set W_2, as this yields the best result in this scenario.

From Table 5.9 can be concluded that the optimization yields the best solution after two iterations

Table 5.9: Results of the TRM in the base scenario, with arrival data from Blaak of November 4th, 2019, weight set W_2

	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						482.37	2576.29	1.39	12.52	2902.05	
1	433.93	2490.71	1.34	11.09	2783.70	462.07	2519.86	1.39	11.98	2831.89	2.4%
2	**435.56**	**2379.20**	**1.29**	**9.176**	**2672.63**	**473.23**	**2510.35**	**1.52**	**12.38**	**2829.97**	**2.5%**
3	442.58	2417.39	1.32	9.99	2715.78	513.37	2607.38	1.82	15.40	2954.76	-1.8%
4	467.64	2504.44	1.72	13.21	2820.60	554.65	2698.30	2.07	16.91	3073.71	-4.7%

before starting to deteriorate, resulting in a 2,5% total cost reduction compared to the reference run scenario. The corresponding time-distance diagram can be found in Figure 5.16. In this figure the original timetable (in grey) is plotted against the optimized timetable (in green). Additionally train arrivals at Rotterdam Blaak that resulted in 50 transfer passengers or more are plotted in the Figure in orange. When plotting the headway distribution at the stations for the original realised run, the rescheduled timetable and the realised rescheduled timetable in Figure 5.17, there can be concluded that in the rescheduled timetable the model tries to steer towards less even headways. However, what does the rescheduling model do with the trains in Blaak that have to deal with peaks in passenger demand?

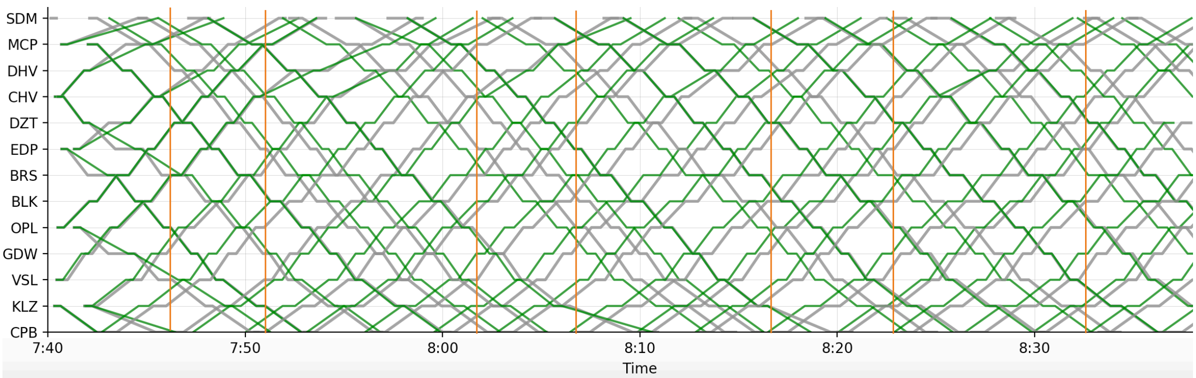


Figure 5.16: Time distance diagram of the best performing solution with reducing in-vehicle time as main objective

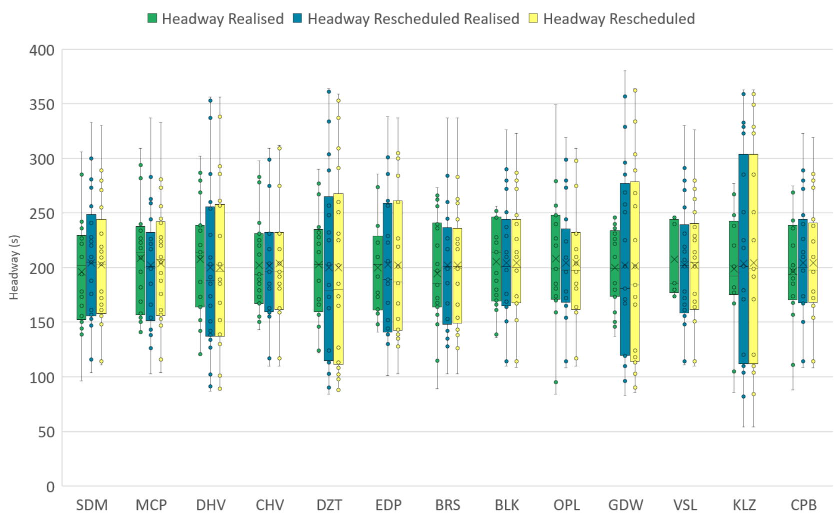


Figure 5.17: Headways for the different stations in the Base run and the optimized timetable and realised optimized timetable

To perform a more in depth analysis on the actions that the rescheduling model performs on trains that deal with peak demands three analyses are performed: first the rescheduling actions that are taken on trains that are identified as trains that deal with a peak in passenger demand at Blaak are compared to the actions taken to other trains that don't have to deal with a peak in passenger demand. Second these actions are then compared to the next simulation run in which the peaks in passenger demand were shifted to different metros. Third the results of this optimized timetable are compared to the results of an optimized timetable with an increased arrival rate at Rotterdam Blaak, which is discussed in the next Section. The results of the first analysis are presented in Figure 5.18.

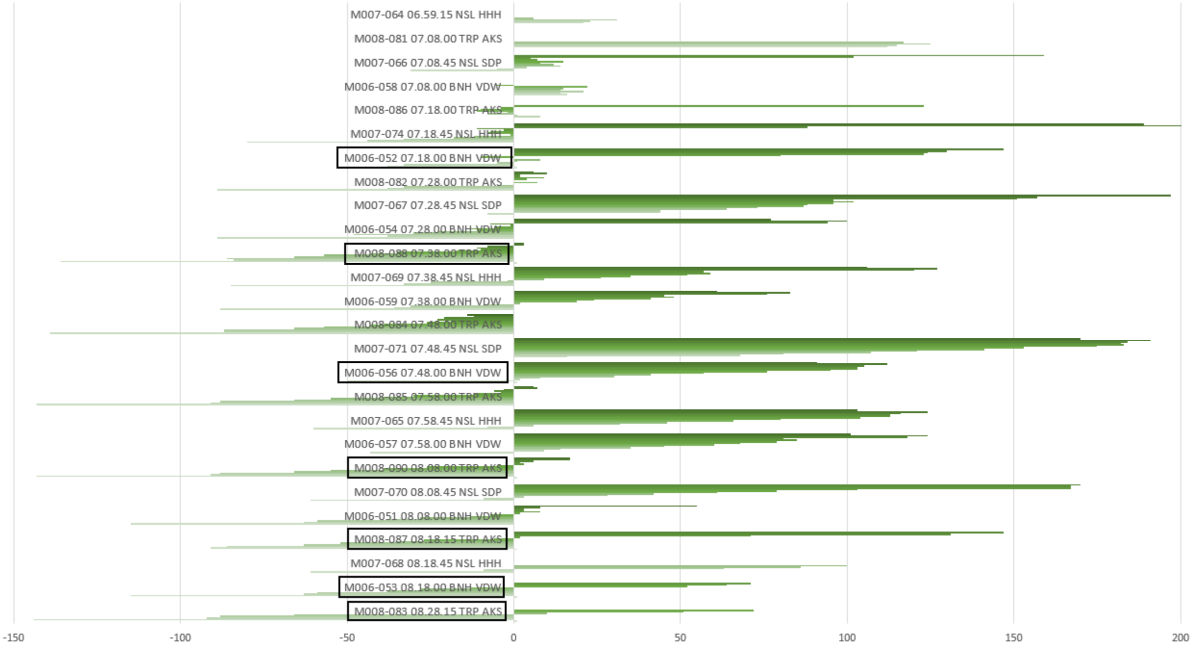


Figure 5.18: Rescheduling actions taken per metro, in deviation from original timetable seconds

In this Figure a negative number represents a metro that is rescheduled earlier than its original time, a positive number means the metro is rescheduled later than its original time. Also it is made up of several bars: these different bars represent the deviation for different stations, with the uppermost bar for each metro representing station Schiedam Centrum (the end of the line), and the lowest bar representing the first station of the line, Capelsebrug. The metros highlighted with a black rectangle are the metros that are the first to arrive at Rotterdam Blaak after a train arrival with at least 50 transfer passengers, which is considered to be a peak in transfer passengers. From this Figure can be concluded that it the rescheduling model mainly tries to make metros that deal with transfer passengers arrive early, as opposed to other metros which tend to get delayed in the rescheduled timetable. On average the TRM schedules the first metro after a peak in transfer passengers 4 seconds earlier as opposed to the other metros, which are on average scheduled 36 seconds later. However, this rule of thumb is definitely not applicable to all metros, there are also metros that don't deal with peak demands scheduled earlier, and metros that deal with peak demands scheduled later. It can also be noted that the metro route that mainly has to deal with these transfer passengers is metroline C between De Terp and De Akkers, which could also be the cause for the difference in rescheduling measures.

To see if this is the case, this analysis is performed on more iterations which used a different arrival distribution at Rotterdam Blaak. All other variables are kept the same. The results of this analysis can be found in Figure 5.19. From this Figure can be concluded that largely the same rescheduling pattern is applied by the TRM, however there are indeed some differences. Some other metro services than in the previous iteration are now dealing with the peak in demand caused by transfer passengers in Rotterdam Blaak. In general this iteration there are more metros that are scheduled later than their original time as opposed to the previous iteration, however a comparison based on Figures 5.18 and Figures 5.19 doesn't yield conclusive answers.

Therefore the average rescheduling action per metro is depicted in Table 5.10. The average rescheduling action is in this case the average change over the timetable that is made, as summed over all the stations on the line. Metros that were the first to arrive after a peak in passenger demand, defined as 50 or more passengers per minute, are made **bold**. Also in this case on average a metro dealing with a peak in transfer passenger demand is rescheduled earlier than other metros, however in this case it is 6 seconds later than its original timetable, opposed to an average of 33 seconds later for all other metros. From this Table can be concluded that though all other variables are kept the same there are quite some difference to be found in the rescheduling decisions made by the TRM, indicating that a different distribution of peaks in passenger demand at Rotterdam Blaak can have a substantial impact on what the optimal schedule is for the metro. There is however no general rescheduling action that should be applied if a metro is dealing with a peak in demand, the best rescheduling measure to be taken is also dependant on other factors in the system.

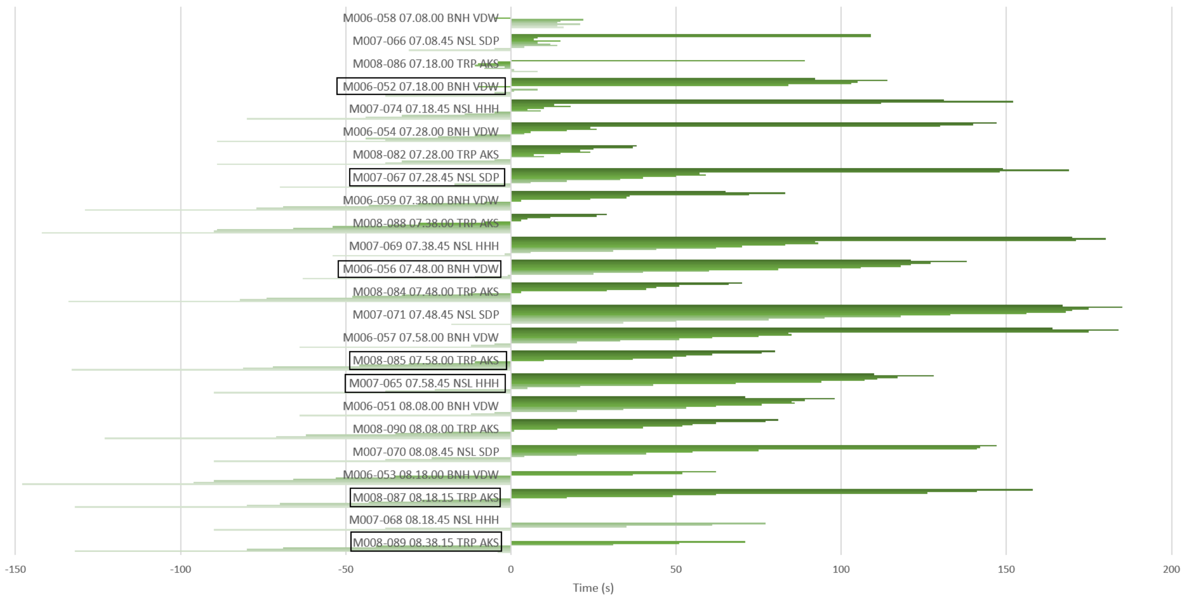


Figure 5.19: Rescheduling actions taken per metro, in deviation from original timetable seconds

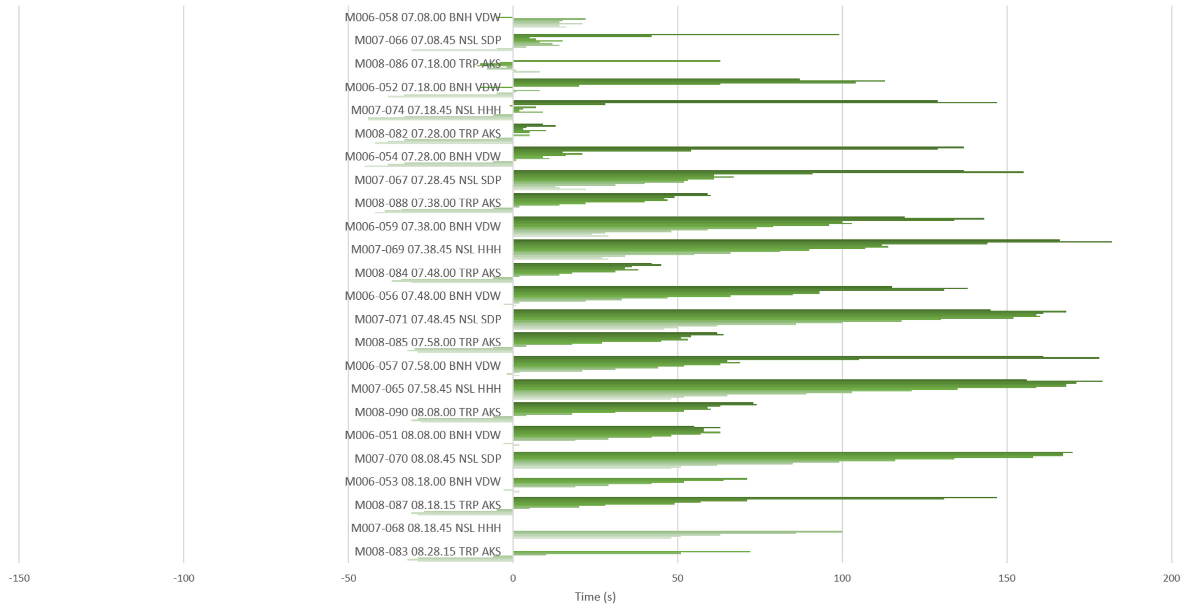


Figure 5.20: Realised Rescheduling actions taken per metro, in deviation from the original timetable

These results plotted in Figures 5.18 and 5.19 are however theoretical results, because these are the actions that the TRM proposes. However, as can be concluded from Table 5.9, there is quite some

Table 5.10: Rescheduling decisions for different iterations, with metros dealing with peak demand in bold

Blaak Arrival Data From:	November 4th, 2019	November 7th, 2019	November 14th, 2019	November 19th, 2019
M008-083 08.28.15 TRP AKS	**-36,7**	**-23,9**	-24,1	**-21,6**
M007-068 08.18.45 NSL HHH	60,0	9,0	9,0	33,8
M008-087 08.18.15 TRP AKS	**-0,8**	**11,4**	**12,0**	**16,3**
M006-053 08.18.00 BNH VDW	**-14,3**	**-37,1**	**-37,1**	-23,6
M007-070 08.08.45 NSL SDP	81,1	41,5	42,4	56,3
M006-051 08.08.00 BNH VDW	-10,8	42,3	52,2	16,2
M008-090 08.08.00 TRP AKS	**-36,0**	**9,1**	9,7	54,8
M007-065 07.58.45 NSL HHH	74,6	54,5	44,2	**50,2**
M006-057 07.58.00 BNH VDW	68,3	62,5	65,5	**-0,6**
M008-085 07.58.00 TRP AKS	-31,8	-2,5	**-3,2**	76,3
M007-071 07.48.45 NSL SDP	146,3	115,1	116,2	127,4
M006-056 07.48.00 BNH VDW	**59,5**	**64,3**	63,8	4,5
M008-084 07.48.00 TRP AKS	-41,2	-7,2	-8,3	**66,3**
M007-069 07.38.45 NSL HHH	44,3	71,9	73,2	83,3
M006-059 07.38.00 BNH VDW	26,9	**-2,5**	-21,2	-24,8
M008-088 07.38.00 TRP AKS	**-42,1**	**-33,8**	-39,7	7,8
M007-067 07.28.45 NSL SDP	99,9	**48,4**	**49,9**	**47,9**
M006-054 07.28.00 BNH VDW	7,8	21,0	20,3	8,4
M008-082 07.28.00 TRP AKS	-3,0	0,9	0,5	**22,3**
M007-074 07.18.45 NSL HHH	28,9	21,6	21,6	29,5
M006-052 07.18.00 BNH VDW	**43,9**	35,1	**35,1**	41,7
M008-086 07.18.00 TRP AKS	12,1	7,0	7,0	7,9
M007-066 07.08.45 NSL SDP	32,1	22,7	22,7	28,1
M006-058 07.08.00 BNH VDW	13,5	13,9	13,9	13,5

difference between the estimation by the TRM and the realisation through the TSM. Therefore it is also interesting to see what the impact of the proposed actions by the TRM is on the realisation through the TSM. Therefore the original timetable and the realised rescheduled time is plotted in Figure 5.20. From this Figure can be concluded that when metros are delayed by the TRM this is generally correctly realised by the TSM, however when a metro is scheduled for an earlier departure by the TRM, the TSM has more trouble realising this. There are metros with an earlier departure, however they are more limited than the TRM suggests. A more in-depth analysis of this effect reveals that this is a limitation of the TRM as used in this research: to limit the noise in the model of other effects impacting rescheduling decisions, the TRM optimizes only a part of the line, between Capeslebrug and Schiedam Centrum. However, to yield an accurate picture of the entire line and to account for the fact that metros can also arrive late, the whole line is simulated through the TSM. This however results in that vehicles scheduled for an earlier departure at the first station used in the TRM, vehicles might not get there in time because at the preceding section of the line they don't depart early. This could also explain why the model converges relatively quickly before starting to deteriorate; options for scheduling a metro earlier than its original time are limited when running the realised timetable. Nevertheless it is still very relevant to analyse the decisions made by the TRM to optimize the timetable; they provide useful input for what rescheduling are relevant in dealing with transfer passenger flows. Additionally this also might represent an accurate picture of real life operations, should the model be applied real time, it is also not possible to make a metro depart early in retrospect.

To better analyse the implementation of the proposed schedule by the TRM through the TSM, a time-distance diagram of the base run from Table 5.9 is presented in Figure 5.21 and a time-distance diagram the second iteration is presented in Figure 5.22. In this Figure the light grey colored paths represent the planned original timetable. The blue colored lines represent a metro running 'on schedule', in this case from the original timetable, measured in deviation from scheduled headway of less than 70%. The red dots represent a metro that has a deviation from the scheduled headway compared to to the following vehicle of more than 70% and is therefore considered to be delayed and the vehicle and is the vehicle that is considered to be bunched. When comparing these figures it can be concluded that some bunching is resolved in the optimized timetable with 52 green cases in Figure 5.21 and 42 in 5.22. Delay is however not resolved, as in both diagrams there are 99 red cases. From these time distance diagrams can be concluded that in general the realised timetable after optimization mainly contains metros that depart later.

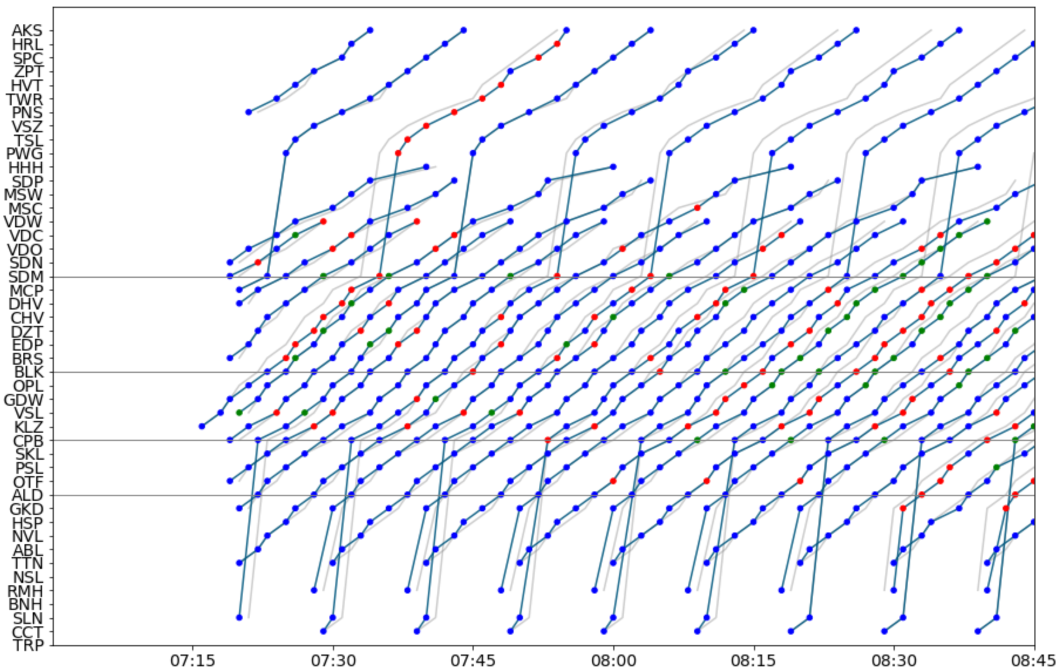


Figure 5.21: Time Distance Diagram of Base run from the base scenario

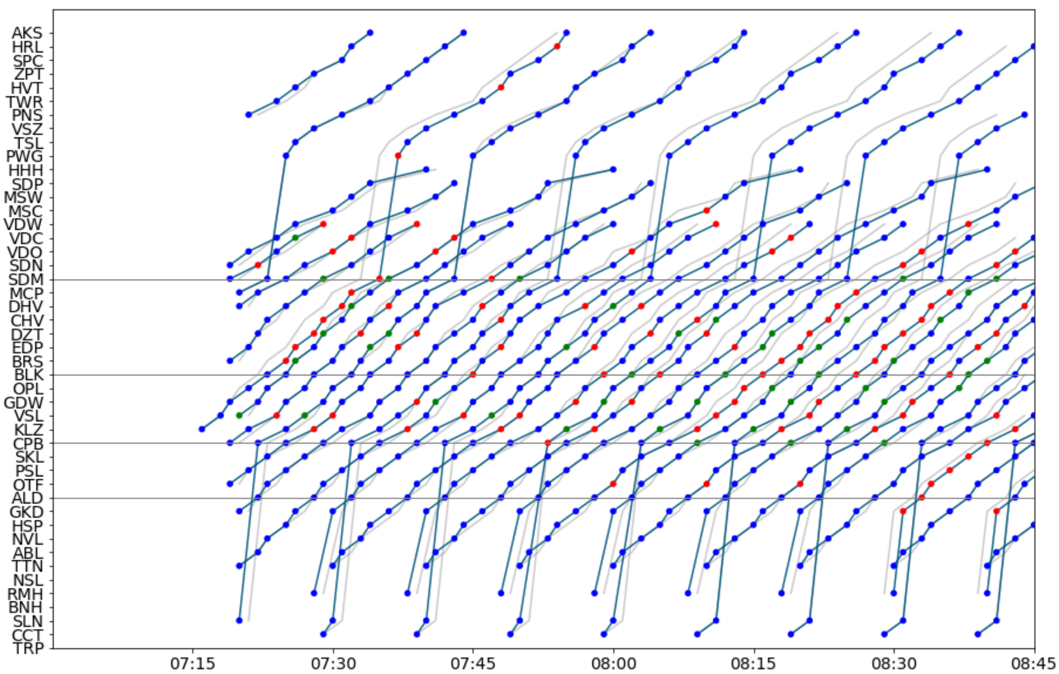


Figure 5.22: Time Distance Diagram of the 2nd iteration from the base scenario

5.5.2. Increased number of Transfer Passengers

To test the impact of more transfer passengers on the metro timetable and to compare the actions taken by the TRM in this scenario to the base scenario, in this scenario the number of transfer passengers is increased with 20 %. The timing of the peaks is kept the same as in the arrival pattern of the 4th of November in the base scenario and also the passenger numbers in the rest of the metro system is kept at the same level. For this experiment also weight set W_2 is used, to make a fair comparison between the base scenario and this scenario. The results of this experiment are presented in Table 5.11. From this Table can be concluded that the most improvement is already achieved after one iteration. To compare to what extent the TRM takes different rescheduling actions compared to the base scenario, also the rescheduling actions of the TRM are plotted in Figure 5.23. From this Figure can be concluded that the general actions of the TRM remain the same, but that the magnitude of the actions is different then for the base scenario.

Table 5.11: Results of the TRM in the scenario with an increased arrival rate at Rotterdam Blaak, weight set W_2

	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						498.99	2656.07	1.43	14.39	2992.99	
1	**447.42**	**2569.88**	**1.41**	**11.89**	**2872.12**	**470.45**	**2581.81**	**1.67**	**14.39**	**2900.24**	**3.1%**
2	434.85	2478.23	1.56	11.99	2772.12	508.25	2696.25	2.09	17.34	3040.86	0.3%
3	470.83	2596.80	2.03	16.16	2916.07						

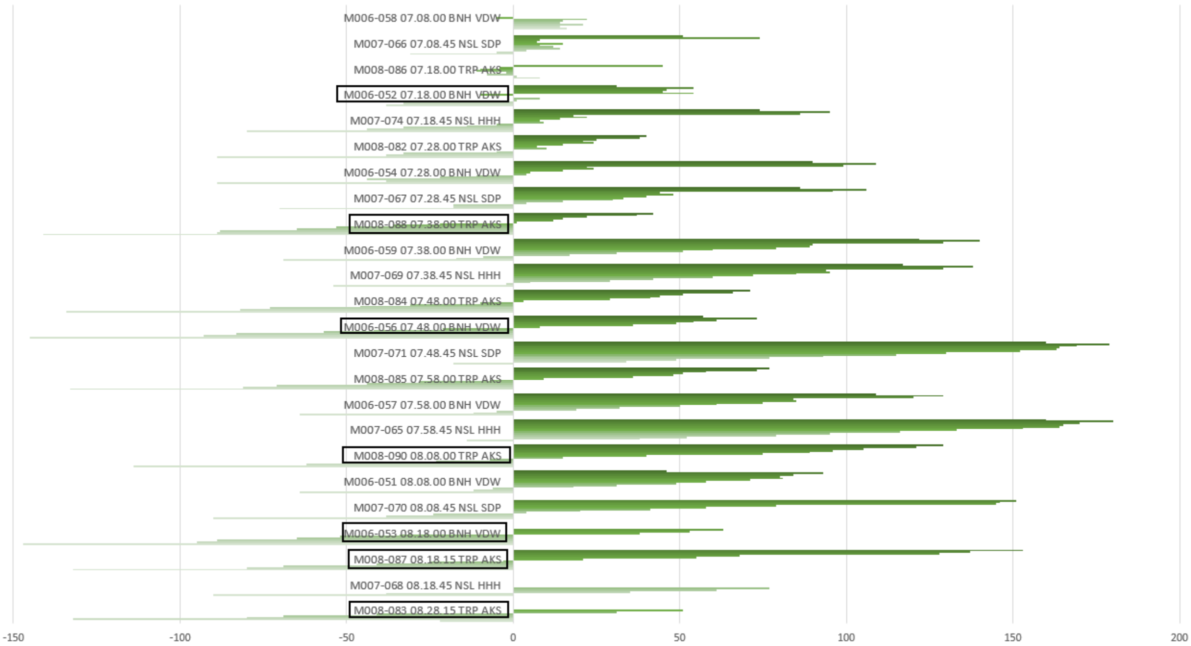


Figure 5.23: Rescheduling actions taken per metro, in deviation from original timetable seconds, with increased passenger numbers at Blaak

From this analysis can thus be concluded that thus both the timing of the arrival of transfer passengers and the number of arriving transfer passengers can impact which rescheduling decisions would yield the optimal result.

5.5.3. Increased Passenger numbers

In this scenario the passenger numbers in the model are increased. As well the number of transfer passengers as the total number of passengers in the metro is increased in this scenario. First the model is ran without the optimization to see what impact increased passenger numbers would have on the system. This is done for different percentages of passenger increase; 10, 20 and 30%. The results of these runs are presented in Figures 5.24 and 5.25. These results were again obtained using weight set W_2. From Figure 5.25 can be concluded that the dwell time of vehicles at each station increase with each increase of passenger numbers. The increase in time can seem relatively small, in the order of magnitude of seconds, so the question is how much impact does this actually have on the schedule?

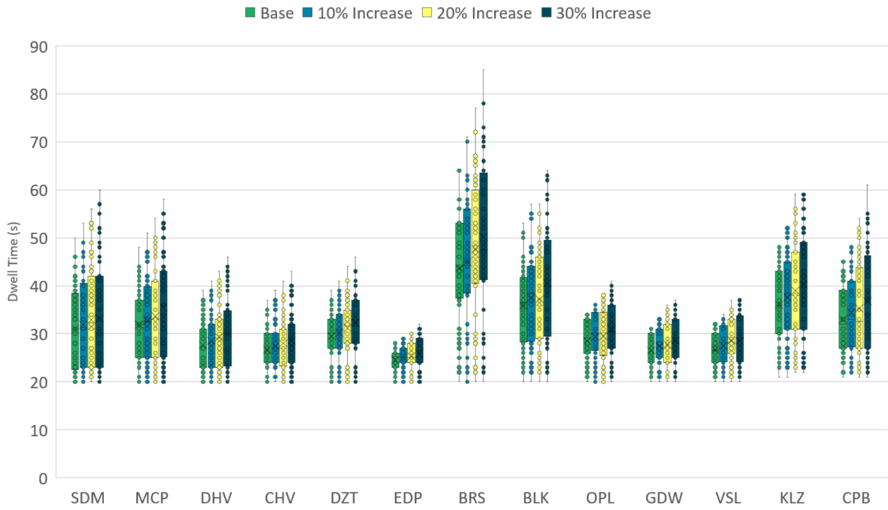


Figure 5.24: Development of delays for different stations with increased passenger numbers

When looking at the delay development in Figure 5.25 for each station there can be concluded that even these relatively small increases in dwell time can have a substantial impact on the delay development over the line for each station, with average delays increasing around 30 seconds when comparing the base scenario to the highest growth scenario. The average dwell times and delays for each growth scenario are also depicted in Table 5.12.

Table 5.12: Average Delays and Dwell Times in Growth Scenarios

Scenario	Average Delay	Average Dwell Time
Base	58,8s	30,9s
10% Increase	70,7s	31,9s
20% Increase	79,4s	32,8s
30% Increase	90,4s	33,9s

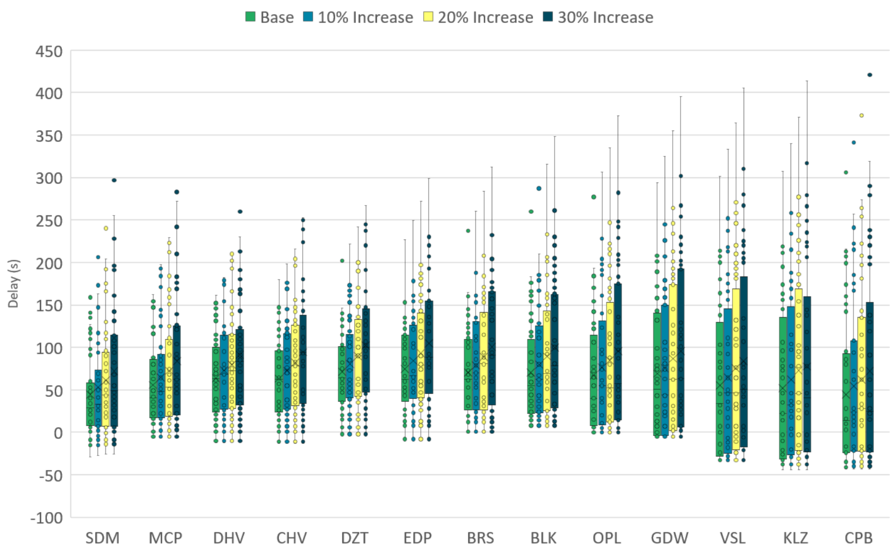


Figure 5.25: Development of delays for different stations with increased passenger numbers

Table 5.13: Results of the TRM in the scenario with an increased arrival rate at all stations, weight set W_2

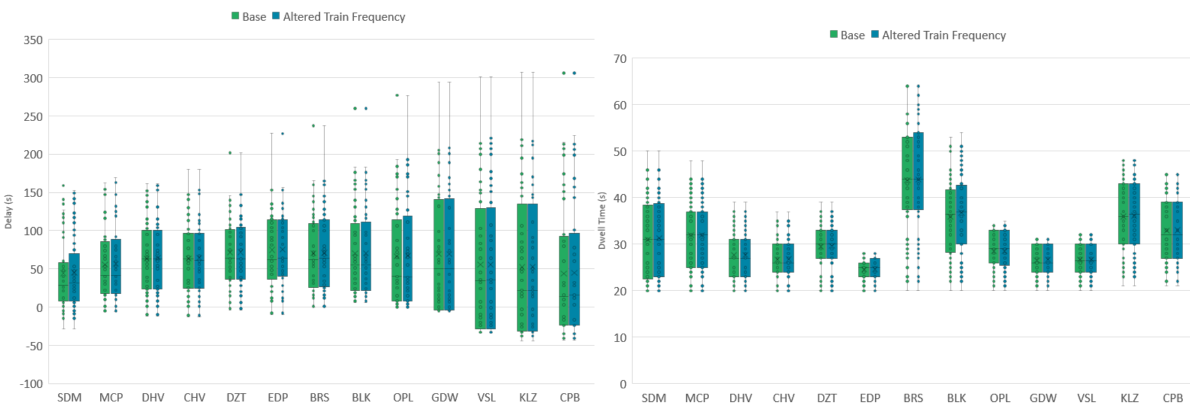
	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						587,61	3466,75	1,78	15,41	3863,62	
1	**534,85**	**3332,87**	**1,65**	**13,43**	**3693,92**	**579,59**	**3381,4**	**1,9**	**16,54**	**3773,3**	**2.3%**
2	541,13	3233,05	1,84	14,48	3598,62	584,05	3394,26	2,1	18,03	3789,64	1.9%
3	541,75	3253,18	1,99	15,32	3619,45	594,23	3424,75	2,33	18,97	3827,22	0.9%

With the current timetable an increase in passenger numbers would thus have a substantial impact on the dwell times of metro vehicles and also on the delay development of the line. To see what improvements to the timetable would be possible in the case of growing passenger numbers, also the TRM is ran for the 20% growth scenario. The results of these TRM runs are presented in Table 5.13

5.5.4. Altered train frequency

In the scenario of an altered train frequency the peaks in passenger demand are differently distributed over the hour to simulate a change in frequency on the train side. From the transfer passenger demand analysis in section 5.3.1 there can be concluded that not every train arrival at the transfer station yields a similar peak in passenger demand. When looking at the peak demand distribution there can be concluded that between 7.30 and 8.30 there are 6 peaks with more than 40 transfer passengers checking-in in one minute. Four of these peaks are caused by the IC Dordrecht - Rotterdam and two are caused by the SPR Dordrecht - Rotterdam. In this scenario it is assumed that the same distribution of these trains causing peaks apply. This will result in a passenger arrival distribution of 9 peaks in transfer passengers between 7.30 and 8.30, of which 6 are caused by by the IC and 3 are caused by the SPR.

Dwell times and delays for this scenario are compared to the dwell times and delays in the base scenario in Figures 5.26a and 5.26b. From these Figures can be concluded that the constructed scenario with an altered train frequency doesn't have much impact on the development of delays and dwell times in the network.



(a) Delays (b) Dwell Time

Figure 5.26: Base scenario delays and dwell times compared to the altered train frequncy scenario

In Figure 5.27 the rescheduling actions per metro that are taken by the TRM for this scenario are plotted. The metros that now have to deal with a peak in demand are highlighted with a black rectangle. When comparing the rescheduling actions in Figure 5.27 with the rescheduling actions presented in Figure 5.19 it can be concluded that this different demand pattern does indeed impact the rescheduling decisions by the TRM and also results in other metros having to deal with the peak in demand than in the Base scenario. However, as from the base scenario can be concluded that a different demand pattern can result in very different solution by the TRM, there is no strong indication that this is due to a different train frequency, but rather just the altered demand pattern.

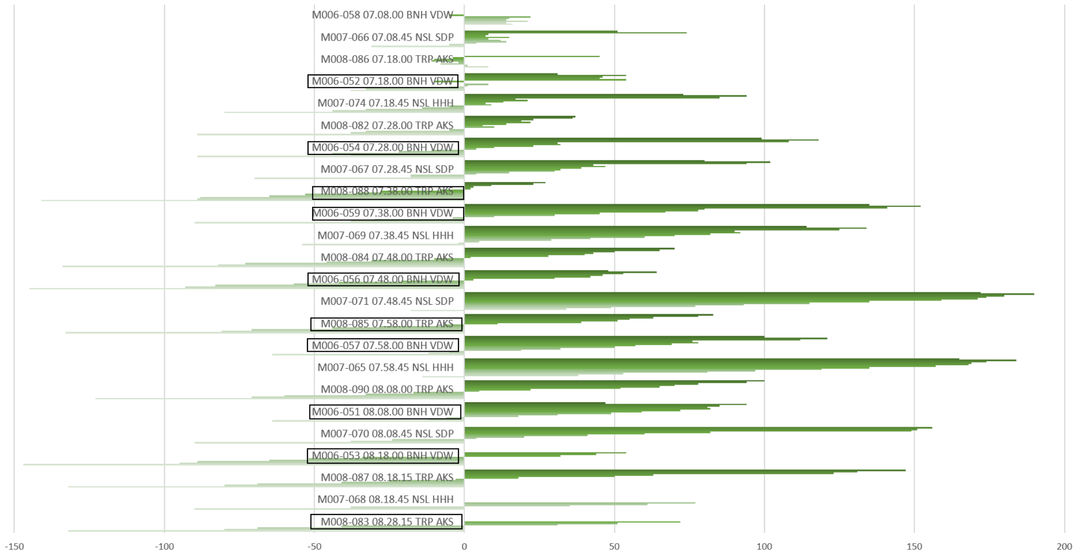


Figure 5.27: Rescheduling actions taken per metro, in deviation from the original timetable in seconds, with an altered train frequency

Table 5.14: Results of the TRM in the scenario with an altered train frequency at Rotterdam Blaak, with reducing in vehcile time as main objective

	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						**491,06**	**2620,77**	**1,41**	**12,64**	**2952,35**	
1	442,09	2534,68	1,39	11,62	2833,28	479,31	2631,8	1,69	14,34	2956,12	-0.1%
2	441,22	2531,79	1,55	11,62	2829,81	504,13	2704,52	2,09	16,87	3046,23	-3.0%
3	471,26	2601,3	2,01	14,56	2920,33						

6 Conclusions and Recommendations

The objective of this Thesis is to gain insight in the dynamic relation between transfer passengers from a lower frequency rail line to a high frequency metro line. This insight is obtained through two ways; first by quantifying the correlation between transfer passenger flows and metro reliability of a real life case study. Four sequential steps in the transfer process from lower frequency rail to higher frequency rail are analysed and correlation analyses on these four sequential steps are performed. Secondly there is researched what rescheduling measures can be applied in this real life case study to minimize the impact of these disturbances. This is done using an existing simulation framework, the Simulation-Based Traffic Management for Metro Network (SBTM-MN). This simulation framework consists of several elements: a Tranpsort Simulation Model (TSM), which simulates the metro network of the case study using the simulation software OpenTrack and accounts for passenger-vehicle interactions during this simulation and a Train Rescheduling Model (TRM), which optimizes the timetable of the metro network for several objectives. With this simulation framework, first is researched what rescheduling measures can be applied in the current situation to reduce the impact of transfer passenger flows and reschedule the timetable for the benefit of the passenger. Additionally several scenarios are researched with this simulation framework to assess the impact of transfer passenger flows in specific scenarios. With these analyses and simulations the research questions can be answered, which is done Section 6.1. The main contributions of this thesis, both societal and scientific, are discussed in Section 6.2. Limitations that should be considered when interpreting the results of this Thesis are discussed in Section 6.3. Finally in Section 6.4 the recommendations and suggestions for future research as a result of this Thesis are presented.

6.1. Answers to research questions

In chapter 1.2 the research questions laying the basis of this research are presented. In this section the answers to all the sub-questions are presented which enables us to answer the main research question.

1. *Using smart card data, what correlations between transfer passengers from lower frequency rail mode and disturbances in an higher frequency railway network can be found and how can this be quantified?*

   To answer this first sub-question, several data analyses are performed. The described correlation is split into 4 separate sequential correlations: the correlation between train arrivals and the passenger demand for the next metro, the correlation between passenger demand and the dwell time of a metro, and the correlations between dwell time of a metro and delays or headway deviations. From these data analyses can be concluded that there is a strong correlation between the number of (transfer) passengers and the arrival of the train, leading to a significantly higher demand for the next metro vehicle. Peaks in passenger demand in the researched transfer station Rotterdam Blaak were clearly caused by passengers checking in from the train platform. From the second data analysis can be concluded that there is also a clear correlation between the number of boarding and alighting passengers and the dwell time of a metro, thus so far a higher passenger demand due to a train arrival would indeed lead to a longer dwell time of a metro.

The next step that is researched is if this longer dwell time could be responsible for causing disturbances and delays in the network. Several different analyses were performed, however there is no clear indication that a longer dwell time at the transfer station **alone** is able to cause disturbances and delays in the network. However, there is still the possibility that it can be a contributing factor. Since the peaks in passenger demand do cause a metro vehicle to have a longer dwell time, a small delay is inevitable. In the researched data however, often it is the case that this delay can be caught up again. However, there are also indications in the data that metros can be delayed in such a way that these delays cannot be caught up again, causing bunching between vehicles. This is also confirmed by the analysis of headway deviation. The average headway deviation over the line is very stable and barely increases along the line, however the 10% most delayed trains do suffer from an increased headway deviation along the line.

There are thus clear quantifiable correlations between the number of transfer passengers and passenger demand for the next metro, with 94% of the peaks in passenger demand being explained by arriving transfer passengers during the morning peak. There is also a clear correlation between passenger demand and the dwell time of a metro, with about 45% of the dwell time being explained by the number of boarding and alighting passengers during the morning peak. The correlation between passenger demand and delay is less clear. As the dwell time is strongly influenced by the number of boarding and alighting passengers, passenger demand and therefore also a higher demand due to transfer passengers, can cause a longer dwell time, but this doesn't necessarily cause a delay for the metro. If a metro is already delayed it can contribute to an increasing delay. The average delay of metros affected by transfer passengers also lies 17 seconds higher than for other metros. The same also holds for headway; a flow of transfer passengers can contribute to an increasing deviation in headway, but doesn't necessarily cause large headway deviations.

2. *What control and rescheduling strategies to minimise disturbances are currently used in railway networks and what KPI's are used to asses their performance?* There are many rescheduling measures possible in railway networks. In this thesis the following rescheduling measures used in public transport networks were considered: Increasing or decreasing driving speed, increasing or decreasing the dwell time of a vehicle, scheduling a metro for an earlier or later departure, changing the route of a vehicle, overtaking another vehicle, rolling stock reservation and short turning. In the network of the case study, the metro network of Rotterdam, only the first three rescheduling measures are applied. For metro networks in general and also the metro network of Rotterdam it is usually practically not feasible to change the route of a vehicle or take over another vehicle. Rolling stock reservation is a rescheduling measure that is applied in metro networks mainly in Asia. It is a very interesting rescheduling measure in very overcrowded networks that are dealing with a lot of cases of denied boarding to balance the demand at different stations. However, as the case study network doesn't deal with a lot of denied boarding, this rescheduling measure is also not considered for the case study. Lastly short turning is considered as an rescheduling option. This is an interesting measure should the network have difficulties dealing with a lot of knock-on delays. However, as there are also no indications that this is a big problem for the network of Rotterdam, this rescheduling measure is also not added to the simulation framework.

   There are several KPI's common to assess the performance in metroway networks. An obvious indicator is ofcourse punctuality. However, what might be even more important, especially in high frequency systems, is the headway between vehicles. Therefore deviation from headway is also included to asses the performance of control and rescheduling measures. As these control and rescheduling measures are becoming more passenger oriented, which is also the case for the SMTB-MN framework in this research, also more passenger oriented KPI's are needed to asses their performance. These KPI's include passenger waiting time and passenger in-vehicle time.

3. *Which control and rescheduling methods can best be applied to minimize disturbances and delays caused by transfer passenger flows?* The rescheduling measures that are considered applicable and relevant as answer of the previous sub question are setup in a modelling study with several

scenarios. To answer this sub question the SBTM-MN framework is used to obtain an optimized timetable for the benefit of the passenger while looking out for schedule adherence as well. This optimized timetable is obtained using an optimization function which accounts for passenger waiting time, passenger in-vehicle time and schedule adherence. Because this optimization function isn't specifically designed to optimize for the arrival of transfer passengers at the researched transfer station, several scenarios are ran in which only the distribution of passenger arrivals was changed and all other parameters were kept the same. Through this simulation and the TRM an optimized timetable was obtained for several days of historical data. From these experiments can be concluded that these different arrival rates have a substantial impact on the optimized timetable and change the decisions made by the TRM. Although there are some indications that the TRM tends to schedule metros affected by transfer passengers earlier than other metros, the rescheduling decisions also remain strongly dependant on other factors in the system.

Concluded can be that with the set of increasing/decreasing running time between two stations, increasing the dwell time or dispatching a metro earlier or later for departure, an improved schedule can be obtained. The recommended rescheduling actions strongly depend on the situation at the transfer station as well as the surrounding stations. For each situation a recommended solution can be obtained through the TRM. Next to the base scenario also a scenario is ran in which the arrival distribution of transfer passengers from historical data is increased with 20% to test what the impact would be on the rescheduling decisions made by the TRM. From this scenario can be concluded that compared to the base scenario a similar pattern in rescheduling decisions can be found as compared to the same data from the base set, but that the decisions are somewhat intensified. For example a metro that is already scheduled earlier in the base scenario will now get scheduled even earlier. Also in this case the rescheduling decisions remain strongly dependant on the situation.

Also a scenario is ran in which the overall passenger numbers are increased. From this scenario can be concluded that without optimizing the timetable dwell times and delays will increase with raising passenger numbers. Through the TRM also an optimized timetable for this scenario can be obtained, however the possible improvements do not increase the same as the dwell times and delays in the network.

4. *What is the impact of a change in frequency on train side to the impact of transfer passenger flows?* The SBTM-MN framework is also ran with an altered train frequency at the transfer station implemented. The results of this run are compared to the base scenario. From the different runs with the base scenario could already be concluded that different distributions of arriving transfer passengers can lead to very different optimal timetables. This is also the case for running the optimization with an altered train frequency. However from the comparison of the simulation with the TSM without an optimized timetable can be concluded that there is no big change in the development of dwell times and delays in the network should the frequency of the train change. This is of course given the fact that assumptions have been made on the distribution of passengers over the 'new' train frequencies, which can turn out to be very different in the future.

What impact do transfer passenger flows from lower frequency railway transportation mode have on disturbances in high frequency metro networks and which control and rescheduling methods are recommended to minimise these disturbances?

In this research is found that transfer passenger flows from a lower frequency railway transportation mode can significantly impact the demand and dwell time of the next arriving metro vehicle. However no strong indications were found that such a peak in demand alone can cause disturbances in the metro network. A peak in demand caused by transfer passengers flows can however contribute to the development of delays over the network. A combination of three different rescheduling methods is used to obtain the optimized schedule for several transfer passenger arrival distributions. A rule of thumb that can be derived from the rescheduling measures obtained is that metro vehicles that deal with a peak in transfer passengers tend to get rescheduled earlier than their original time. However, each distribution resulted in different rescheduling decisions and improvement possibilities. Through the usage of the SBTM-MN framework recommended rescheduling decisions can be obtained for each situation.

6.2. Main Contributions

This Thesis has several main contributions. The contribution of this research can be seen twofold: scientific and societal. These two main contributions are discussed in this section.

6.2.1. Scientific contribution

Recent public transport research is shifting more and more towards passenger oriented real time control strategies, demand prediction, at-stop control measures and the ever continuing search for possible improvements to the reliability and attractiveness of public transport systems. This research contributes to several topical research topics by touching upon the combination of peaks in passenger demand, service reliability, vehicle bunching and rescheduling measures. Especially rescheduling measures have been researched frequently in the past years, however the number of applications remains limited. With the application of this combination of research topics in a microscopic simulation tool this study aims to bring these research topics one step closer to a more broader application in real life. The main scientific contributions of this research are:

- The analysis and quantification of the impact of peaks in passenger demand caused by transfer passengers in case of a difference in service frequency on the reliability of the high frequency system. This research quantified the relation between peaks in (transfer)passenger demand and delays and headway deviations in a high frequency metro system.
- Develop adaptations to a simulation-based framework to simulate the impact of peaks in passenger demand and simulate their impact on dwell time and delay development over the line in combination with simulating for according passenger numbers and dwell times on other parts of the simulated networks as well.
- Develop insights in the usage of rescheduling measures in the context of peak demand at transfer stations in a high frequency metro network.
- Explore several possible scenarios in the case study to estimate the impact of increasing numbers of transfer passengers, an increasing number of passengers on the entire line and a change in frequency on the train side.

6.2.2. Societal contribution

This research also has several societal contributions. With the increasing demand for public transport worldwide and also in the Netherlands, where the case study is situated, there is a growing need for improving efficiency in these public transport systems as they grow towards their capacity limits. With the application of this research in the case study of Rotterdam this research provides more insight into the possible improvements in this network next to providing insights for similar metro networks worldwide. The specific societal contributions of this research are:

- Providing a clear insight for the operators in the impact of transfer passenger flows and to what extent they are able to cause disturbances in their networks.
- How to reschedule the timetable for the benefit of the passenger, reducing the overall travel time of passengers while looking out for operational schedule adherence.
- Providing some insight in possible development of dwell times and delays for future growth scenario's.

6.3. Limitations

This Thesis is written with limited time and limited resources, therefore several assumptions and limitations are applicable to the results of this Thesis. These assumptions and limitations are discussed in this section.

- The quantified correlations between transfer passenger demand and the reliability of the metro line were obtained using case study data. The results of these exact quantification's are thus only applicable to the used case study. In similar networks the interactions and found quantification's might be similar, however as they can be dependant on a lot of factors such as station composition, passenger behaviour, train composition and schedules and many other factors, careful considerations should be made when applying the results of this research to other case studies.

- A limited number of iterations is ran in obtaining the improved timetable for the different scenarios. Many more combinations of objective weights and passenger data usage are possible, possibly resulting in better outcomes than currently achieved.
- This study focused on the situation mainly during the morning peak. Also the optimization of the schedule is done using a simulation of morning peak hours only. Simulating other times of the day could result in very different outcomes, though the correlation analysis already pointed out the effect of transfer passenger numbers is less substantial when looking at the entire day. It could however be interesting to look at the difference between morning peak and evening peak hours.
- The used simulation framework is adapted in such a way that the arrival of transfer passengers to the network is modelled as realistically as possible. Due to limited resources and to be able to measure the pure effect of this one transfer station the surrounding transfer stations are using a flat arrival based on the historical data during peak hours, resulting in an accurate picture of total passengers but eliminating peaks in passenger demand on other stations. In real life this can also influence the behaviour of metro vehicles, resulting in more complex recommendations for rescheduling measures.
- Only a part of the total metro network of the case study was used to perform the optimizations on. Expanding the optimization area of this research can lead to different outcomes for the researched areas as well, as more variables are introduced in the model.
- The optimized timetables from the TRM used as input for the TSM generally correctly implement metros that are delayed in the optimized timetable. To limit the noise in the model of other effects impacting rescheduling decisions, the TRM optimizes only a part of the line, between Capeslebrug and Schiedam Centrum. However, to yield an accurate picture of the entire line and to account for the fact that metros can also arrive late, the whole line is simulated through the TSM. This however results in that vehicles scheduled for an earlier departure at the first station used in the TRM, vehicles don't get there in time because in the proceeding section of the line they don't depart early. Because of some of the optimized earlier departure get lost in the realisation of the optimization, the resulting timetable might be less optimal than predicted.

6.4. Recommendations and Future Research

The conclusions of this Thesis result in several recommendations and input for future research. In this research the specific situation for rescheduling for transfer passenger flows is studied. However, this increased demand in passengers for the next vehicle doesn't necessarily have to come from a train arrival. A connection to another metro line could be a possible source, especially in the case of a difference in service frequency. But there are also many more factors that can cause a peak in passenger demand, such as a large event, the end of a concert or a show, resulting in a lot of people arriving in or leaving the area at the same time. With the knowledge that this can contribute to a longer dwell time of a vehicle and can contribute to delay development on the line it is interesting to research what the how the developed framework would perform in such circumstances as well.

From an operator perspective, specifically for the RET in the case study of the metro network of Rotterdam, there are also several recommendations. As opposed to the expectations indicated by the RET the correlation analysis indicated a less strong correlation between transfer passenger arrivals and disturbances in the metro network than expected. Nevertheless, as peaks in passenger demand can impact the dwell time significantly and this effect increases with increasing passenger numbers towards the coming years, there are recommended rescheduling strategies to deal with these peaks in passenger demand. A rule of thumb advice for the RET is that when is known upfront that a metro has to deal with a peak in passenger demand at the transfer station, the metro needs to be rescheduled earlier or being allowed a longer dwell time in the schedule to deal with this peak in demand. However as the obtained rescheduling measures are also strongly dependent on the situation at the surrounding stations as well, there should be continuously looked for improvements as the situation changes.

There are still many areas in which the used modelling framework can be expanded. The obtained improvement could be further improved further with more computational capacity, also enabling a broader improvement of the timetable over the entire network, resulting in a more balanced timetable which would account for more factors downstream than the current model. Also in the case of scheduling earlier departures for a part of the network, as was done in this research, additional implementations need to be made to ensure that metros are able to arrive earlier to the first stop of the optimized part. This can either be done through adapting the model or optimzing for the entire line.

The current framework is only suited to analyse realised data. Each run still includes a lot of manual labour to run each iteration. Further developments of the SBTM-MN framework are needed to further automate the process to make it potentially interesting for real-time applications. Additionally the run time of the model is currently a limiting factor. As the obtained solution keeps changing as the situation on the line and on the stations changes, the iterations need to be performed very fast to update to the latest situation. This would be a necessity for eventually being able to apply rescheduling decisions real time. The current produced solutions could provide a general direction for rescheduling measures for similar situations.

References

Altazin, E., Dauzère-Pérès, S., Ramond, F., & Tréfond, S. (2020). A multi-objective optimization-simulation approach for real time rescheduling in dense railway systems. *European Journal of Operational Research*, *286*(2), 662 - 672. doi: https://doi.org/10.1016/j.ejor.2020.03.034

Berrebi, S. J., Óg Crudden, S., & Watkins, K. E. (2018). Translating research to practice: Implementing real-time control on high-frequency transit routes. *Transportation Research Part A: Policy and Practice*, *111*, 213 - 226. doi: https://doi.org/10.1016/j.tra.2018.03.008

Binder, S., Maknoon, Y., & Bierlaire, M. (2016, 01). The multi-objective railway timetable rescheduling problem. *Transportation Research Part C: Emerging Technologies*, *78*. doi: 10.1016/j.trc.2017.02.001

Bosina, E., & Weidmann, U. (2017). Estimating pedestrian speed using aggregated literature data. *Physica A: Statistical Mechanics and its Applications*, *468*, 1 - 29. doi: https://doi.org/10.1016/j.physa.2016.09.044

Cacchiani, V., Huisman, D., Kidd, M., Kroon, L., Toth, P., Veelenturf, L., & Wagenaar, J. (2014). An overview of recovery models and algorithms for real-time railway rescheduling. *Transportation Research Part B: Methodological*, *63*, 15 - 37. doi: https://doi.org/10.1016/j.trb.2014.01.009

Cats, O. (2014). Regularity-driven bus operation: Principles, implementation and business models. *Transport Policy*, *36*, 223 - 230. doi: https://doi.org/10.1016/j.tranpol.2014.09.002

Cats, O., West, J., & Eliasson, J. (2016, 06). A dynamic stochastic model for evaluating congestion and crowding effects in transit systems. *Transportation Research Part B Methodological*, *89*, 43-57. doi: 10.1016/j.trb.2016.04.001

Christoforou, Z., Chandakas, E., & Kaparias, I. (2020). Investigating the impact of dwell time on the reliability of urban light rail operations. *Urban Rail Transit*, 1–16.

Cornet, S., Buisson, C., Ramond, F., Bouvarel, P., & Rodriguez, J. (2019, March). *Methods for quantitative assessment of passenger flow influence on train dwell time in dense traffic areas.* Retrieved from `https://hal.archives-ouvertes.fr/hal-01909708` (working paper or preprint)

dell'Olio, L., Ibeas, A., & Cecin, P. (2011). The quality of service desired by public transport users. *Transport Policy*, *18*(1), 217-227. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0967070X10001009` doi: https://doi.org/10.1016/j.tranpol.2010.08.005

Dicembre, A., & Ricci, S. (2011). Railway traffic on high density urban corridors: Capacity, signalling and timetable. *Journal of Rail Transport Planning Management*, *1*(2), 59 - 68. doi: https://doi.org/10.1016/j.jrtpm.2011.11.001

Fabian, J. J., & Sánchez-Martínez, G. E. (2017). Simulation-based comparison of holding strategies for a multibranch light rail service. *Transportation Research Record*, *2648*(1), 23-32. doi: 10.3141/2648-03

Fonzone, A., Schmöcker, J.-D., & Liu, R. (2015). A model of bus bunching under reliability-based passenger arrival patterns. *Transportation Research Procedia*, *7*, 276 - 299. (21st International Symposium on Transportation and Traffic Theory Kobe, Japan, 5-7 August, 2015) doi: https://doi.org/10.1016/j.trpro.2015.06.015

Gavriilidou, A., & Cats, O. (2019). Reconciling transfer synchronization and service regularity: real-time control strategies using passenger data. *Transportmetrica A: Transport Science*, *15*(2), 215-243. doi: 10.1080/23249935.2018.1458757

Gkiotsalitis, K., & Cats, O. (2021). At-stop control measures in public transport: Literature review and research agenda. *Transportation Research Part E: Logistics and Transportation Review*, *145*, 102176. doi: https://doi.org/10.1016/j.tre.2020.102176

Guo, H., Bai, Y., Hu, Q., Zhuang, H., & Feng, X. (2020). Optimization on metro timetable considering train capacity and passenger demand from intercity railways. In B. Liu, L. Jia, Y. Qin, Z. Liu, L. Diao, & M. An (Eds.), *Proceedings of the 4th international conference on electrical and information technologies for rail transportation (eitrt) 2019* (pp. 141–152). Springer Singapore.

Harris, N. G. (2006). Train boarding and alighting rates at high passenger loads. *Journal of Advanced Transportation*, *40*(3), 249-263. Retrieved from `https://onlinelibrary.wiley.com/doi/abs/10.1002/atr.5670400302` doi: https://doi.org/10.1002/atr.5670400302

Harris, N. G., & Anderson, R. J. (2007). An international comparison of urban rail boarding and alighting rates. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *221*(4), 521-526. doi: 10.1243/09544097JRRT115

Hassannayebi, E., Zegordi, S. H., Yaghini, M., & Amin-Naseri, M. R. (2017). Timetable optimization models and methods for minimizing passenger waiting time at public transit terminals. *Transportation Planning and Technology*, *40*(3), 278-304. doi: 10.1080/03081060.2017.1283156

Hofmann, M., & O'Mahony, M. (2005). Transfer journey identification and analyses from electronic fare collection data. In *Proceedings. 2005 ieee intelligent transportation systems, 2005.* (p. 34-39).

Hänseler, F., van den Heuvel, J., Cats, O., Daamen, W., & Hoogendoorn, S. (2020). A passenger-pedestrian model to assess platform and train usage from automated data. *Transportation Research Part A: Policy and Practice*, *132*, 948-968. (cited By 1) doi: 10.1016/j.tra.2019.12.032

Hörcher, D., Graham, D. J., & Anderson, R. J. (2017). Crowding cost estimation with large scale smart card and vehicle location data. *Transportation Research Part B: Methodological*, *95*, 105 - 125. doi: https://doi.org/10.1016/j.trb.2016.10.015

Hürlimann, D. (2002). *Objektorientierte modellierung von infrastrukturelementen und betriebsvorgängen im eisenbahnwesen* (Doctoral dissertation, ETH Zurich, Zürich). doi: 10.3929/ethz-a-004223151

Ingvardson, J. B., Nielsen, O. A., Raveau, S., & Nielsen, B. F. (2018). Passenger arrival and waiting time distributions dependent on train service frequency and station characteristics: A smart card data analysis. *Transportation Research Part C: Emerging Technologies*, *90*, 292 - 306. doi: https://doi.org/10.1016/j.trc.2018.03.006

Jiang, Z., Hsu, C.-H., Zhang, D., & Zou, X. (2016). Evaluating rail transit timetable using big passengers' data. *Journal of Computer and System Sciences*, *82*(1, Part B), 144 - 155.

Kusakabe, T., Iryo, T., & Asakura, Y. (2010). Estimation method for railway passengers' train choice behavior with smart card transaction data. *Transportation*, *37*(5), 731–749.

Leurent, F., & Xie, X. (2017). Exploiting smartcard data to estimate distributions of passengers' walking speed and distances along an urban rail transit line. *Transportation Research Procedia*, *22*, 45 - 54. doi: https://doi.org/10.1016/j.trpro.2017.03.006

Lin, T.-m., & Wilson, N. H. (1992). Dwell time relationships for light rail systems. *Transportation Research Record*(1361).

Luangboriboon, N., Seriani, S., & Fujiyama, T. (2020). The influence of the density inside a train carriage on passenger boarding rate. *International Journal of Rail Transportation*, *0*(0), 1-16. doi: 10.1080/23248378.2020.1846633

Lüthi, M. (2009). *Improving the efficiency of heavily used railway networks through integrated real-time rescheduling* (Vol. 147). ETH Zurich.

NS. (2017, Sep). *test: extra korting tegen drukke hyperspits.* Nederlandse Spoorwegen. Retrieved from `https://nieuws.ns.nl/ns-test-extra-korting-tegen-drukke-hyperspits/`

Pardini-Susacasa, L. (2020). *Towards passenger-oriented simulation-based rescheduling in metro lines* (Unpublished doctoral dissertation).

Prorail. (2019, Mar). *Meer en snellere treinen.* Retrieved from `https://www.prorail.nl/nieuws/meer-en-snellere-treinen`

Puong, A. (2000). Dwell time model and analysis for the mbta red line. *Massachusetts Institute of Technology Research Memo*, 02139–4307.

Puylaert, G. (2019, Sep). *Waarom ret investeert in overvol metronet.* Retrieved from `https://www.ovmagazine.nl/2019/09/metro-is-onze-ruggengraat-we-raken-in-de-knel-1206/`

RET. (2020).

Suazo-Vecino, G., Dragicevic, M., & Muñoz, J. C. (2017). Holding boarding passengers to improve train operation on basis of an economic dwell time model. *Transportation Research Record*, *2648*(1), 96-102. doi: 10.3141/2648-11

Sun, L., Jin, J. G., Lee, D.-H., Axhausen, K. W., & Erath, A. (2014). Demand-driven timetable design for metro services. *Transportation Research Part C: Emerging Technologies*, *46*, 284 - 299. doi: https://doi.org/10.1016/j.trc.2014.06.003

Tirachini, A., & Cats, O. (2020). Covid-19 and public transportation: Current assessment, prospects, and research needs. *Journal of Public Transportation*, *22*(1), 1.

van Oort, N. (2014). Incorporating service reliability in public transport design and performance requirements: International survey results and recommendations. *Research in Transportation Economics*, *48*, 92 - 100. (Competition and Ownership in Land Passenger Transport (selected papers from the Thredbo 13 conference)) doi: https://doi.org/10.1016/j.retrec.2014.09.036

van Oort, N. (2019, Oct). *Service reliability and control.* TU Delft.

Velzen, J. v. (2019, Apr). *De rotterdamse metro kan het groeiende aantal passagiers bijna niet meer aan.* Retrieved from `https://www.trouw.nl/nieuws/de-rotterdamse-metro-kan-het-groeiende-aantal-passagiers-bijna-niet-meer-aan~b0687cc3`

Yin, J., Tang, T., Yang, L., Gao, Z., & Ran, B. (2016). Energy-efficient metro train rescheduling with uncertain time-variant passenger demands: An approximate dynamic programming approach. *Transportation Research Part B: Methodological*, *91*, 178 - 210. doi: https://doi.org/10.1016/j.trb.2016.05.009

Zhu, Y., Koutsopoulos, H. N., & Wilson, N. H. (2017). A probabilistic passenger-to-train assignment model based on automated data. *Transportation Research Part B: Methodological*, *104*, 522 - 542. doi: https://doi.org/10.1016/j.trb.2017.04.012

A

TIL Research Paper

Analysing the impact of peak demand and rescheduling of high frequency metro networks

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Abstract—**Sudden peaks in passenger demand for high frequency metro systems can cause an unexpected increase in dwell time and can contribute to delay development in the network. In this research a quantification for this effect is researched in the case of a train to metro transfer. Determined is to what extend peaks in passenger demand can contribute to delay development in network, and what rescheduling measures are applicable for dealing with these peaks in demand. Peaks in passenger demand can contribute to delay development in the network, but a single peak is unlikely to cause a large delay to a metro service. Nevertheless simulating this effect yields various rescheduling possibilities to improve the timetable for this effect, and decreasing the weighted travel time for the passengers. The rescheduling advises generated by the model can be used to improve rescheduling decisions in high frequency metro networks dealing with peaks in passenger demand.**

Index Terms—**Public Transport, Peak demand, Rescheduling, Metro, Train, Transfer.**

I. Introduction

PUBLIC transport systems all over the world are dealing with increasing demand. These systems are often running at almost their maximum capacities. Therefore there is an increasing need to find ways to operate these systems in an increasingly efficient manner, as especially for metro networks it can be very expensive and can have a high impact on the urban environment to add capacity through new infrastructure. In recent transportation research there is an increasing attention for the operational conditions of public transportation systems and the impact of passenger-vehicle interactions on the timetables of these networks, as these interactions play an important part in determining the line capacity and reliability [1]. However, traditional simulation models assume that these (small) delays caused by passenger-vehicle interactions are caught up using the buffer times in the schedule. However, the modelling study by Pardini Susacasa [2] in which passenger-vehicle interactions are included, concludes that these interactions can prevent vehicles from catching up on these delays or even worsen the development of delays and disturbances in the network.

One of the causes of small delays can be a strong fluctuation in passenger demand per vehicle. Peaks in passenger demand can have a strong impact on the dwell time of a vehicle, as most of the dwell time of a vehicle is explained by the number of boarding and alighting passengers [3]. When the passenger demand is higher for a longer period of time, this can be accounted for in the timetable. However, this is harder for unexpected or short peaks in demand. In high frequency metro networks with transfer stations to lower frequency intercity rail networks the arrival flow of passengers can strongly depend on the arrival of intercity rail services [4]. The demand for the next metro vehicle becomes unexpectedly high, causing a longer dwell time for the next vehicle and could possible trigger or contribute to delays. When correctly accounting for passenger-vehicle interactions these delays can then easily propagate throughout the network [2].

By better understanding how peaks in demand or flows of transfer passengers can impact the schedule of a metro network, measures can be taken to minimize the disturbances and delays caused by these transfer passenger flows. This can be done using real time traffic rescheduling measures. Examples of these rescheduling measures include increasing the dwell time of a vehicle, skipping a stop or scheduling an earlier or later departure of a vehicle [5]. These rescheduling measures can be applied with different objectives which can include passenger waiting time or adherence to the timetable [6].

This paper studies the impact of transfer passenger flows from train to metro on the development of delays and headway deviations in the metro network. With this impact analysis this paper studies rescheduling possibilities to reduce the overall travel time for the passenger while looking out for the development of delays on the line. The main contributions of this study include gaining more insight in the dynamic relation between transfer passenger arrivals and the development of delays and deviations in a metro network and reducing delays and headway deviations on this metro line by a simulation study with rescheduling measures.

The objectives of this study are twofold: (I) quantifying the correlation between arrivals of transfer passenger flows and disturbances in high frequency metro networks, and (II) to find rescheduling strategies to accommodate for these transfer passenger flows.

The outline if this paper is as follows: a literature review on transfer passenger modelling, dwell time, vehicle bunching and rescheduling is given in section II. Then the methodology for the correlation analysis is presented in Section III, followed by the methodology of the simulation study to find rescheduling strategies in section IV. The case study and results of this study are presented in Section V, finally followed by the conclusions in Section VI.

II. Literature Review

This study touches upon several relevant research fields. Looking at a transfer from train to metro from a passenger perspective, there are several research fields this study touches upon when capturing the correlation between the arrival of transfer passengers and the reliability of the metro. Firstly, analysis of transfer passenger flows is considered. Secondly the impact of a difference in service frequency. Thirdly passenger demand and the impact on vehicle dwell time is discussed, followed by vehicle bunching and lastly real time rescheduling methods.

A. *Transfer passenger flows*

Smart card data is increasingly used to model the behaviour of passengers in a network. Examples of applications include determining which train a passenger took based of on a combination of smart card data and automatic vehicle location data for single lines [7] or for lines with a transfer included [8]. Besides passenger train assignment models, also the behaviour of passengers in stations themselves are relevant study topic. It is only very recent that passenger behaviour and vehicle ridership are combined in one study [9]. This study provides possible applications for crowding estimation, transit optimization and disruption management.

Another important factor in the modelling of transfer passenger flows is the consideration that passenger behaviour can strongly depend on demographic characteristics, as well as environmental aspects of the station [10]. All these factors provide important input for this study. The contribution of this study will lie in the combination of passenger behaviour characteristics in the case of a transfer between services with a difference in frequency.

B. *Difference in service frequency*

A difference in service frequency can have a significant impact on what would be the optimal timetable solution. Using a mathematical optimization model it is possible to minimize the waiting time of transfer passengers at the connecting station [11]. There is recognized that indeed these intercity train arrivals can play an important role in the passenger demand at this station. Looking at a metro timetable from a more demand-driven perspective, there can be concluded that current timetables for metro services can prove to be inadequate to accommodate for the dynamic nature of passenger demand [4]. What is not yet covered in these researches however is the impact of these peaks in demand on the reliability of the metro network.

C. *Dwell time*

Dwell time is a widely researched topic in public transpiration research. Deviations in dwell time play an important role in determining the capacity of a line, especially in high frequency systems [12]. A small deviation in dwell time of several seconds can already significantly affect the operation of a line [13]. Not accounting for these fluctuating dwell times in simulation and timetable studies can cause underestimation of delay developments throughout a metro line [2].

One of the main determinants of dwell time is the number of passengers boarding and alighting the vehicle. With fluctuating passenger numbers, dwell times of vehicles can therefore differ strongly. However, when these passenger numbers are known, it is also possible to calculate this dwell time [14]. In systems with a very high demand on board crowding also plays an important role. Crowding levels contribute to the dwell time in a non-linear way [13]. Taking into account peaks in passenger demand and being able to predict the dwell time of a vehicle based on these passenger demand peaks and crowding levels are an important contributing factor to this research.

D. *Vehicle bunching*

In high frequency networks, with vehicles arriving upto every 2 or 3 minutes, a small delay can already cause a vehicle to get in close proximity of the following vehicle. When this happens, bunching of these vehicles can occur. Especially for bus systems, bunching has already been researched for many years. However, applications of mitigating effects for both bus [15] and rail [5] remain limited. Because of the high frequency of metro systems, it is not necessarily the case that bunching is only caused by large delays, smaller delays can also eventually lead to bunching [16].

E. *Rescheduling Measures*

Rescheduling measures can be used to reschedule trains from the original timetable to decrease delays in the system. Several rescheduling measures that are often used include: increasing the dwell time of a vehicle, increase or decrease vehicle speed between stations, dispatching a vehicle early, skipping a stop, changing the route, overtaking another vehicle and short turning [17]. Using rescheduling measures can help prevent vehicle bunching. Especially for high frequency railway lines, aiming at more even headway on the line can turn out to be more effective measure than aiming for schedule adherence [18]. However, using regularity based operations would require a significant shift current agreements with authorities, which usually require certain on-time performances [19].

F. *Research Gap*

Based on this review can be concluded that this study touches upon multiple relevant fields resulting in two scientific gaps: (I) Studying the development of delays and headway deviations in a metro network in the context of peak demands caused by transfer passengers in case of a difference in service frequency. (II) Using a simulation framework to improve the timetable for the benefit of the passenger in the context transfer stations and of peaks in passenger demand at these transfer stations.

III. Transfer Passenger Impact Analysis

In this section the methodology for the analysis of the impact of transfer passengers on disruptions and delays is presented. The aim of this analysis is to quantify to what extent peak demand caused by transfer passengers can cause disturbances and delays in the metro network. To achieve this a smart card data analysis is performed. For this there is made use of a case study, in which several metro lines and intercity railway lines share a single transfer station. In this case study the metro lines run with a frequency 18 metros per direction per hour in total, on alternating lines. The railway lines run with a frequency of 8 trains per hour per direction in total, also on alternating lines and with alternating vehicle types. The focus lies on the train to metro transfer, the other way around is not considered. To assess the propagation of delays throughout the metro network, the stations surrounding the transfer station in the metro network should also be considered. Because the busiest section of the line is serviced by multiple lines, which then separate into different directions at certain stations, a decision is made to focus on the part of the network where the different lines are running on the same infrastructure. The stations that are covered on this part of the line will be considered, other stations disregarded. This is done because in this part of the network the chance of bunching vehicles is the highest and the impact of small delays is expected to be the largest. The case study is further discussed in section V.

A. *Input data*

For the correlation analysis several types of input data are used. Data is gathered for the same period of time from different sources. The time period selected is November 2019. This month is selected because there are no major holidays in the Netherlands during this period of time, resulting in an accurate representation of each weekday. Additionally there is chosen for data from before the Covid-19 pandemic due to the drastic change in travel behaviour during this pandemic. The expectation is that the impact of transfer passengers is the largest during rush hours, the focus of the correlation analysis therefore lies in the rush hours.

The first data set that is used contains passenger smart card data from the researched transfer station for the metro network. Based on the location of the tap-in of a passenger can be derived whether a passenger at this station was an originating passenger or a transfer passenger. Based on this data an arrival pattern of originating and transfer passengers can be constructed. This is then linked to the next set of input data; vehicle data. Vehicle data for the relevant lines of the metro network is collected for the same period of time as the passenger data. The vehicle data set contains automatic vehicle location data for all metros including scheduled and realised arrival and departure times at all stations and the number of boarding and alighting passengers at each stop and the passenger load after the boarding and alighting process. The third data set contains train arrival data, with the scheduled and realised departure for all trains in the same time period at the researched transfer station.

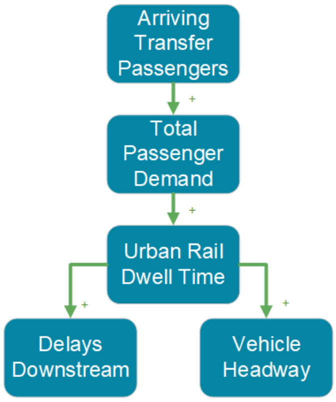

Fig. 1. Schematic overview of the studied correlations

B. *Correlation Analyses*

With this input data the correlation analysis can be performed. The correlation analysis is split up in several analyses of each step of the transfer process. The first analysis concerns to what extend the arrival of transfer passengers impacts the passenger demand for the next metro vehicle. For each peak in demand in the data during the morning peak, there is analysed to what extend these peaks are caused by the arrival of transfer passengers. The next step is to look at to what extend the passenger demand impacts the dwell time of a metro vehicle. The final two steps are to asses the impact of an increased dwell time on the development of delays in the network and deviation in headway. An overview of these correlation analyses is given in Figure 1.

Each correlation in studied separately using statistical processing software SPSS. For each correlation presented in Figure 1 a linear regression analysis is performed. The current variable (Var_n) is used to predict the next variable (Var_n+1). For the first regression analysis the number of arriving transfer passengers is thus used to predict the total passenger demand for the next metro vehicle. The formulas used for the regression analyses are presented in Equations 1, 3, 2 and 4.

$$Var_{n+1} = \beta_0^{Var_n} + \beta_1^{Var_n} Var_n + \epsilon \tag{1}$$

$$\beta_1^{Var_{n+1}} = \frac{\sum_{i=1}^{n}(Var_{n+1} - \overline{Var_{n+1}})(Var_n - \overline{Var_n})/n}{\sum_{i=1}^{n}(Var_{n+1} - \overline{Var_{n+1}})^2/n} \tag{2}$$

$$\beta_0^{Var_{n+1}} = \overline{Var_{n+1}} - \beta_1^{Var_{n+1}}\overline{Var_n} \tag{3}$$

$$R^2_{Var_{n+1}} = \frac{\sum_{i=1}^{n}(\hat{Var}_{n+1_i} - \overline{Var_{n+1}})^2}{\sum_{i=1}^{n}(Var_{n+1_i} - \overline{Var_{n+1}})^2} \tag{4}$$

In the first correlation, the number of arriving transfer passengers and passenger demand, the passenger demand per minute is used. The total passenger demand per minute is correlated to the transfer passenger demand per minute. The R^2 is used to determine to what extend peaks in passenger demand are caused by transfer passengers, the β_0 and β_1 are parameters used to predict the total passenger demand based on the number of transfer passengers.

In second correlation, the total passenger demand and metro dwell time, the aim is to find parameters for calculating the dwell time of a metro vehicle based on the number of boarding and alighting passengers and the passenger load of the vehicle. This regression analysis is performed on all cases, but also on several subsets of the data. This is done because when considering all cases in this regression analysis there is a high chance of picking up a lot of 'noise' in determining the correlation. Other variables that have an impact on the dwell time have a higher impact in certain subsets then others. One of the subsets that is explored are delayed metros. In this subset extra dwell time due to the vehicle arriving early to stop is eliminated, enabling a more pure estimation of the boarding and alighting element in the dwell time of a metro. Additionally also for this correlation the subset of morning peak only, between 6am and 10am is explored, due to the higher passenger volumes in this time period. Also a separate analysis is performed of metros marked as 'affected by transfer passengers', which is defined by the first metro arriving after a peak in transfer passengers of more than 50 transfer passengers.

In the third correlation is tested to what extend an increased dwell time at the transfer station can lead to delays downstream. This is tested for several stations downstream, again using a regression analysis. The fourth and final correlation analysis is performed with also dwell time at the transfer station and deviation in headway.

These correlation analyses only concern the transfer stations. To model passenger demand and dwell times at the surrounding stations accurately as well, for each station considered in the model, the average number of arriving passengers for the morning peak is determined. Also using passenger numbers, a dwell time function is constructed for each of these stations, enabling the model to predict the dwell time based on the number of boarding and alighting passengers and the passenger loads at each of these stations.

With the obtained parameters from the correlation analysis the next step of this study is to apply the quantified correlations in a simulation framework, enabling to test several rescheduling measures and run several scenarios with an accurate representation of peaks in demand caused by transfer passengers.

IV. Model Development and Rescheduling Methods

The next part of this study consists of a simulation study. The aim of this is to obtain rescheduling strategies to deal with peaks in passenger demand, in this case caused by transfer passengers. For this study an existing simulation framework is used, the Simulation-Based Traffic Management for Metro Networks (SBTM-MN) [2].

A. *Simulation-Based Traffic Management for Metro Networks (SBTM-MN)*

In this framework the metro network of the case study is simulated in OpenTrack, an object oriented railway simulation tool [20]. The framework consists of several elements: a Transport Simulation Model (TSM), a Transport Simulation Model of the Real World (TSM-RW) and a Train Rescheduling Model (TRM). A schematic overview of the framework can be found in Figure 2. A simulation iteration is started with the TSM-RW which simulates the metro network for a given time horizon with Real-World data. It consists of a passenger module and a train module. The train module uses OpenTrack to simulate train movements, the passenger module is used to keep track of passenger movements throughout the network and calculates the dwell time for each metro at each station based on the number of boarding and alighting passengers and the passenger load of a metro. The Real-World data used consists of a set of passenger chipcard data and the original timetable of the metro network. The aim of the TSM-RW is to mimic the real life situation of the case study as realistically as possible. The TSM-RW then feeds information such as train and station occupation and realised train events to the TSM.

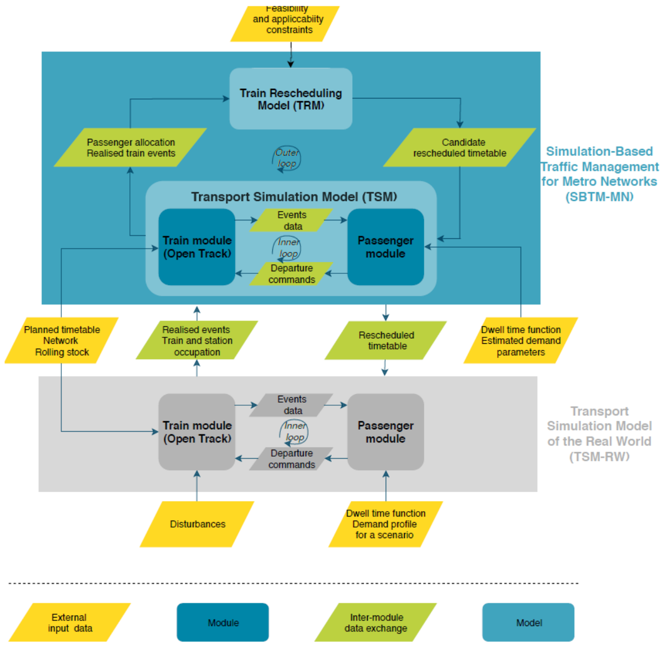

Fig. 2. SBTM-MN Framework [2]

The TSM predicts passenger demand and distribution over the network and simulates train movements for a given time horizon. The TSM also consists of a passenger module and a train module. Where the TSM-RW uses historical chipcard data to generate passengers throughout the network, the TSM uses average arrivals at stations to generate passengers, allowing the exploration of different scenarios. The results of a run with the TSM-RW and TSM are then used as input for the TRM. The TRM interacts iteratively with the TSM to reschedule the timetable for the benefit of the passengers. The TRM computes a rescheduled timetable for the given input of passenger demand and aims to minimize passenger journey times. It comes up with a tentative solution that is evaluated throughout a run in the simulation and is considered to be a linear programming problem [2]. This process is performed iteratively until the timetable no longer improves or starts to deteriorate. The best performing solution is then selected. The TRM makes use of the following rescheduling measures:

- Increasing the dwell time of a train at the station
- Increasing or decreasing the speed of a train in a segment between two stations
- Dispatching a vehicle earlier or later than scheduled

The objective function of the TRM aims to minimize the waiting time for all passengers (W_t), the in vehicle time of all passengers (Ivt) , the deviation from the departure times of all metros at all stations ($Y_{s,m}$) and the deviation of arrival time of metro vehicles at the terminal (X_m). The weights that can be adjusted are to minimize for: passenger waiting time (β_w), minimize passenger in-vehicle time (β_i), the total deviation from the timetable (β_a) and to delays at the terminal station (β_t). All these factors are weighted accordingly to stress the importance of specific terms. These weights can be changed to tweak the objective, as they weight the different objectives in the objective function. The mathematical formulation of the TRM is as follows:

$$min \quad \beta_w * Wt + \beta_i * Ivt + \beta_a * \sum_{m \in M} \sum_{s \in S^m} Y_{s,m} + \beta_t * \sum_{m \in M} X_m \tag{5}$$

Subject to [2]:

$$t^{dep}_{s,m} - t^{arr}_{s,m} \geq e^{min}_s \qquad \forall s \in S^m, m \in M \tag{6}$$

$$t^{arr}_{s+1,m} - t^{dep}_{s,m} \geq q^{min}_{s,s+1} \qquad \forall s \in S^m, m \in M \tag{7}$$

$$t^{dep}_{s,m+1} - t^{arr}_{s,m} \geq h^{out}_s \qquad \forall m \in M^{-,s}, s \in S \tag{8}$$

$$t^{dep}_{s,m+1} - t^{arr}_{s,m} \geq h^{in}_s \qquad \forall m \in M^{+,s}, s \in S \tag{9}$$

$$t^{dep}_{s,n} - t^{arr}_{s,m} \geq c^{min}_{m,n,s} \qquad \forall m, n, s \in V \tag{10}$$

$$t^{arr}_{l,m} - t^{arrs}_m \leq x_m \qquad \forall m \in M \tag{11}$$

$$t^{arrs}_m - t^{arr}_{l,m} \leq x_m \qquad \forall m \in M \tag{12}$$

$$t^{deps}_{s,m} - t^{dep}_{s,m} \leq Y_{s,m} \qquad \forall m \in M, s \in S^m \tag{13}$$

$$t^{dep}_{s,m} - t^{deps}_{s,m} \leq Y_{s,m} \qquad \forall m \in M, s \in S^m \tag{14}$$

$$t^{dep}_{s,m} - t^{depo}_{s,m} \leq u \qquad \forall S \in S, m \in M \tag{15}$$

$$t^{depo}_{s,m} - t^{dep}_{s,m} \leq u \qquad \forall S \in S, m \in M \tag{16}$$

In which equation (5) is the objective function. This objective function minimizes the weighted waiting time for all passengers (W_t), In-vehicle time for all passengers (Ivt), Deviation from departure time at all stations ($Y_{s,m}$) and Deviation from schedule at the terminal station (X_m). The corresponding weights are represented by their corresponding β.

The waiting and in-vehicle time is calculated using passenger data from the TSM. The waiting time can be calculated as the average number of passengers over time waiting at a station, multiplied by the time elapsed between arrivals. The waiting time is calculated using equation (17) [2].

$$W_t = \sum_{s \in S} ((t^{arr}_{s,0} - t_0) * \frac{(w_{s,0} + \hat{w}_s)}{2}) + \sum_{s \in S} \sum_{m \in M^s} ((t^{arr}_{s,m} - t^{arr}_{s,m-1} * \frac{(w_{s,m} + r_{s,m-1})}{2}) \tag{17}$$

Also the In Vehicle Time is calculated using data from the TRM. Using the capacity of a metro vehicle, with the load for each metro there can be determined whether a passenger is standing or not. Assuming that a passenger perceives invehcile time more negative when standing, the in-vehicle time can be calculated using equation (18) [2].

$$Ivt = \sum_{m \in M} \sum s \in S^m (l^{sit}_{s,m} * \gamma_{sit} + l^{stand}_{s,m} * \gamma_{stand}) * (t^{arr}_{s+1,m} - t^{arr}_{s,m}) \tag{18}$$

The objective function is subject to the following constraints: constraint (6) ensures that the time spent by train at a station should be greater than or equal to the minimum dwell time. Constraint (7) ensures that the travel time between two stations cannot be smaller than the minimum driving time, while constraints (8) and (9) ensure that the headway between two trains cannot be smaller than the minimum safety headway. Constraint (10) is used for the minimum connection time between two consecutive train services, service can only depart if inbound train has arrived. Constraints (11), (12), (13) and (14) are used for the linearization of schedule adherence term in objective function. Finally constraints (15) and (16) ensure a limitation of the step size between the current and previous iteration. A complete list of indices, sets, variables and parameters and their explanation can be found in Appendix A

B. Adaptations to the SBTM-MN framework

There are several adaptations to the SBTM-MN framework [2] to make the framework suitable for usage in this study. The framework has to be update to work with the metro lines under review in this study, as well as with updated data such that all data corresponds to the data used for the correlation analysis. An adaptation to the passenger module of the TSM is made such that it is able to simulate peaks in demand caused by arriving transfer passengers as found in the correlation analysis from the previous section.

C. Validation and KPI's

The validation of the models used in this study can be seen twofold: first the outcomes of the TSM and the TSM-RW are validated against historical data to ensure a correct representation of metro vehicle behaviour in the model, especially on the line segment of interest around the researched transfer station. Second the timetable resulting from the TRM should be validated in terms of performance and improvement compared to the existing timetable.

To measure the performance of the different models and to check their validity they need to be compared to historical data and to each other. To make this comparison, Key Performance Indicators (KPI's) are needed to asses the performance of the different models. As the passenger vehicle interaction is one of the main contributing factors of the SBTM-MN framework and play an important role in the definition of the transfer passenger problem, it is very important that the **passenger numbers** are correctly represented in the model. Next, with the correct passenger numbers, the **dwell times** generated with the model are compared to actual dwell times from the data to ensure a correct representation. Also the **delays** generated in the model are validated. Especially in high frequency systems it's also very common to look at regularity or deviation headways [21]. This is measured as the scheduled headway minus the actual headway divided by the scheduled headway.

More recently there are also more passenger oriented KPI's for public transport networks coming up. Rather than measuring the punctuality of a train, the delay of individual passengers is calculated based on chip card data [22]. Also in the SBTM-MN the optimization can be performed with this passenger objective rather than the vehicle perspective, with as KPI's **passenger waiting time** and **passenger in vehicle time**. Therefore these KPI's are also in this research used to assess the performance of schedules created with the SBTM-MN framework, with also vehicle delay in mind.

D. *Objective weights*

The TRM can optimize for different objectives. Because of the limited time and resources available for this study a limited number of objective weights can be tested. The first weight two sets W_1 and W_2 presented in Table I are expected to yield the best performing solutions in terms of percentages total weighted improvement when optimizing for the passenger objective while still looking out for delay development in the network [2]. Because the interest of this research also lies in improving the service reliability of metro networks, also the performance of W_3 is tested in which there is only optimized for schedule adherence. Using the base scenario there is tested which of these three objective combinations yields the highest improvement, this set objectives will then be used to run the other scenarios.

TABLE I
OBJECTIVE WEIGHTS USED

	Waiting Time β_w	In-Vehicle Time β_i	Train delays at all stations β_a	Train delays at terminal β_t
W_1	1	2/3	1/3	0
W_2	2/3	1	1/3	0
W_3	0	0	1	0

The number of combinations used to obtained results for this study are a limitation for this study. As not all combinations are explored, there is a possibility that there are better combinations of weights possible to obtain a more suitable timetable. However with the current set of weight sets chosen the Timetable will be rescheduled for the benefit of the passenger using W_1 and W_2, yielding a balanced solution. The comparison with W_3 is made to see what happens when only optimizing for the timetable objective, and a consideration can be made on how desirable this would be.

V. CASE STUDY AND RESULTS

In this section the case study used in this research is explained in section V-A. Scenarios that are tested with the simulation framework are explained in section V-B. The results of the Transfer Passenger Impact Analysis are presented in section V-C followed the results of the modelling study in V-D.

A. *Case Study*

The case study used in this study is the metro network of Rotterdam. In this network there are several transfer stations. The transfer station on which is focused in this study is Rotterdam Blaak. This is the station with the highest passenger numbers after Rotterdam Centraal. However, as Rotterdam Centraal has train arrivals in such a frequent way that the passenger flow becomes more or less continuous and is also the starting point of metro line D, this station is disregarded.

The set of stations considered around Rotterdam Blaak is the section on which the three metro lines A, B and C serving Rotterdam Blaak run on the same infrastructure. After these stations the lines separate, which makes it less likely that metros still interfere with each oter and have a lower chance of bunching after these stations.

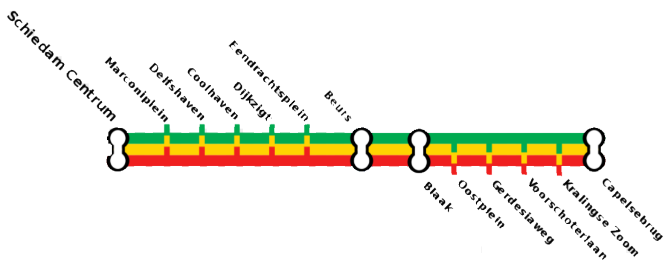

Fig. 3. Study area of this research

To check whether the chosen study area is suitable for this study, a time-distance diagrams for the morning peak is constructed. This is done for the eastern direction, as the majority of passengers arriving at Rotterdam Blaak travels towards the city center. This is presented in Figure 4. In this figures the light grey colored paths represent the planned timetable. The blue colored lines represent a metro running 'on schedule', in this case measured in deviation from scheduled headway of less than 70%. The red dots represent a metro that has a deviation from the scheduled headway compared to to the following vehicle of more than 70% and is therefore considered to be delayed and the vehicle and is the vehicle that is considered to be bunched.

The updated SBTM-MN framework is used to test for different scenarios and find what rescheduling decisions would be the best choice for these specific scenarios. To ensure valid results of the rescheduling measures obtained with the framework, several validations are performed. The model is validated against actual data in terms of the number of passengers generated for each station, the dwell times realised by the model and the delays developed in the network. Results of these validations indicate that the model yields a very

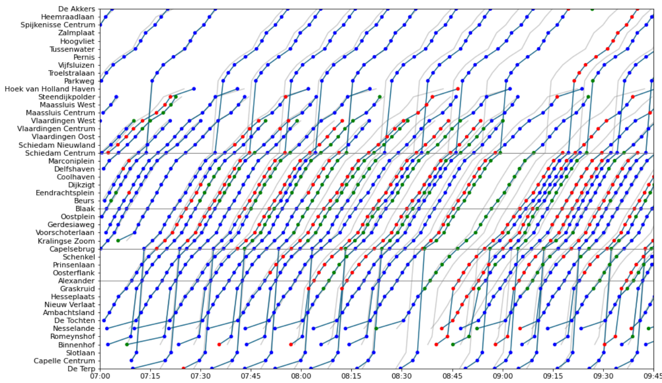

Fig. 4. Time Distance Diagrams of Metrolines A, B and C direction east from the morning peak of Thursday November 28th, 2019h

accurate representation of the network when compared to the historical data set.

B. Scenarios

With the adaptions to the model in place, several scenario's are explored and tested with the model. The goal is to evaluate the rescheduled timetables with the TRM for different scenarios.

1) **Base scenario:** In this scenario is explored how the existing timetable can be improved. This is done with passenger arrival data from four different historical days in the data set, including the day with the most transfer passengers in the data set. These runs are compared to see what the impact of different transfer passenger arrival rates is on the optimal rescheduled timetable. Also the distribution of the passengers numbers over these different train arrivals will be varied, however the total number of passengers will be kept in the same magnitude. The outcomes of this scenario are used to understand what rescheduling measures can be used under current circumstances to improve the timetable.
2) **Increasing the number of transfer passengers:** In this scenario the number of transfer passengers is increased with 20%. The timing of the peaks is kept the same as in the in the base scenario and also the passenger numbers in the rest of the metro system is kept at the same level. This is also used to test to what extent other rescheduling decisions are best applicable in case of a 20% increase in transfer passengers. This percentage is chosen as average growth scenario from the next scenario, in which overall passenger growth is tested.
3) **Increasing passenger numbers:** Overall passenger numbers in the metro system and for the train are increased. This scenario is used to discover to what extent increasing passenger numbers over the coming years will have an increasing impact on the daily operation of the metro. Based on expected passenger growth numbers [23], different growth scenarios are considered: 10%, 20% and 30%.
4) **Higher frequency of Train Services:** This scenario is used to test what the impact is of a higher frequency on the train side. In this scenario the frequency of the train is from 15 minutes per line per direction to 10 minutes per line per direction. The total number of passengers is kept the same as in the base scenario, however the distribution of the passengers is changed to simulate a 10 minute interval of trains. This also means that the number of transfer passengers per train is lower.

C. Results Transfer Passenger Impact Analysis

The correlation analyses as explained in Section III is carried out with data sets from the case study.

Total Passenger Demand - Number of Transfer Passengers The first correlation that is tested is the correlation between the arrival of transfer passengers and the passenger demand for the next metro vehicle. The results of the data for one morning peak is plotted in Figure 5. From this Figure can be concluded that almost all high peaks in passenger demand are caused by the arrival of transfer passengers. This can also be concluded from the parameters obtained from linear regression analysis over all morning peaks, presented in Table II. There can also be concluded that the impact per train service can strongly differ. From the Figure can be concluded that mainly the trains in the direction of Rotterdam Centraal are responsible for peaks in demand.

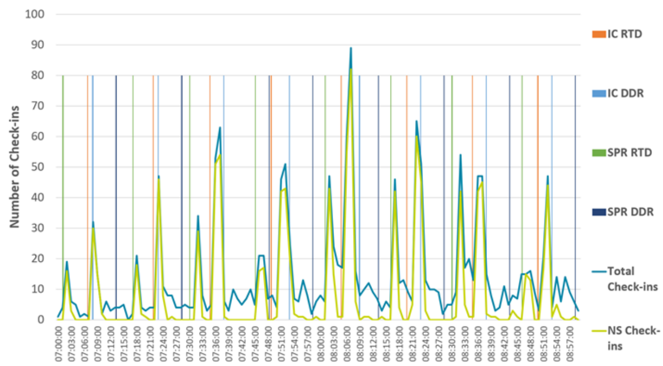

Fig. 5. Total passenger demand - Number of transfer passengers at Rotterdam Blaak, with train arrivals

TABLE II
RESULTS REGRESSION ANALYSIS TOTAL PASSENGER DEMAND - NUMBER OF TRANSFER PASSENGERS

Cases Selected	Param	Value	Param	Value	Param	Value
Entire Day	R^2_{day}	0.638	β_{0day}	6.790	β_{1day}	0.976
Morning Peak	R^2_{am}	0.935	β_{0am}	4.479	β_{1am}	1.019

The goodness of fit is estimated through the adjusted R^2. Here can be concluded that during the day the variance in overall passenger demand can be explained for 64% by transfer passengers, and during the morning peak this increases to 94%. The estimated parameters for β_1 is a logical result, lying around 1 meaning that for every passenger that transfers from the train, demand for the next metro also raises with 1, indicating a largely 1:1 relation. β_0 in this case would then represent the base number of check-ins per minute.

When thus having a good insight in the arrival of trains to the station peaks in passenger demand can easily be predicted.

Dwell Time - Total Passenger Demand

The next regression analysis that is performed is between passenger demand and the dwell time of a metro, in which several subsets of the data are explored. The results of these analyses are presented in Table III. Concluded can be that the dwell time of metro vehicles can for 25% be explained by the number of boarding passengers. This almost doubles when is aimed to filter out as much other effects as possible, which is the case for metros during the morning peak or in case of delayed metros.

TABLE III
RESULTS REGRESSION ANALYSIS PASSENGER DEMAND - DWELL TIME

Cases Selected	Param	Value	Param	Value	Param	Value
Entire Day	R^2_{day}	0.253	β_{0day}	27.534	β_{1day}	0.097
Delayed metros	R^2_{del}	0.488	β_{0del}	25.615	β_{1del}	0.141
Morning peak	R^2_{am}	0.450	β_{0am}	26.597	β_{1am}	0.102

Because the interest of this study lies in the metros that are dealing with peak demands, a distinction is made between metros that are dealing with a peak in demand and metros that are not. A peak in demand is defined as a metro that is dealing with more than 50 arriving transfer passengers since the previous metro. The results of this analysis is presented in Figure 6. The R^2 found for peak demand cases only is 0.450. Concluded can be that metros dealing with peaks in passenger demand are mainly on the higher end of the dwell time and passenger number spectrum, making it more likely for these metros to deal with an increase in dwell time.

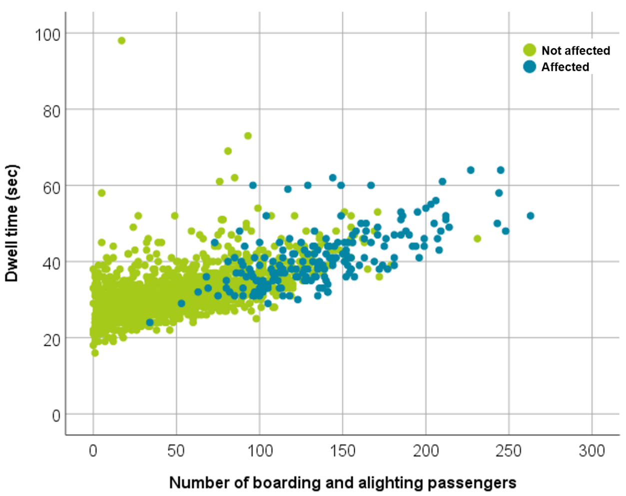

Fig. 6. Dwell time - Number of boarding passengers at Rotterdam Blaak, with metros affected by transfer passengers highlighted, morning peak only.

Delay - Dwell Time

The third correlation that is researched is between dwell time at Rotterdam Blaak and delay. A regression analysis between dwell time at Rotterdam Blaak and delay at the next station, Beurs, is performed. The results of this analysis are presented in Table IV. From this analysis can be concluded that only 7,5% of the variance in delay can be explained by dwell time at Blaak. This does increase for metros affected by transfer passengers, however.

TABLE IV
RESULTS REGRESSION ANALYSIS DWELL TIME BLAAK - BEURS DEPARTURE DELAY

Cases	Param	Value	Param	Value	Param	Value
All Cases	R^2_{all}	0.075	β_{0all}	-2.201	β_{1all}	1.825
Affected by transfer pax	R^2_{aff}	0.174	β_{0aff}	-25.475	β_{1aff}	2.380

The average departure delay at the next stop, Beurs, of metro vehicles during the morning peak affected by transfer passengers, significantly differs from the other metro vehicles during the morning peak. This can be concluded from Table V. Concluding that there is an impact on the delay when a metro has to pick up a substantial load of transfer passengers. However, as the explained variance from the regression analysis remains limited, to what extent it has an impact can differ strongly. The dwell time at the transfer station, Rotterdam Blaak, can thus be a contributing factor in the development of delays over the line, but there is no clear indication that a large increase in delay is systematically caused by longer dwell times at Blaak.

TABLE V
AVERAGE DEPARTURE DELAYS AT BEURS FOR METRO'S THAT ARE OR AREN'T AFFECTED BY TRANSFER PASSENGERS

Affected by Transfer Passengers	Average Departure Delay Beurs (s)	Standard Error
No	55.31	1.17
Yes	72.41	3.18

Headway - Dwell Time

The last regression analysis that is performed is correlating the dwell time at Blaak to headway deviations along the line. When correlating the dwell time at Blaak at the headway deviation at the next station an R^2 of 0.02 is found, concluding that no useful parameters can be obtained for this correlation. The same analysis was also done for other stations on the line, but no clear correlation was found. Concluding that the dwell time at Blaak only is a significant enough contributor to cause headway deviations, however it can still be a contributing factor in causing headway deviations.

D. *Results Simulation with Adapted SBTM-MN Framework*

1. Base Scenario

The actions of the TRM are compared to see the impact of these different arrival distributions, while everything else is kept the same. The results of the best performing run, obtained with passenger arrival data from November 4th, 2019, are presented in Table VI. In this table the waiting time, in-vehicle time, deviation from schedule at the final station and the total deviation from schedule for all vehicles is presented. The total cost is the weighted sum of these cost, weighted for the weight set used, in this case W_2. This is done for each estimate by the TRM and the results of the realised run of the corresponding timetable from the optimization. From this Table can be concluded that an overall 2,5% improvement in total cost can be obtained by using rescheduling.

TABLE VI
RESULTS OF THE TRM IN THE BASE SCENARIO

Run	Waiting Time [h]	In-Vehilce Time [h]	Deviat. at Termin [h]	Dep. Deviat-ion all dep. [h]	Total Cost [h]	Impro-vement
Estimated by TRM						
Base						
1	433.93	2490.71	1.34	11.09	2783.70	
2	**435.56**	**2379.20**	**1.29**	**9.176**	**2672.63**	
3	442.58	2417.39	1.32	9.99	2715.78	
4	467.64	2504.44	1.72	13.21	2820.60	
Realised through TSM						
Base	482.37	2576.29	1.39	12.52	2902.05	
1	462.07	2519.86	1.39	11.98	2831.89	2.4%
2	**473.23**	**2510.35**	**1.52**	**12.38**	**2829.97**	**2.5%**
3	513.37	2607.38	1.82	15.40	2954.76	-1.8%
4	554.65	2698.30	2.07	16.91	3073.71	-4.7%

When running the TRM for different arrival rates at Rotterdam Blaak, resulting in other metros having to deal with peaks in demand due to arriving transfer passengers quite different solutions are obtained. The results of these different runs are presented in Table VII, in which the average time a metro is rescheduled compared to the original timetable over the line is presented. On average, a metro dealing with a peak in transfer passenger demand is rescheduled 6 seconds later than its original timetable, opposed to an average of 33 seconds later for all other metros. The impact of arriving passengers at Rotterdam Blaak is thus substantial enough to result in very different decisions for the TRM to reschedule a metro.

TABLE VII
RESCHEDULING DECISIONS FOR DIFFERENT ITERATIONS, WITH METROS DEALING WITH PEAK DEMAND IN BOLD

Blaak Arrival Data From:	4/11, 2019	7/11, 2019	14/11, 2019	19/11, 2019
M008-083 08.28.15 TRP AKS	**-36,7**	**-23,9**	-24,1	**-21,6**
M007-068 08.18.45 NSL HHH	60,0	9,0	9,0	33,8
M008-087 08.18.15 TRP AKS	**-0,8**	**11,4**	**12,0**	**16,3**
M006-053 08.18.00 BNH VDW	**-14,3**	**-37,1**	**-37,1**	-23,6
M007-070 08.08.45 NSL SDP	81,1	41,5	42,4	56,3
M006-051 08.08.00 BNH VDW	-10,8	42,3	52,2	16,2
M008-090 08.08.00 TRP AKS	**-36,0**	**9,1**	9,7	54,8
M007-065 07.58.45 NSL HHH	74,6	54,5	44,2	**50,2**
M006-057 07.58.00 BNH VDW	68,3	62,5	65,5	**-0,6**
M008-085 07.58.00 TRP AKS	-31,8	-2,5	**-3,2**	76,3
M007-071 07.48.45 NSL SDP	146,3	115,1	116,2	127,4
M006-056 07.48.00 BNH VDW	**59,5**	**64,3**	63,8	4,5
M008-084 07.48.00 TRP AKS	-41,2	-7,2	-8,3	**66,3**
M007-069 07.38.45 NSL HHH	44,3	71,9	73,2	83,3
M006-059 07.38.00 BNH VDW	26,9	**-2,5**	-21,2	-24,8
M008-088 07.38.00 TRP AKS	**-42,1**	**-33,8**	-39,7	7,8
M007-067 07.28.45 NSL SDP	99,9	**48,4**	**49,9**	**47,9**
M006-054 07.28.00 BNH VDW	7,8	21,0	20,3	8,4
M008-082 07.28.00 TRP AKS	-3,0	0,9	0,5	**22,3**
M007-074 07.18.45 NSL HHH	28,9	21,6	21,6	29,5
M006-052 07.18.00 BNH VDW	**43,9**	35,1	**35,1**	41,7
M008-086 07.18.00 TRP AKS	12,1	7,0	7,0	7,9
M007-066 07.08.45 NSL SDP	32,1	22,7	22,7	28,1
M006-058 07.08.00 BNH VDW	13,5	13,9	13,9	13,5

To better analyse the implementation of the proposed schedule by the TRM through the TSM, a time-distance diagram of the base run from Table VI is presented in Figure 7 and a time-distance diagram the second iteration is presented in Figure 8. In this Figure the same colors as in Figure 4 are used. A rough rule of thumb that can be concluded is that metros dealing with a peak in passenger demand tend to get rescheduled a little earlier or less later than other metros. Other metros get rescheduled later. However, this is not applicable to all cases. Concluded can be that rescheduling decisions remain very dependant on a lot of different variables, and that for each case a recommended rescheduling strategy can be obtained through the TRM.

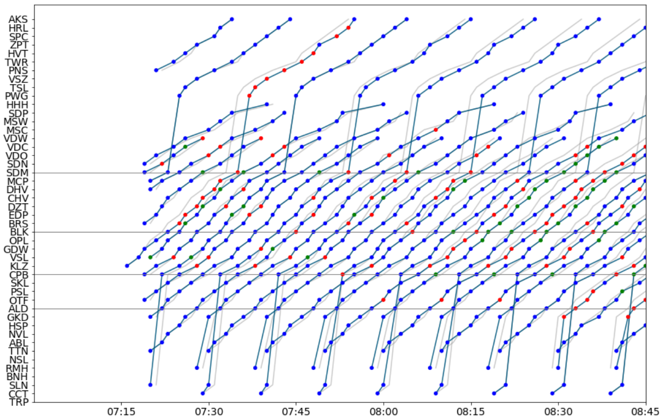

Fig. 7. Time Distance Diagram of the best performing solution in the base scenario using weight set W_2

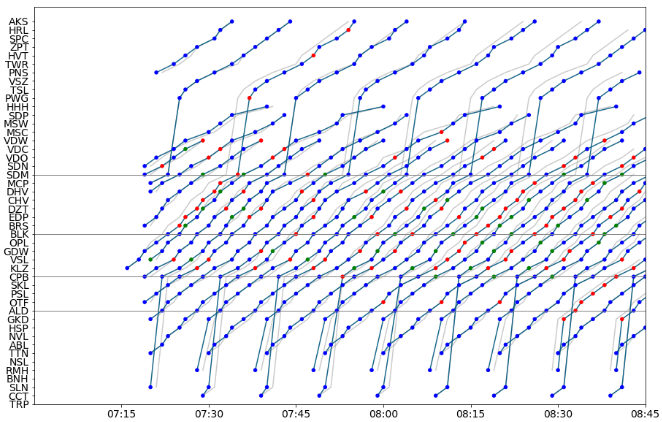

Fig. 8. Time Distance Diagram of the best performing solution in the base scenario using weight set W_2

2. Increased Number of Transfer Passengers

The results of this experiment are presented in Table VIII. For this experiment the arrival data of the 4th of November is used and increased with 20%. A slightly higher improvement of 3.1% is achieved in this scenario. Comparing the actions of the TRM to the same day used as in the base scenario, concluded can be that the general actions of the TRM remain the same, but that the magnitude of the actions is different then for the base scenario. From this analysis can thus be concluded that thus both the timing of the arrival of transfer passengers and the number of arriving transfer passengers can impact which rescheduling decisions would yield the optimal result.

TABLE VIII
RESULTS OF THE TRM IN THE SCENARIO WITH AN INCREASED ARRIVAL RATE AT ROTTERDAM BLAAK

Run	Waiting Time [h]	In-Vehilce Time [h]	Deviat. at Termin [h]	Dep. Deviat-ion all dep [h]	Total Cos t [h]	Impro-vement
Estimated by TRM						
Base						
1	**447.42**	**2569.88**	**1.41**	**11.89**	**2872.12**	
2	434.85	2478.23	1.56	11.99	2772.12	
3	470.83	2596.80	2.03	16.16	2916.07	
Realised through TSM						
Base	498.99	2656.07	1.43	14.39	2992.99	
1	**470.45**	**2581.81**	**1.67**	**14.39**	**2900.24**	**3.1%**
2	508.25	2696.25	2.09	17.34	3040.86	0.3%
3						

3. Increased Number of Passengers

The results of these runs are presented in Table IX. It be concluded that increasing passenger numbers will indeed cause in increase in average dwell time, also resulting in an increase in delay development over the line.

TABLE IX
AVERAGE DELAYS AND DWELL TIMES IN GROWTH SCENARIOS

Scenario	Average Delay	Average Dwell Time
Base	58,8s	30,9s
10% Increase	70,7s	31,9s
20% Increase	79,4s	32,8s
30% Increase	90,4s	33,9s

For the 20% increase scenario also the TRM is ran to see the impact on rescheduling possibilities with an overall increase in passenger numbers. The results of this experiment are presented in Table X. From this table can be concluded that the improvement percentage remains similar to the base scenario. Looking at the actions of the TRM, again a different set of actions is recommended by the TRM, making it again as case specific as in the base scenarios.

TABLE X
RESULTS OF THE TRM IN THE SCENARIO WITH AN INCREASED ARRIVAL RATE AT ALL STATIONS

Run	Waiting Time [h]	In-Vehilce Time [h]	Deviat. at Termin [h]	Dep. Deviat-ion all dep. [h]	Total Cost [h]	Impro-vement
Estimated by TRM						
Base						
1	**534,85**	**3332,87**	**1,65**	**13,43**	**3693,92**	
2	541,13	3233,05	1,84	14,48	3598,62	
3	541,75	3253,18	1,99	15,32	3619,45	
Realised through TSM						
Base	587,61	3466,75	1,78	15,41	3863,62	
1	**579,59**	**3381,4**	**1,9**	**16,54**	**3773,3**	**2.3%**
2	584,05	3394,26	2,1	18,03	3789,64	1.9%
3	594,23	3424,75	2,33	18,97	3827,22	0.9%

4. Altered Train Frequency

In the scenario of an altered train frequency the peaks in passenger demand are differently distributed over the hour to simulate a change in frequency on the train side. When comparing the average dwell times and delays developing in the network, concluded can be that there is no big difference between the base scenario and an altered train frequency. The TRM is also ran for this scenario, the results are presented in Table XI. In this scenario the TRM fails to improve the timetable. However, as from the base scenario can be concluded that a different demand pattern can result in very different solution by the TRM, there is no strong indication that this is due to a different train frequency, but rather just the altered demand pattern.

TABLE XI
RESULTS OF THE TRM IN THE SCENARIO WITH AN ALTERED TRAIN FREQUENCY AT ROTTERDAM BLAAK

Run	Waiting Time [h]	In-Vehilce Time [h]	Deviat. at Termin [h]	Dep. Deviat-ion all dep. [h]	Total Cost [h]	Impro-vement
Estimated by TRM						
Base						
1	442,09	2534,68	1,39	11,62	2833,28	
2	441,22	2531,79	1,55	11,62	2829,81	
3	471,26	2601,3	2,01	14,56	2920,33	
Realised through TSM						
Base	**491,06**	**2620,77**	**1,41**	**12,64**	**2952,35**	
1	479,31	2631,8	1,69	14,34	2956,12	-0.1%
2	504,13	2704,52	2,09	16,87	3046,23	-3.0%

VI. CONCLUSION

The objective of this study is to gain insight in the dynamic relation between transfer passengers from a lower frequency rail line to a high frequency metro line. This insight is obtained through two ways; first by quantifying the correlation between transfer passenger flows and metro reliability of a case study. Four sequential steps in the transfer process from lower frequency rail to higher frequency rail are analysed and correlation analyses on these four sequential steps are performed. Secondly there is researched what rescheduling measures can be applied in this real life case study to minimize the impact of these disturbances. This is done using an existing simulation framework. Several scenarios are researched with this simulation framework to assess the impact of transfer passenger flows in specific scenarios.

There are clear quantifiable correlations between the number of transfer passengers and passenger demand for the next metro, with 94% of the peaks in passenger demand being explained by arriving transfer passengers during the morning peak. There is also a clear correlation between passenger demand and the dwell time of a metro, with about 45% of the dwell time being explained by the number of boarding and alighting passengers during the morning peak. The correlation between passenger demand and delay is less clear. As the dwell time is strongly influenced by the number of boarding and alighting passengers, passenger demand and therefore also a higher demand due to transfer passengers, can cause a longer dwell time, but this doesn't necessarily cause a delay for the metro. If a metro is already delayed it can contribute to an increasing delay. The average delay of metros affected by transfer passengers also lies 17 seconds higher than for other metros. The same also holds for headway; a flow of transfer passengers can contribute to an increasing deviation in headway, but doesn't necessarily cause large headway deviations.

With the set of increasing/decreasing running time between two stations, increasing the dwell time or dispatching a metro earlier or later for departure, an improved schedule can be obtained. The recommended rescheduling actions strongly depend on the situation at the transfer station as well as the surrounding stations. For each situation a recommended solution can be obtained through the TRM. Next to the base scenario also a scenario is ran in which the arrival distribution of transfer passengers from historical data is increased with 20% to test what the impact would be on the rescheduling decisions made by the TRM. From this scenario can be concluded that compared to the base scenario a similar pattern in rescheduling decisions can be found as compared to the same data from the base set, but that the decisions are somewhat intensified. For example a metro that is already scheduled earlier in the base scenario will now get scheduled even earlier. Also in this case the rescheduling decisions remain strongly dependant on the situation. Also a scenario is ran in which the overall passenger numbers are increased. From this scenario can be concluded that without optimizing the timetable dwell times and delays will increase with raising passenger numbers. Through the TRM also an optimized timetable for this scenario can be obtained, however the possible improvements do not increase the same as the dwell times and delays in the network. From the different runs with the base scenario could already be concluded that different distributions of arriving transfer passengers can lead to very different optimal timetables. This is also the case for running the optimization with an altered train frequency.

In this study is found that transfer passenger flows from a lower frequency railway transportation mode can significantly impact the demand and dwell time of the next arriving urban rail vehicle. However no strong indications were found that such a peak in demand alone can cause disturbances in the urban rail network. A peak in demand caused by transfer passengers flows can however contribute to the development of delays over the network. A combination of three different rescheduling methods is used to obtain the optimized schedule for several transfer passenger arrival distributions. Though there are some indications that generally urban rail vehicles that deal with a peak in transfer passengers tend to get rescheduled earlier than other urban rail vehicles, each distribution resulted in different rescheduling decisions and improvement possibilities. Through the usage of the SBTM-MN framework recommended rescheduling decisions can be obtained for each situation.

Limitations and Future Research

There are several limitations that should be taken into account when interpreting the conclusions of this study.

- The quantified correlations between transfer passenger demand and the reliability of the metro line were obtained using case study data. The results of these exact quantification's are thus only applicable to the used case study. In similar networks the interactions and found quantification's might be similar, however as they can be dependant on a lot of factors such as station composition, passenger behaviour, train composition and schedules and many other factors, careful considerations should be made when applying the results of this research to other case studies.
- A limited number of iterations is ran in obtaining the improved timetable for the different scenarios. Many more combinations of objective weights and passenger data usage are possible, possibly resulting in better outcomes than currently achieved.
- This study focused on the situation mainly during the morning peak. Also the optimization of the schedule is done using a simulation of morning peak hours only. Simulating other times of the day could result in very different outcomes.
- The used simulation framework is adapted in such a way that the arrival of transfer passengers to the network is modelled as realistically as possible. Due to limited resources and to be able to measure the pure effect of this one transfer station the surrounding transfer stations are using a flat arrival based on the historical data during peak hours, resulting in an accurate picture of total passengers but eliminating peaks in passenger demand on other stations. In real life this can also influence the behaviour of metro vehicles, resulting in more complex recommendations for rescheduling measures.
- Only a part of the total metro network of the case study was used to perform the optimizations on. Expanding the optimization area of this research can lead to different outcomes for the researched areas as well, as more variables are introduced in the model.

There are still many areas in which the used modelling framework can be expanded. The obtained improvements could be further improved further with more computational capacity, also enabling a broader improvement of the timetable over the entire network, resulting in a more balanced timetable which would account for more factors downstream than the current model.

The current framework is only suited to analyse realised data. Each run still includes a lot of manual labour to run each iteration. Further developments of the SBTM-MN framework are needed to further automate the process to make it potentially interesting for real-time applications. As the obtained solution keeps changing as the situation on the line and on the stations changes, this would be a necessity for eventually being able to apply rescheduling decisions real time. The current produced solutions could provide a general direction for rescheduling measures for similar situations.

REFERENCES

[1] N. G. Harris and R. J. Anderson, "An international comparison of urban rail boarding and alighting rates," *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, vol. 221, no. 4, pp. 521–526, 2007.

[2] L. Pardini-Susacasa, "Towards passenger-oriented simulation-based rescheduling in metro lines," 2020.

[3] G. Suazo-Vecino, M. Dragicevic, and J. C. Muñoz, "Holding boarding passengers to improve train operation on basis of an economic dwell time model," *Transportation Research Record*, vol. 2648, no. 1, pp. 96–102, 2017.

[4] L. Sun, J. G. Jin, D.-H. Lee, K. W. Axhausen, and A. Erath, "Demand-driven timetable design for metro services," *Transportation Research Part C: Emerging Technologies*, vol. 46, pp. 284 – 299, 2014.

[5] E. Altazin, S. Dauzère-Pérès, F. Ramond, and S. Tréfond, "A multi-objective optimization-simulation approach for real time rescheduling in dense railway systems," *European Journal of Operational Research*, vol. 286, no. 2, pp. 662 – 672, 2020.

[6] E. Hassannayebi, S. H. Zegordi, M. Yaghini, and M. R. Amin-Naseri, "Timetable optimization models and methods for minimizing passenger waiting time at public transit terminals," *Transportation Planning and Technology*, vol. 40, no. 3, pp. 278–304, 2017.

[7] Y. Zhu, H. N. Koutsopoulos, and N. H. Wilson, "A probabilistic passenger-to-train assignment model based on automated data," *Transportation Research Part B: Methodological*, vol. 104, pp. 522 – 542, 2017.

[8] D. Hörcher, D. J. Graham, and R. J. Anderson, "Crowding cost estimation with large scale smart card and vehicle location data," *Transportation Research Part B: Methodological*, vol. 95, pp. 105 – 125, 2017.

[9] F. Hänseler, J. van den Heuvel, O. Cats, W. Daamen, and S. Hoogendoorn, "A passenger-pedestrian model to assess platform and train usage from automated data," *Transportation Research Part A: Policy and Practice*, vol. 132, pp. 948–968, 2020, cited By 1.

[10] E. Bosina and U. Weidmann, "Estimating pedestrian speed using aggregated literature data," *Physica A: Statistical Mechanics and its Applications*, vol. 468, pp. 1 – 29, 2017.

[11] H. Guo, Y. Bai, Q. Hu, H. Zhuang, and X. Feng, "Optimization on metro timetable considering train capacity and passenger demand from intercity railways," in *Proceedings of the 4th International Conference on Electrical and Information Technologies for Rail Transportation (EITRT) 2019*, B. Liu, L. Jia, Y. Qin, Z. Liu, L. Diao, and M. An, Eds. Springer Singapore, 2020, pp. 141–152.

[12] N. G. Harris, "Train boarding and alighting rates at high passenger loads," *Journal of Advanced Transportation*, vol. 40, no. 3, pp. 249–263, 2006. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/atr.5670400302

[13] N. Luangboriboon, S. Seriani, and T. Fujiyama, "The influence of the density inside a train carriage on passenger boarding rate." *International Journal of Rail Transportation*, vol. 0, no. 0, pp. 1–16, 2020.

[14] O. Cats, J. West, and J. Eliasson, "A dynamic stochastic model for evaluating congestion and crowding effects in transit systems," *Transportation Research Part B Methodological*, vol. 89, pp. 43–57, 06 2016.

[15] S. J. Berrebi, S. Óg Crudden, and K. E. Watkins, "Translating research to practice: Implementing real-time control on high-frequency transit routes," *Transportation Research Part A: Policy and Practice*, vol. 111, pp. 213 – 226, 2018.

[16] A. Fonzone, J.-D. Schmöcker, and R. Liu, "A model of bus bunching under reliability-based passenger arrival patterns," *Transportation Research Procedia*, vol. 7, pp. 276 – 299, 2015, 21st International Symposium on Transportation and Traffic Theory Kobe, Japan, 5-7 August, 2015.

[17] K. Gkiotsalitis and O. Cats, "At-stop control measures in public transport: Literature review and research agenda," *Transportation Research Part E: Logistics and Transportation Review*, vol. 145, p. 102176, 2021.

[18] J. J. Fabian and G. E. Sánchez-Martínez, "Simulation-based comparison of holding strategies for a multibranch light rail service," *Transportation Research Record*, vol. 2648, no. 1, pp. 23–32, 2017.

[19] O. Cats, "Regularity-driven bus operation: Principles, implementation and business models," *Transport Policy*, vol. 36, pp. 223 – 230, 2014.

[20] D. Hürlimann, "Objektorientierte modellierung von infrastrukturelementen und betriebsvorgängen im eisenbahnwesen," Ph.D. dissertation, ETH Zurich, Zürich, 2002.

[21] N. van Oort, "Service reliability and control," Oct 2019.

[22] V. Cacchiani, D. Huisman, M. Kidd, L. Kroon, P. Toth, L. Veelenturf, and J. Wagenaar, "An overview of recovery models and algorithms for real-time railway rescheduling," *Transportation Research Part B: Methodological*, vol. 63, pp. 15 – 37, 2014.

[23] "Meer en snellere treinen," Mar 2019. [Online]. Available: https://www.prorail.nl/nieuws/meer-en-snellere-treinen

APPENDIX

TABLE XII
VARIABLES, SETS AND PARAMETERS OF THE TRM [2]

Parameter	Explanation
Indices and Sets	
S	Set of stations in the network
s	Current station in set stations s ∈ S
M	Set of vehicles, with M^+ for inbound trains and M^- for outbound trains
m	Single metro in set of metros m ∈ M
S^m	Set of stations to be served by metro m
M^s	Set of metros that serve station s
V	Set of trains pairs m,n that have a connection at station s
Decision Variables	
$t_{s,m}^{arr}$	Time of arrival of vehicle m at station s
$t_{s,m}^{dep}$	Time of departure of vehicle m from station s
X_m	Extra variable to linearize absolute deviations from scheduled arrivals
at terminal stations	
Parameters obtained from the simulation	
$l_{s,m}$	Passenger occupation in vehicle m at the moment of departure from station s
$r_{s,m}$	Passengers left behind by vehiclem at station s
$w_{s,m}$	Passengers waiting at station s when vehicle m arrives
$\hat{w_s}$	Passengers waiting at a station s at the time in which the optimization is triggered
t_0	Time in which the optimization is triggered
e_s^{min}	Minimal dwell time at station s. This is the maximumbetween the originally scheduled dwell time and the time needed for passenger exchange in the last iteration.
$t_{s,m}^{depo}$	Realised departure time of trainm from station s in the last simulation
t_m^{arrs}	Originally scheduled time of arrival of trainm at its destination station
$t_{s,m}^{deps}$	Originally scheduled time of departure of trainm from station s
General Parameters	
γ_{sit}	Crowding multiplier for sitting passengers
γ_{stand}	Crowding multiplier for standing passengers
β_w	Cost coefficientmultiplier for waiting time
β_i	Cost coefficientmultiplier for in vehicle time
β_o	Cost coefficientmultiplier for schedule deviation at the terminal station
$q_{s,h}^{min}$	Minimal running time for the stretch between two consecutive stations s and h
h_s^{out}	Required headway between two consecutive outbound trains at station s
h_s^{in}	Required headway between two consecutive inbound trains at station s
u	Allowed margin of difference between iterations
k_m	Sitting capacity of train m
$c_{m,n,s}^{min}$	Minimal connection time between trainsm and n at station s

B

Time Distance Diagrams

In this appendix all the time-distance diagrams that were plotted using the available data are presented, for weekdays only.

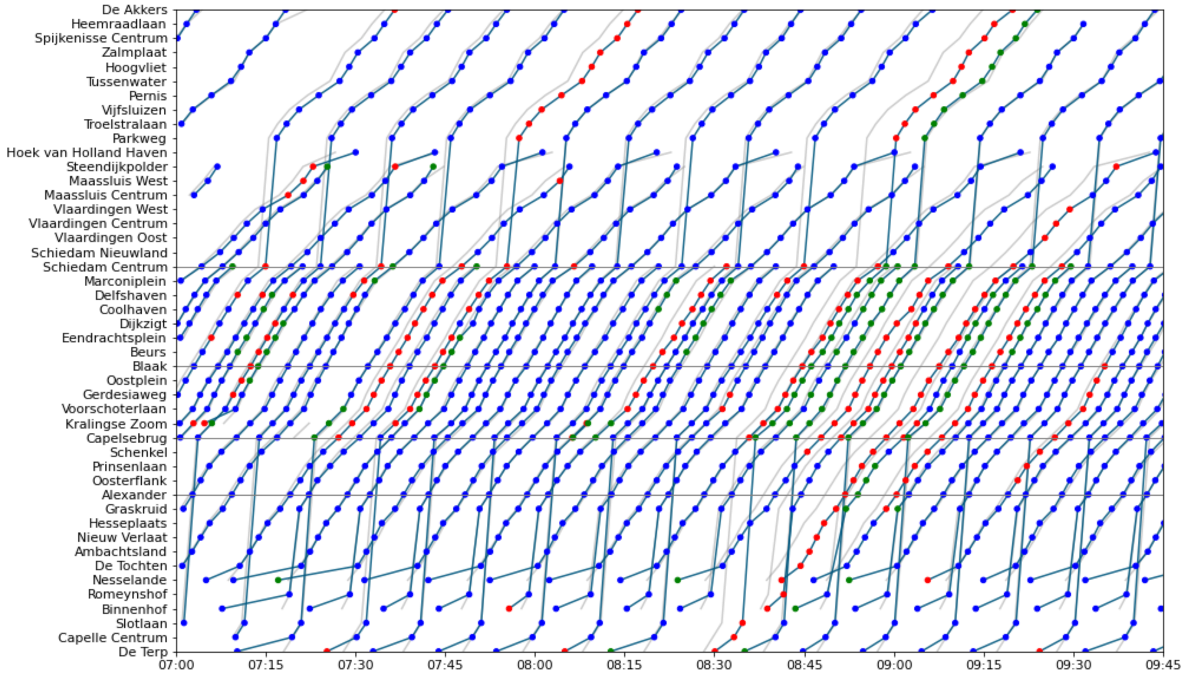

Figure B.1: Friday November 1st, 2019

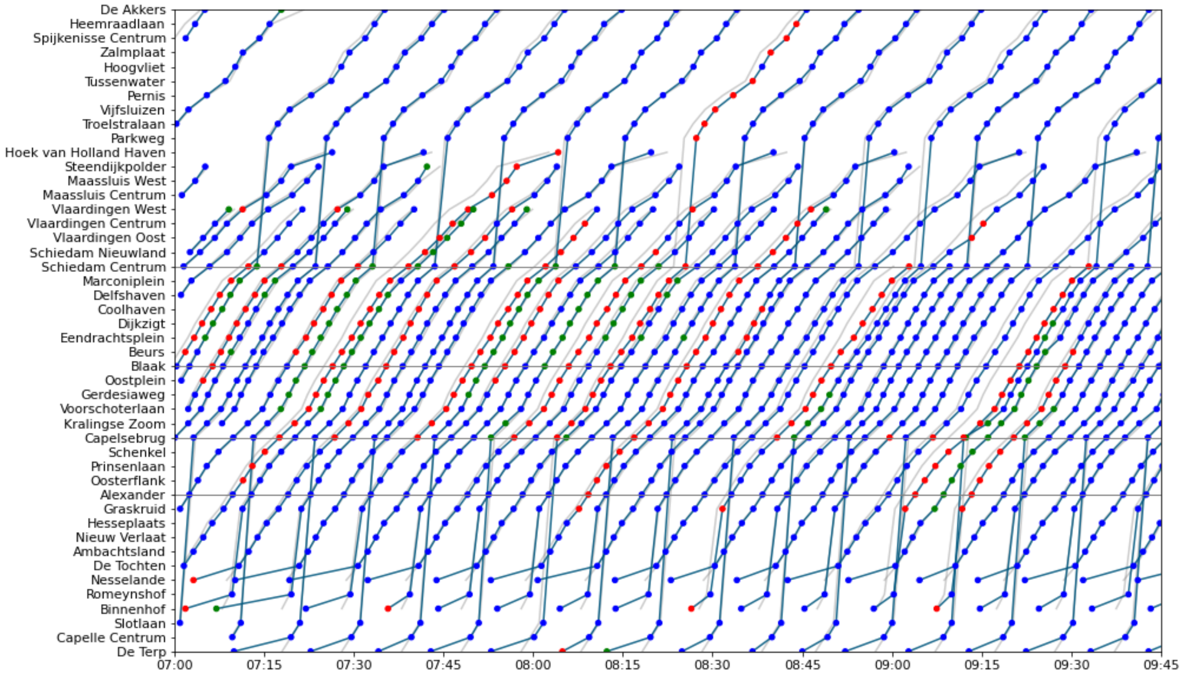

Figure B.2: Monday November 4th, 2019

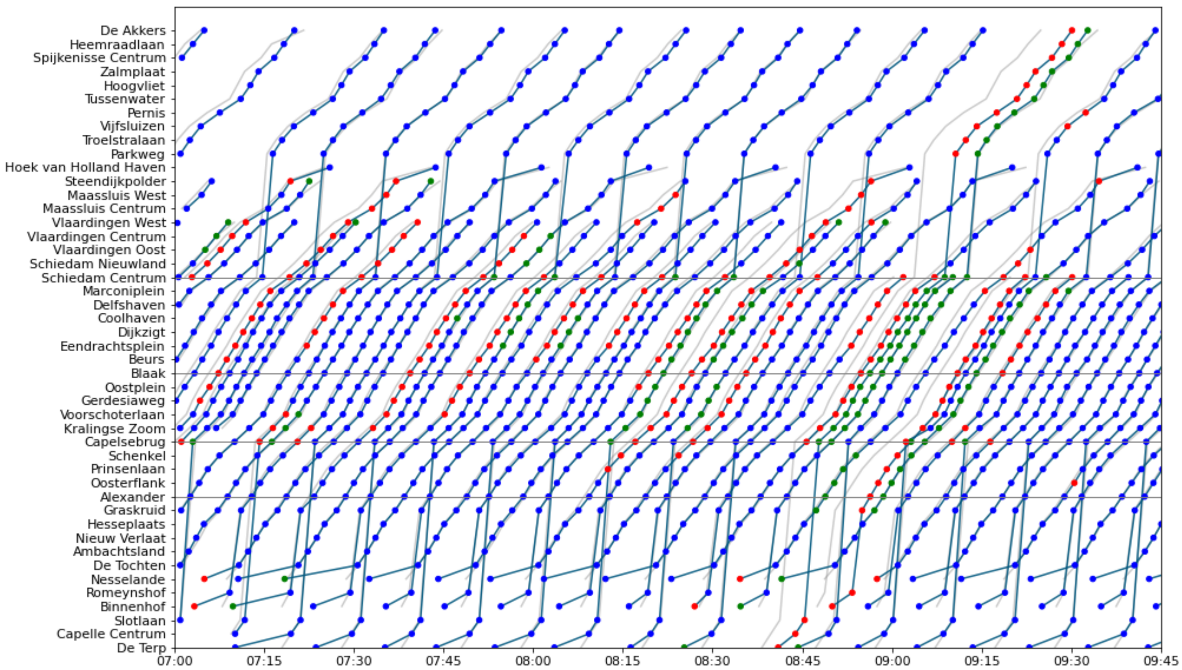

Figure B.3: Tuesday November 5th, 2019

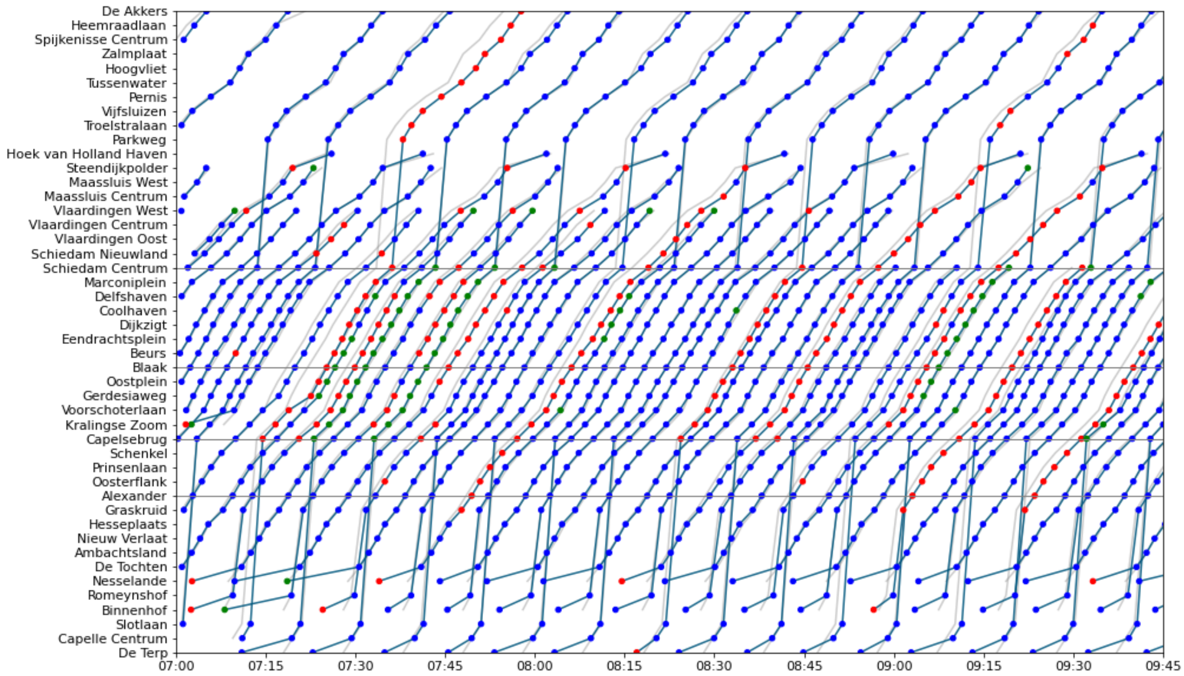

Figure B.4: Wednesday November 6th, 2019

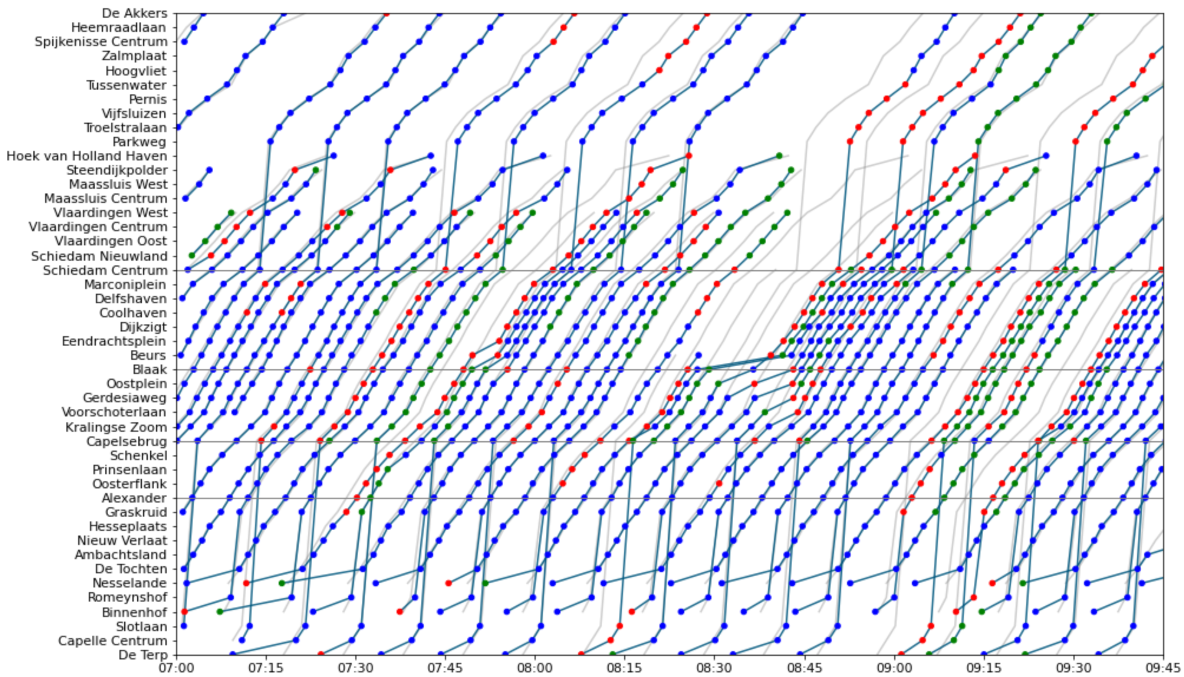

Figure B.5: Thursday November 7th, 2019

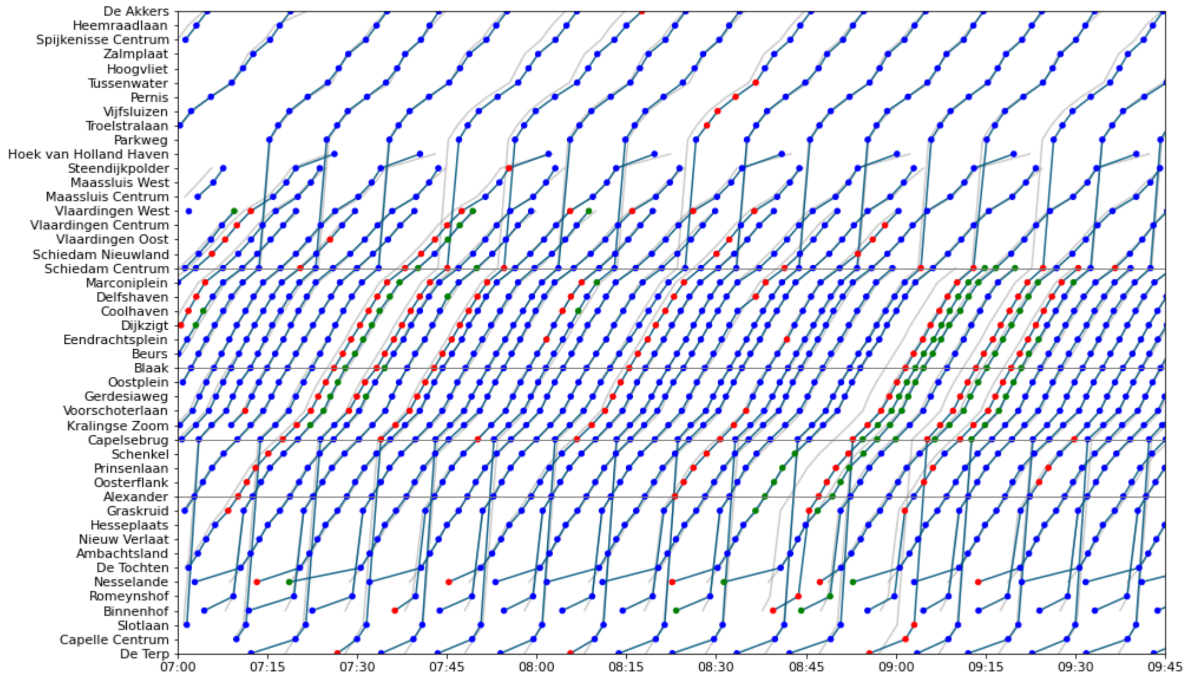

Figure B.6: Friday November 8th, 2019

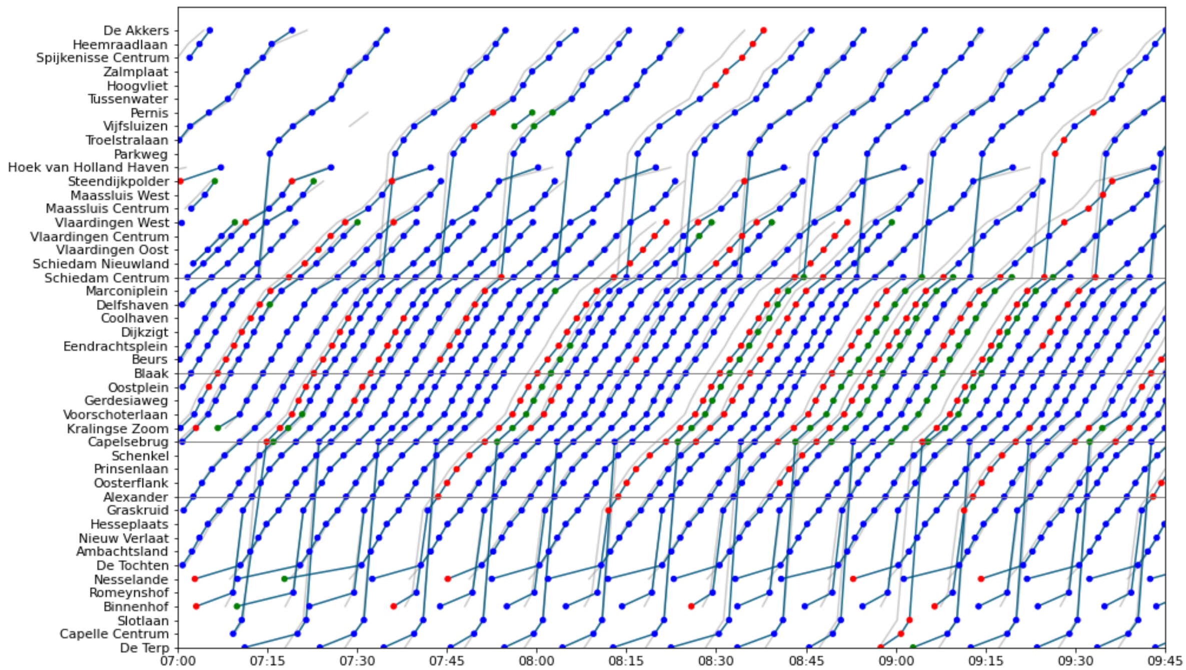

Figure B.7: Monday November 11th, 2019

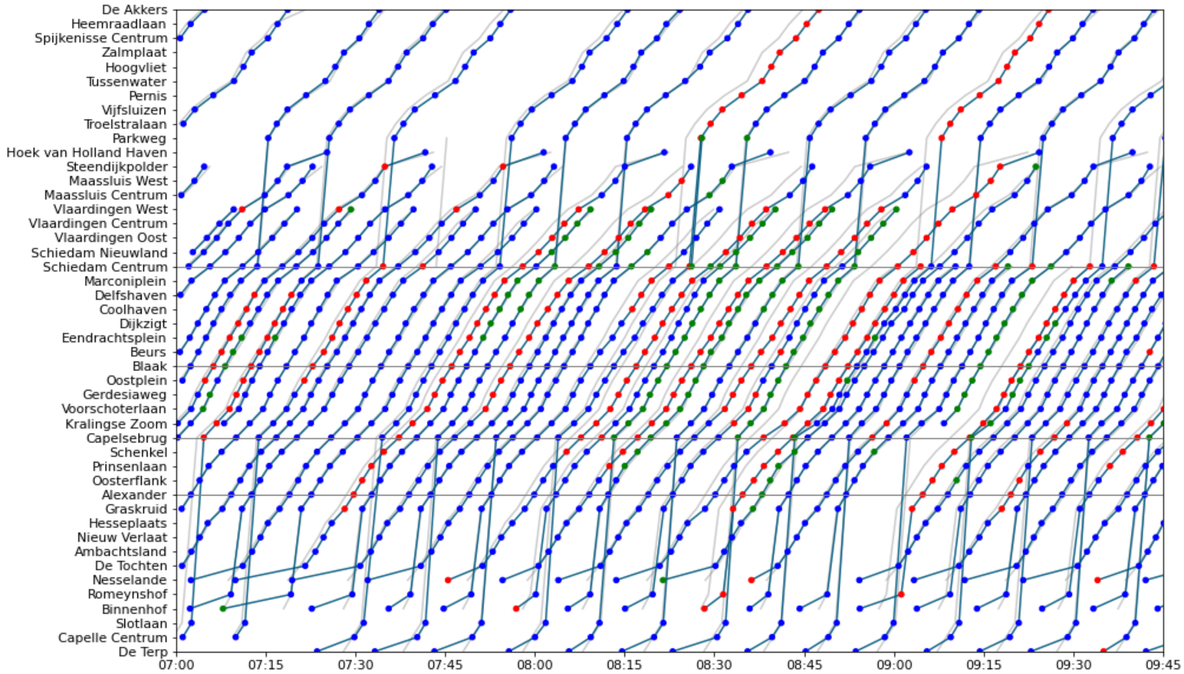

Figure B.8: Tuesday November 12th, 2019

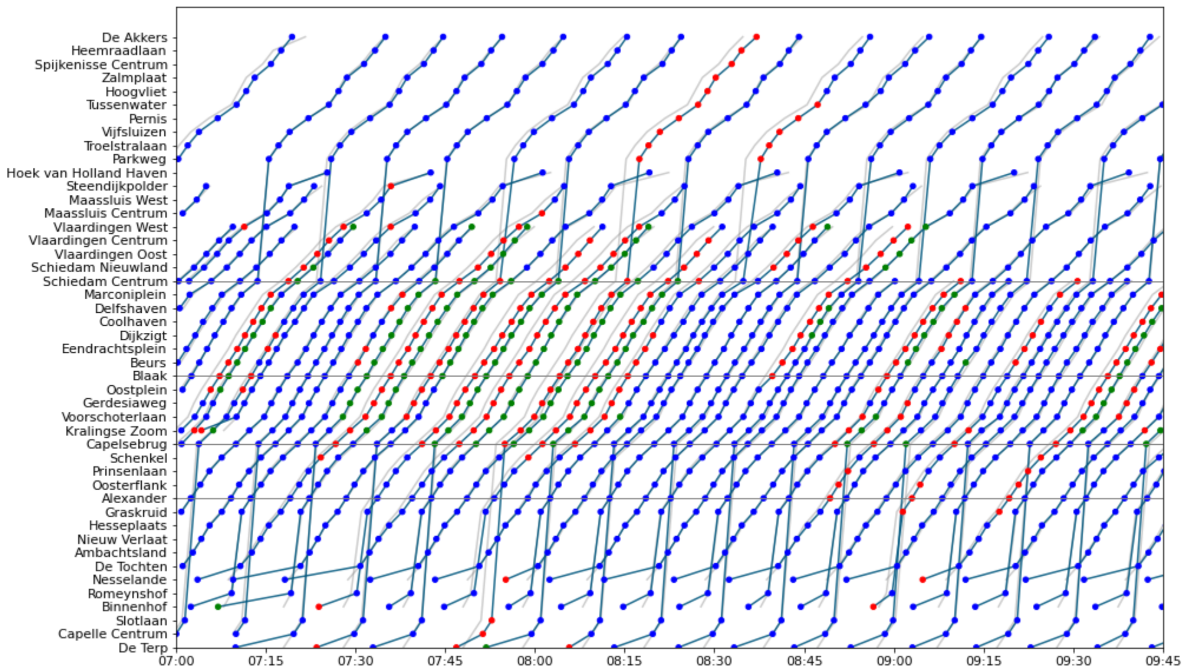

Figure B.9: Wednesday November 13th, 2019

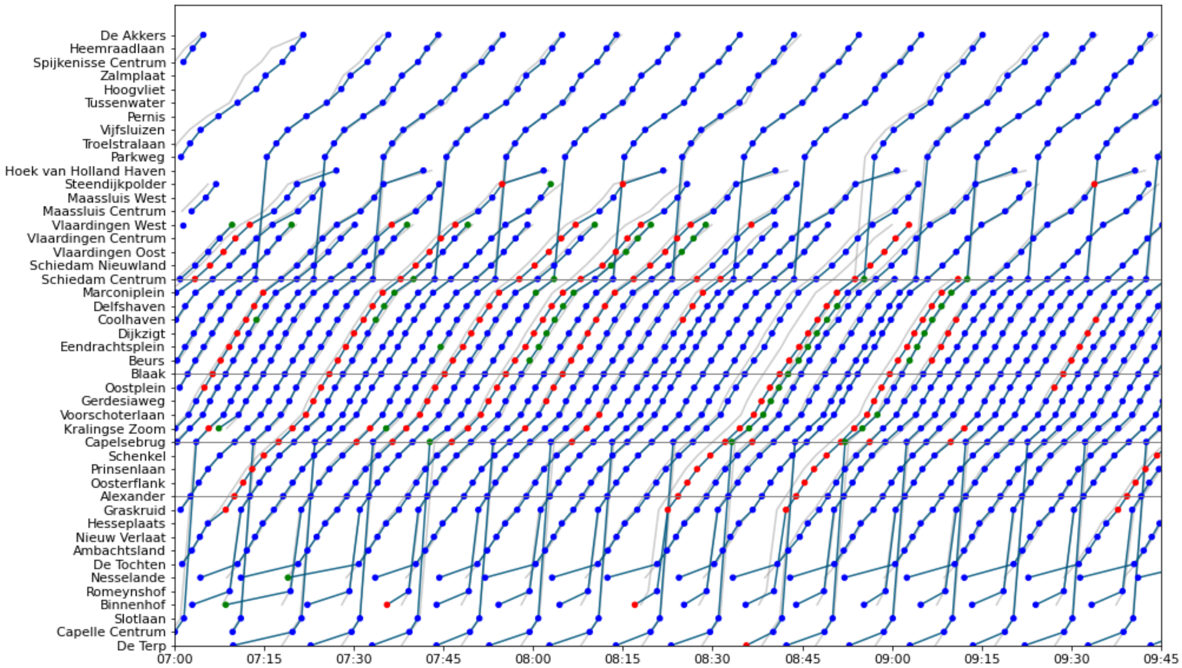

Figure B.10: Thursday November 14th, 2019

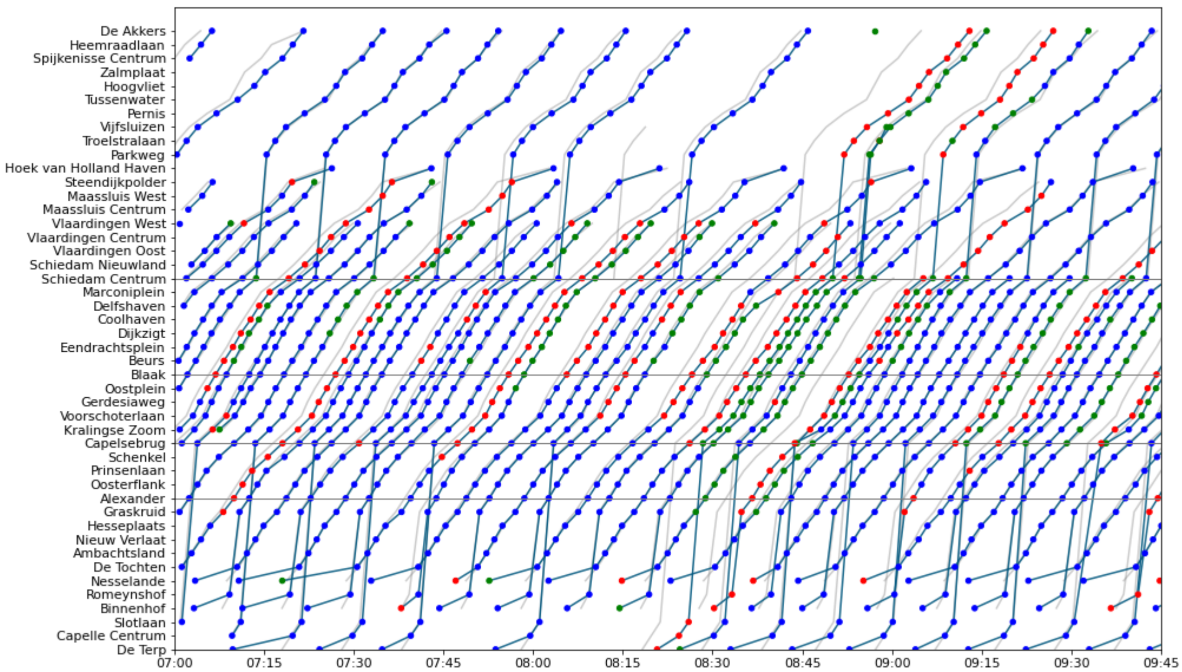

Figure B.11: Friday November 15th, 2019

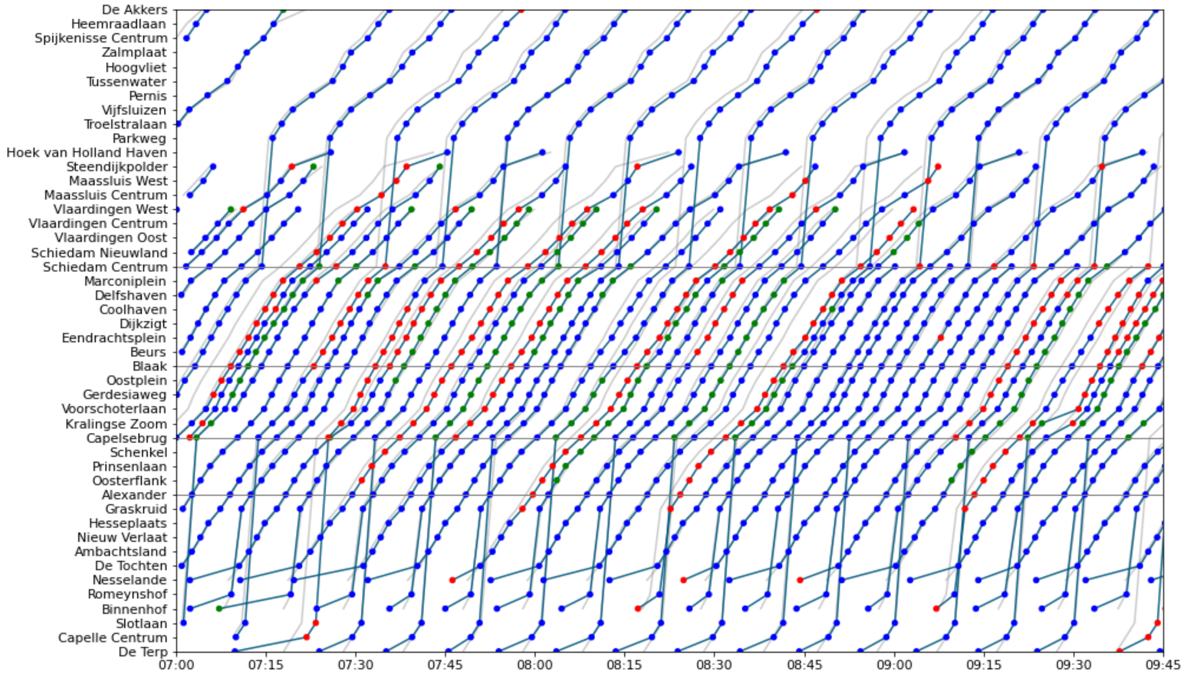

Figure B.12: Monday November 18th, 2019

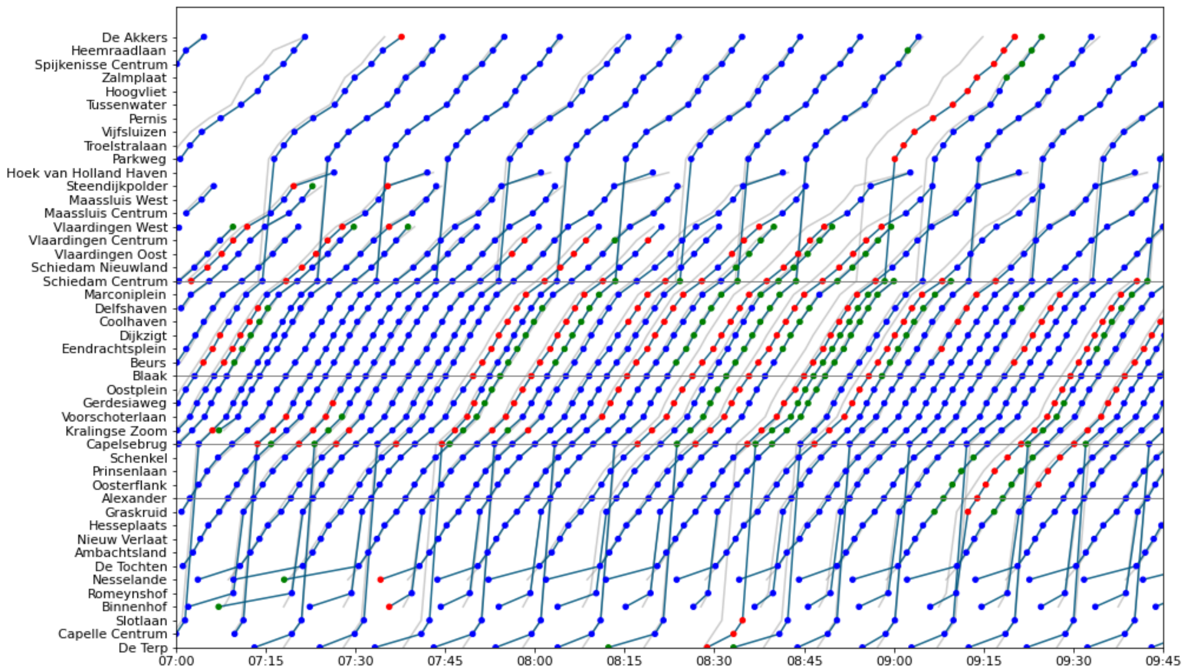

Figure B.13: Tuesday November 19th, 2019

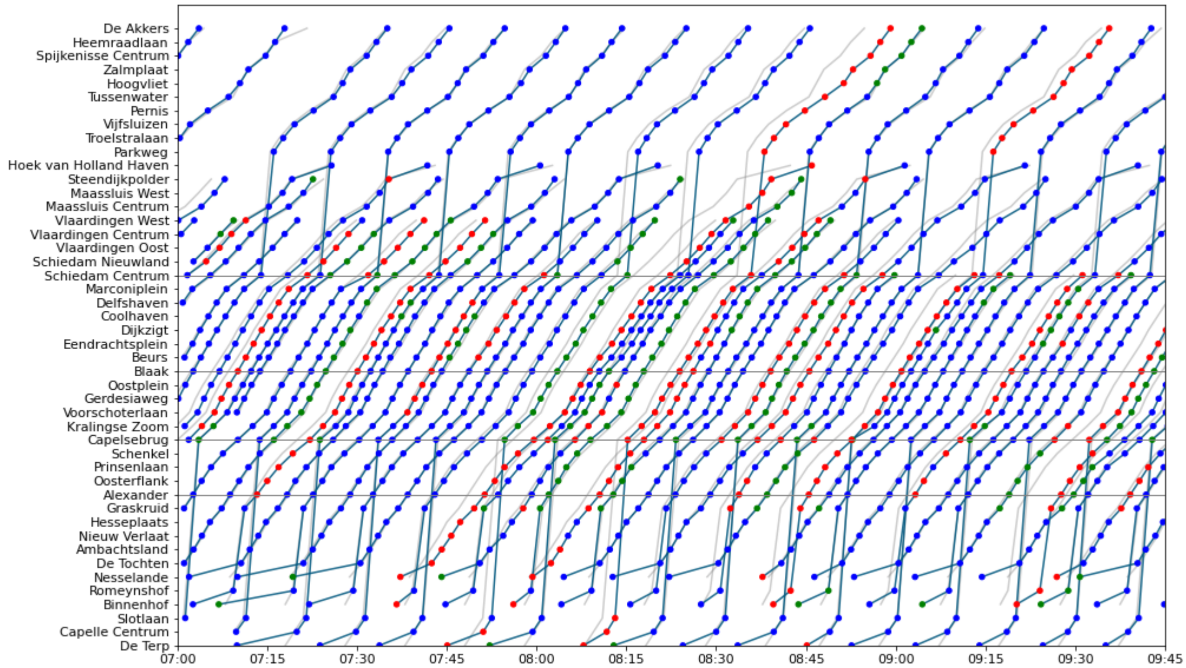

Figure B.14: Wednesday November 20th, 2019

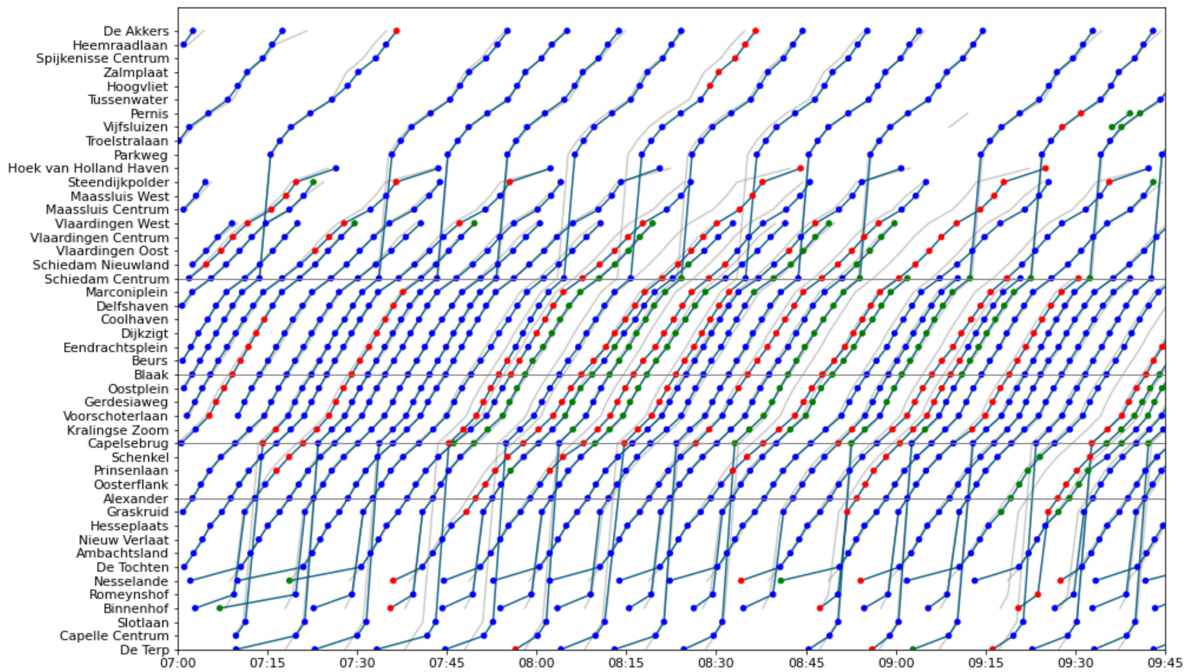

Figure B.15: Thursday November 21th, 2019

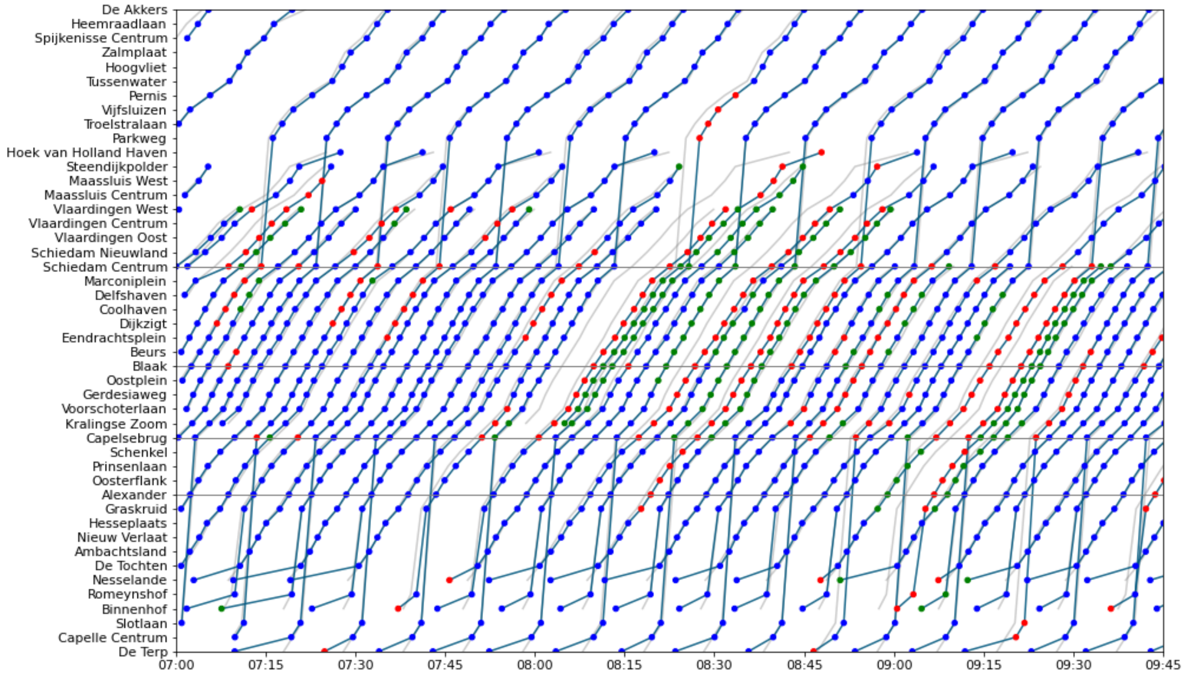

Figure B.16: Friday November 22th, 2019

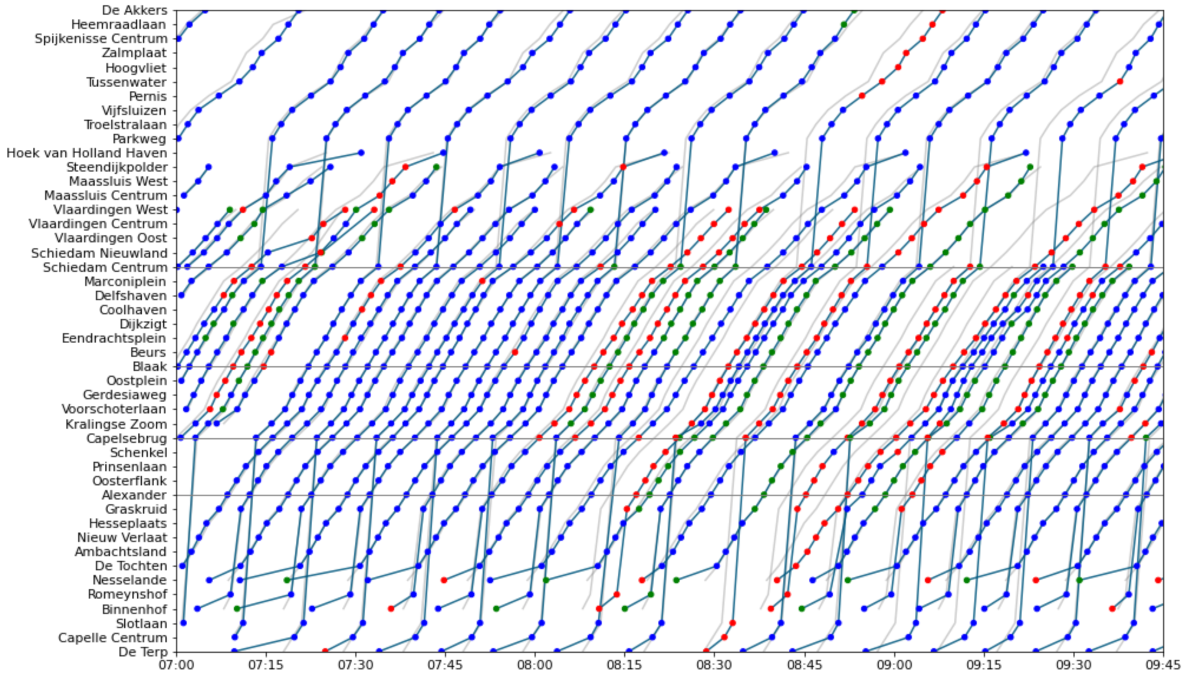

Figure B.17: Monday November 25th, 2019

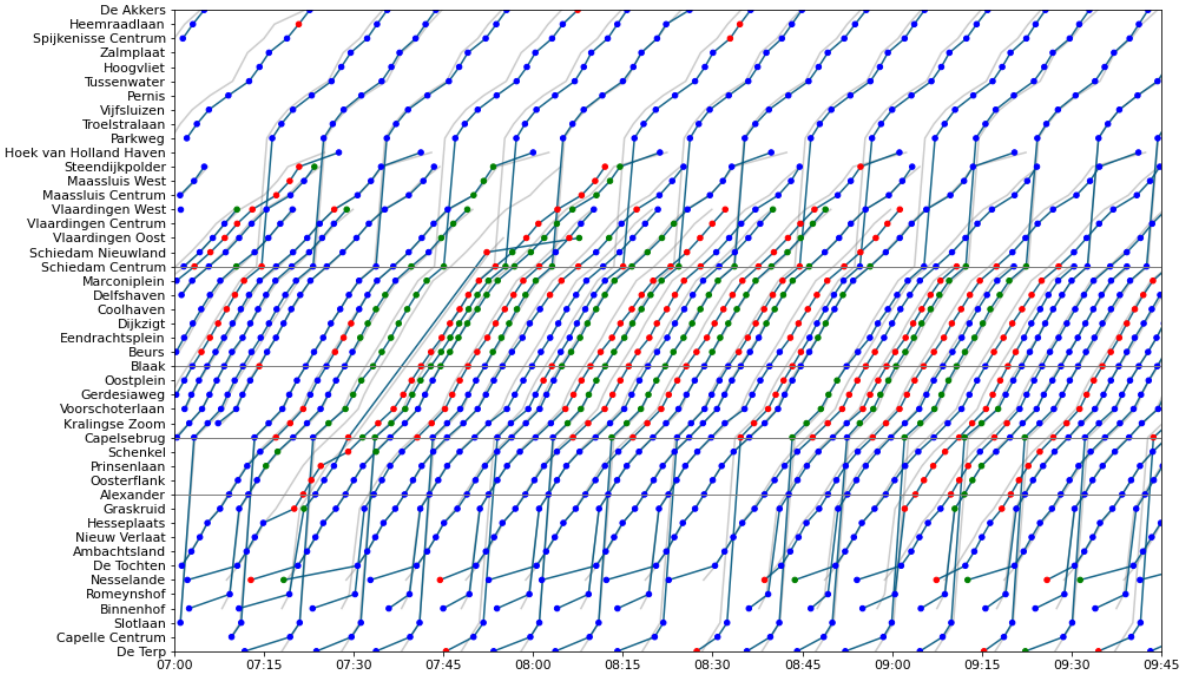

Figure B.18: Tuesday November 26th, 2019

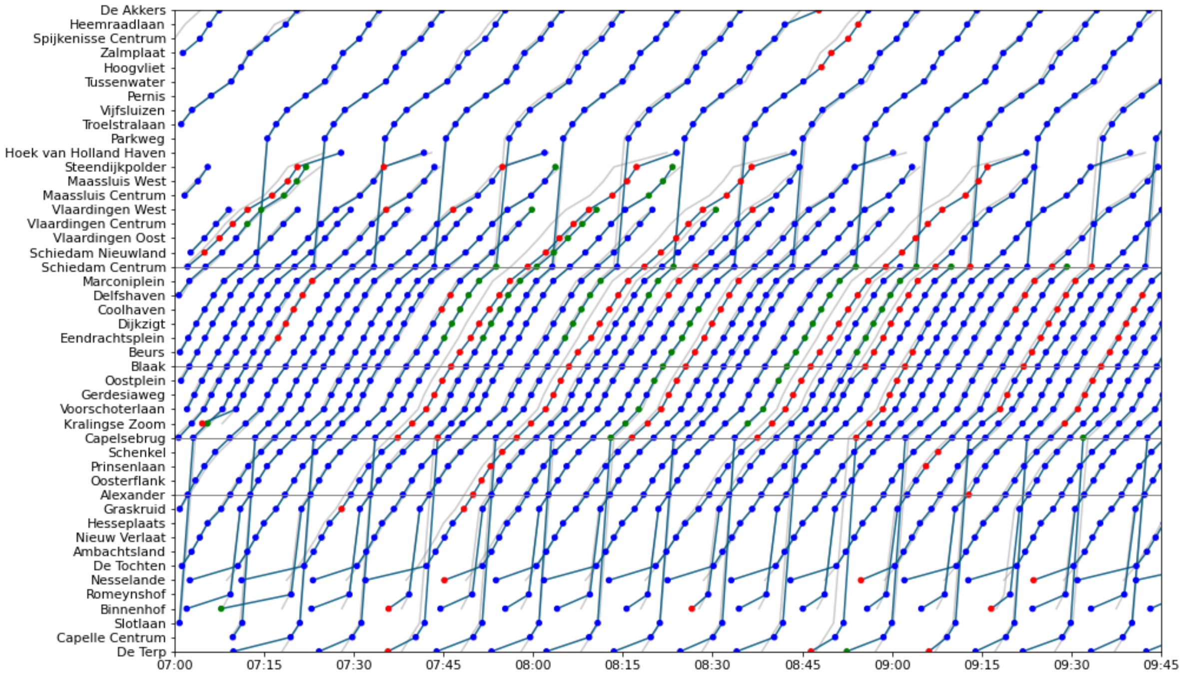

Figure B.19: Wednesday November 27th, 2019

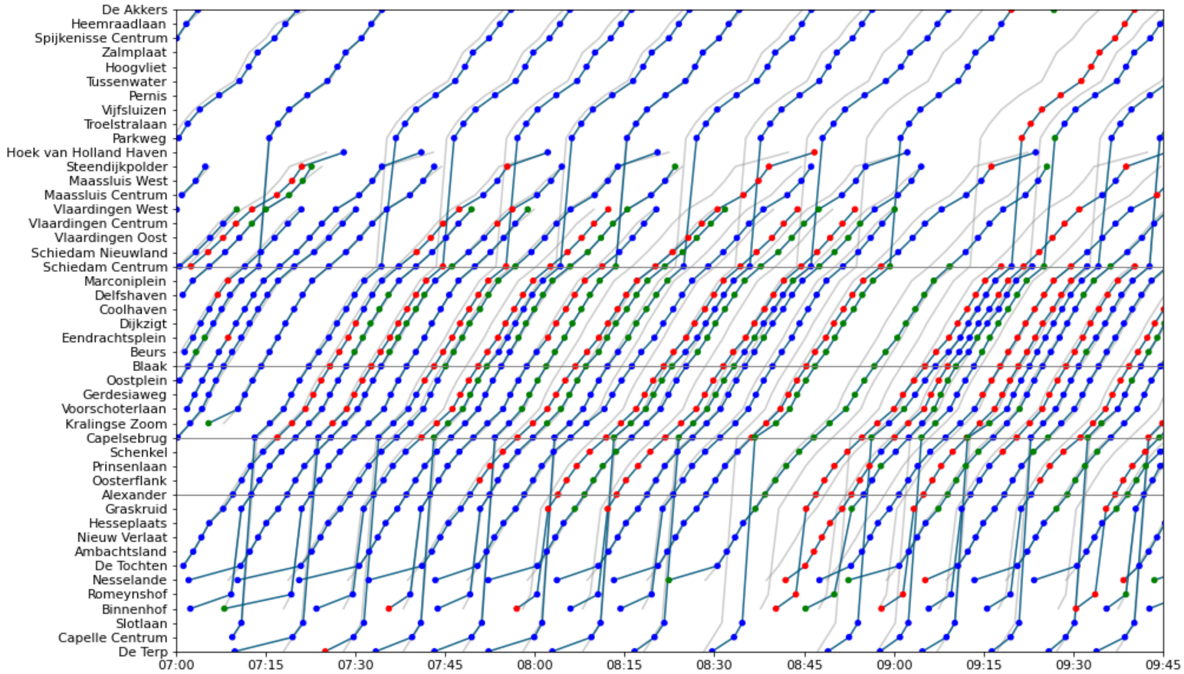

Figure B.20: Thursday November 28th, 2019

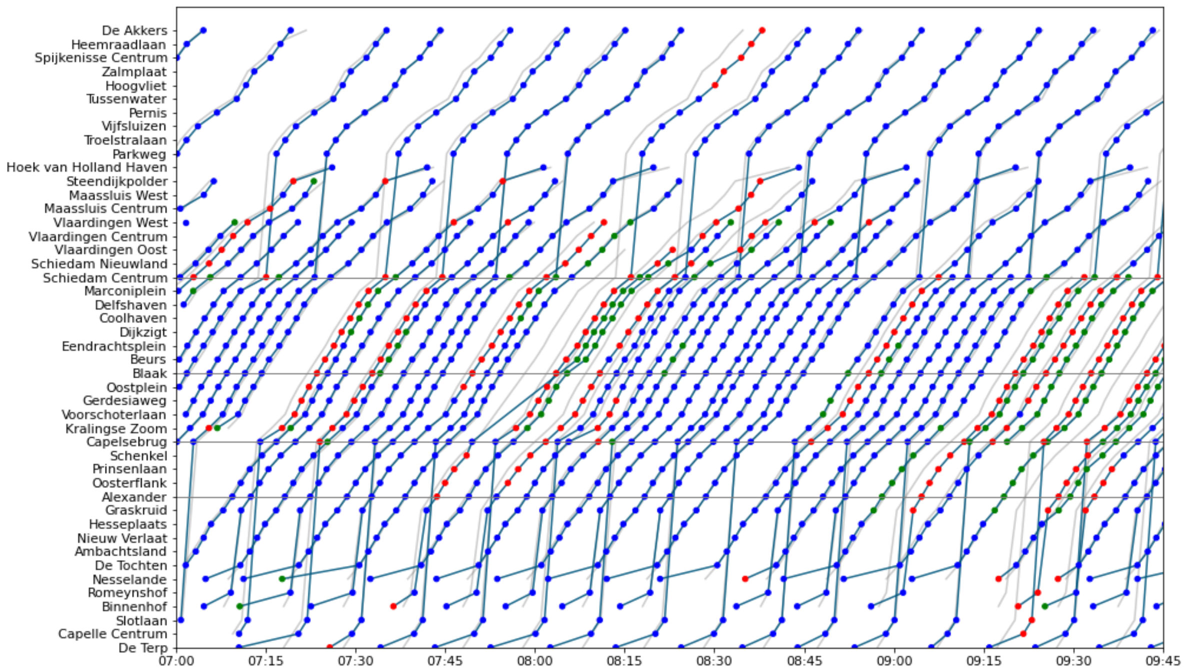

Figure B.21: Friday November 29th, 2019

C

Acronyms Used

For the readabilities of some tables acronyms are used to indicate certain stations in the network. Their acronym and their corresponding full name can be found in table C.1.

Table C.1: Acronyms Used

Acronym	Full Station Name	Acronym	Full Station Name
ALD	Alexander	HVT	Hoogvliet
ABL	Ambachtsland	KLZ	Kralingse Zoom
BRS	Beurs	MCP	Marconiplein
BNH	Binnenhof	NSL	Nesselande
BLK	Blaak	NVT	Nieuw Verlaat
CCT	Capelle Centrum	OTF	Oosterflank
CPB	Capelsebrug	OPL	Oostplein
CHV	Coolhaven	PWG	Parkweg
AKS	De Akkers	PNS	Pernis
TRP	De Terp	PSL	Prinsenlaan
TTN	De Tochten	RMH	Romeynshof
DHV	Delfshaven	SKL	Schenkel
DZT	Dijkzigt	SDM	Schiedam Centrum
EDP	Eendrachtsplein	TSL	Troelstralaan
GDW	Gerdesiaweg	TWR	Tussenwater
GKD	Graskruid	VSZ	Vijfsluizen
HRL	Heemraadlaan	VSL	Voorschoterlaan
HSP	Hesseplaats	ZPT	Zalmplaat

D

Model Runs with less performing objectives

Table D.1: Results of the TRM in the base scenario, Weight set W_1

	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						482.47	2568.79	1.39	12.52	2204.18	
1	**423.01**	**2500.58**	**1.45**	**11.66**	**2093.94**	**466.23**	**2538.00**	**1.53**	**12.89**	**2162.53**	**1.9%**
2	423.59	2416.01	1.58	10.73	2037.84	485.81	2559.87	1.88	14.17	2197.12	0.3%
3	432.95	2477.02	1.96	10.73	2088.66	519.58	2645.07	2.35	17.87	2288.92	-3.8%

Table D.2: Results of the TRM in the base scenario, Weight set W_3

	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						**482,47**	**2576,29**	**1,39**	**12,52**	12,52	
1	470,36	2515,24	0,95	7,8	7,8	482,05	2575,28	1,4	12,6	12,6	-0.6%
2	470,43	2514,01	0,96	7,84	7,84	514.97	2689.28	1.74	15.17	15.17	-21.2%
3	498.87	2661.86	1.27	9.66	9.66						

Table D.3: Results of the TRM in the scenario with a 30% increase in passengers, weight set W_2

	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						**634,47**	**3851,45**	**1,41**	**12,09**	**4278,46**	
1	567,07	3705,74	1,29	11,18	4087,52	650,24	4016,19	2,11	17,69	4455,58	-4.1%
2	598,4	3847,91	1,93	15,19	4251,9	677,93	4054,21	2,58	21,04	4513,17	-5.5%
3	638,75	3869,59	2,44	18,45	4301,58						

Table D.4: Results of the TRM in the base scenario with a Blaak arrival data from November 19th, weight set W_2

	Estimated by TRM					Realised through TSM					
Iter.	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Waiting Time [h]	In-Vehilce Time [h]	Deviation at Terminal [h]	Deviations from all departures [h]	Total Cost [h]	Improve-ment
Base						496	2641,48	1,43	12,69	2976,38	
1	**446,99**	**2555,24**	**1,4**	**11,71**	**2857,14**	**484,32**	**2632,46**	**1,69**	**14,47**	**2960,17**	**0.3%**
2	448,61	2530,89	1,57	11,81	2833,9	531,2	2776,7	2,23	17,81	3136,76	-5.4%
3	491,92	2669,79	2,12	15,72	3002,97	562,6	2892,56	2,64	21,75	3274,88	-10.0%