Towards passenger-oriented simulation-based rescheduling in metro lines

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Royal HaskoningDHV
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by

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List of Abbreviations

APC	Automatic Passenger Counting
API	Application Programming Interface
AVL	Automatic Vehicle Location
EGTRAIN	Environment for the desiGn and simulaTion of RAIlway Networks
LP	Linear Programming
OD	Origin-Destination
RET	Rotterdamse Elektrische Tram
ROMA	Railway traffic Optimization by Means of Alternative graphs
SBTM-MN	Simulation-based Traffic Management for Metro Networks
TRM	Train Rescheduling Model
TSM	Transport Simulation Model
TSM-RW	Transport Simulation Model of the Real World
UN	United Nations
VKL	VerKeersLeider system
ZUB	ZUgBeeinussung

Executive Summary

With the on-going growth of transport demand in cities, the public transport sector needs ways of improving the efficiency and quality of its services. In metro networks, increasing the capacity by adding trains in the schedule threatens the reliability of the system. One of the measures to deal with unreliability issues is the real-time rescheduling of the services. Amongst them, holding strategies and speed adjustments are the focus of this study.

In the public transport sector, a shift has been taking place from vehicle-based to passenger-oriented real-time control strategies. This change in the approach is possible due to recent developments in technologies that make passenger and train data available even in real-time. Authorities and operators are more keen on incorporating passenger perspective within their objective. However, this is a rather recent approach. Most research on real-time rescheduling for metros is train oriented. Furthermore, the impact of demand on the realisation of the timetable is often neglected or overly simplified. In heavily utilized metro lines, passenger demand can trigger or worsen the propagation of delays and cause the bunching of vehicles. This phenomenon occurs when the delay of a train increases along its trip due to the excessive dwell time. The latter is caused by the increasing demand at each station, aggravated by the on-going growth of headway with the preceding vehicle. This is a feedback loop that explicitly depends on the headway between trains and the passenger demand, and is often neglected in real-time rescheduling studies for metros. Furthermore, most research on the matter relies solely on mathematical models, with a rather theoretical approach. To the best of the author's knowledge, this is the first study that combines passenger-oriented metro rescheduling with a microscopic simulation tool that considers passenger influence on disturbances and keeps track of passenger allocation. In this way, this research helps to pave the path towards real-time rescheduling that considers passenger movements and their impact in the network, besides planning for their benefit.

The goal of this research is, thus, to develop models and algorithms to mitigate the impact of disturbances on passengers by rescheduling the timetable whilst considering the dynamic variation of demand and its impact on train operations. To achieve this, the models and algorithms to be developed have to: (i) accurately represent the impact that passenger demand has on reliability; (ii) keep track of passenger allocation, and; (iii) optimize the rescheduled timetable with an emphasis on passenger benefits.

The main research question of this study is: ***Considering a disturbance in a metro network, what is the effect of passenger demand on the performance of the timetable and what is the recommended rescheduling strategy for passengers and operator?***

To answer this question, a conceptual framework for rescheduling metro lines, the Simulation-Based Traffic Management for Metro Network (SBTM-MN), is developed. This comprises two models that interact iteratively, the Transport Simulation Model (TSM), and the Train Rescheduling Model (TRM). The TSM integrates a train simulation in OpenTrack, with a passenger module. This allows the modelling of passenger-train interactions and keeps track of passenger allocation. Each time a train arrives at a station, the simulation in OpenTrack notifies the passenger module. This calculates the dwell time according to the passengers boarding and alighting, registers the passenger exchange, and retrieves the time at which the train should depart. The TRM modifies arrival and departure times of trains according to a base schedule and the corresponding passenger allocation provided by the TSM.

To represent the usage of the SBTM-MN in real-life operations, these are simulated in a TSM version specifically designed to mimic real-world operations (TSM-RW). The SBTM-MN is triggered at a certain point in time by the TSM-RW. The latter provides the framework with real-time data related to the state of the network, namely the realised train events and the station and train occupation. Based on this data and the original timetable, the TSM simulates train and passenger movements for a given horizon. As a result, the passenger allocation is estimated and fed to the TRM along with the realised timetable. This allows the TRM to estimate the cost of the timetable and modify the arrival and departure times to reduce the perceived travel time of passengers. The figure below represents the developed framework, its components and the interactions between them.

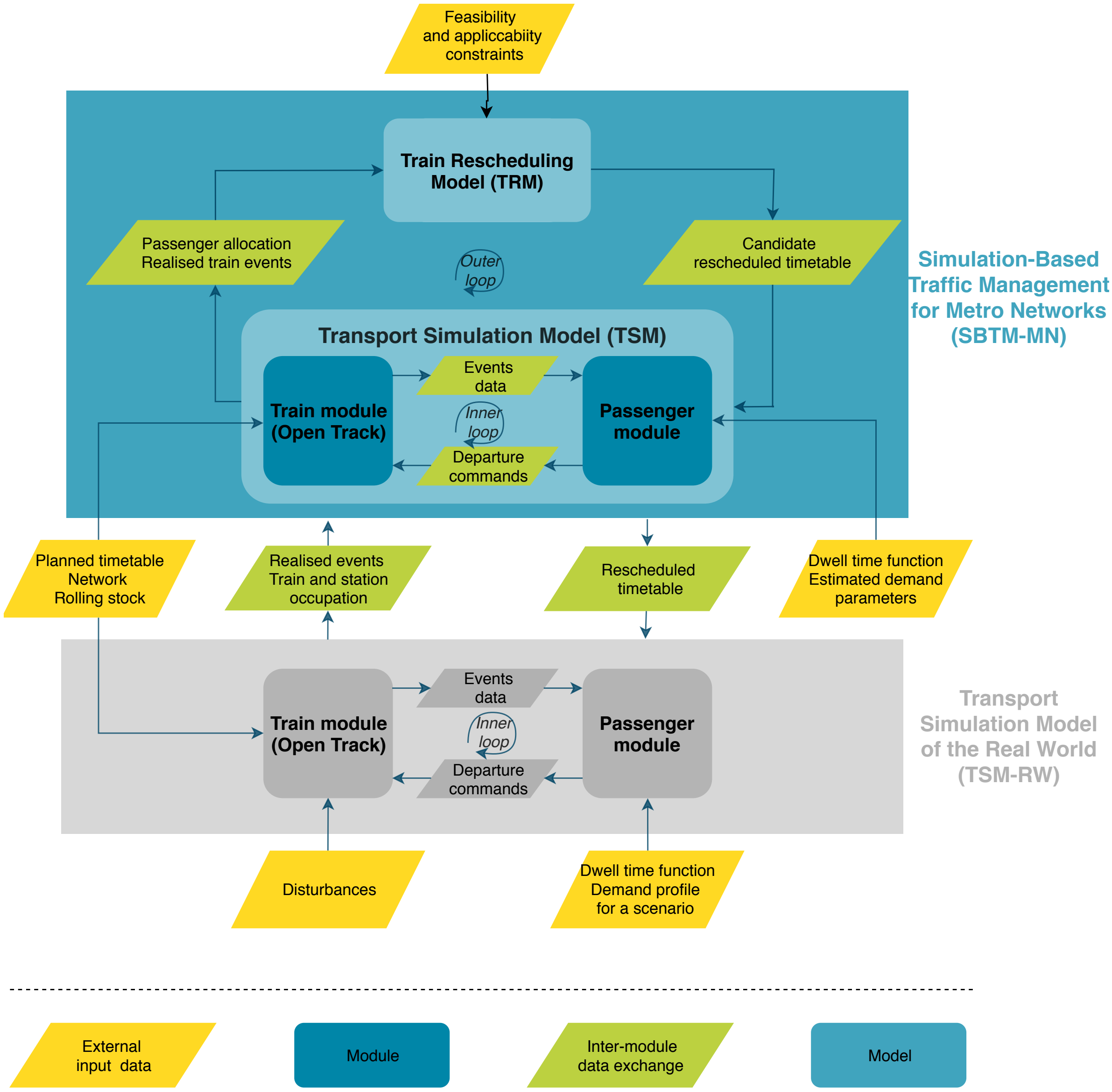


Figure 1: Representation of the Simulation-based traffic management for metro network framework

To evaluate the applicability of the developed framework, a series of experiments are carried out. The case study consisted of the lines D and E of the Rotterdam metro network, with northerly direction. The following tests are performed:

- The TSM is run for different disturbances in the busiest stretch of the lines, as well as at the beginning of line D. These scenarios are also run excluding the influence of passengers in the dwell time of trains, to evaluate the value of adding passenger movements in the simulation of the train timetable.
- The TRM is run for alternative objectives in the optimization. The resulting rescheduled timetables are evaluated in terms of passenger waiting and perceived in-vehicle time, total train departure delays, and deviation from the arrival at the terminal station.
- The SBTM-MN is run for a small set of iterations on two disturbance scenarios, as a preliminary indication on the value of the model. The rescheduled timetables are compared using the base strategy of RET when dealing with disturbances, i.e. running trains at top allowed speed to regain schedule adherence

The TSM experiments prove the significant difference in the development of delays when considering passenger-train interactions. In scenarios where passenger-train interaction is neglected, delays and passenger travel time are consistently smaller. When including passenger-train interaction, delays increase along the trip instead of diminishing by using the buffer time. Furthermore, the influence of the location and time of the triggered disturbance on the spread of delays is shown. The TRM tests confirm that regaining schedule adherence is not necessarily the strategy that yields the highest benefits for passengers. The iterations performed with the SBTM-MN show the importance of considering passenger allocation when rescheduling a timetable. The reallocation of passengers in each iteration heavily influence the performance of the rescheduled timetable, suggesting that passengers should be further integrated into the modelling if the development of an optimal scheduled is pursued.

Overall, there are three main scientific contributions of this study:

- A conceptual simulation-based rescheduling framework for metro networks (SBTM-MN)
- The development of a transport simulation model (TSM) that combines a commercial microscopic simulation tool with a passenger module, being able to track passenger allocation and represent the impact of demand on dwell times of trains
- The development of a passenger-oriented rescheduling model (TRM) that includes passenger level of comfort in the generalized cost function according to the level of crowding in trains.

The developed framework proves the value of adding passenger modelling when simulating and rescheduling metro networks. Neglecting passenger-train interactions consistently provides misleading results, minimizing train delays in one hand, and underestimating crowding levels on the other. Furthermore, modelling passenger allocation is a necessary step to reschedule for the passenger benefit, since the literature shows that crowding has a high impact on passenger perceived in-vehicle time.

Regarding practical suggestions, the performed experiments show that, in scenarios in which the priority is to cater for passenger travel experiences, steering the timetable towards more even headways, rather than towards schedule adherence, benefit passengers. However, the recommended rescheduling strategy depends on the location of the initial disturbance and the demand pattern. Overall, rescheduling strategies that attempt to reduce perceived travel time should include the modelling of passenger-train interaction and take into account on-board crowding. Neglecting these factors would lead to a significantly different rescheduling decision, suitable only for scenarios where the dwell time is completely independent of passenger exchange.

The SBTM-MN can currently be used to assess the impact of rescheduling measures in metro lines on passenger travel time and comfort. However, to use the framework for real-time rescheduling, some improvements are suggested, which suggest areas of future research. Firstly, the computation efficiently could be improved, in order to increase the feasible number of iterations. This is also a crucial step to obtain rescheduling measures in a short time as required when disturbances occur in daily operations. Secondly, the SBTM-MN has been tested in lines and not in networks. To expand its usability in metro networks, the interaction between different lines has to be modelled in the TRM as well as in the TSM. Otherwise, timetables that seem feasible at the macroscopic level of the TRM will not be attainable at the microscopic level of the TSM.

With regards to other areas of future application, the SBTM-MN could be used at a tactical level to develop more demand-oriented timetables, by providing a representative demand pattern as an input and extending the horizon of the TSM to a day. Finally, the SBTM-MN could be useful to design automated metro services that are completely demand-responsive. Since automated metros do not have the constraint of crew scheduling, schedule adherence might be less important, allowing for more flexibility in train operations.

1

Introduction

According to the United Nations United Nations (UN), urbanization levels are expected to keep on rising all over the world. One of the cornerstones to lead this growth towards inclusive, green and smart cities, is guaranteeing suitable and attractive urban mobility for everyone. In this context, public transport plays a fundamental role as a provider of accessible, sustainable and efficient transport (European Commission, 2013). Increasing the cost efficiency whilst improving passenger experience, thus inducing higher ridership, are amongst the main challenges the public transport sector faces nowadays. The handling of these issues is certain to become more difficult in the following decades.

As the demand for transport increases rapidly in cities, the supply of public transport services struggles to adjust to it. Particularly in the case of rail-bound transport, the high costs of constructing new infrastructure makes it is necessary to use the existing one in the most efficient way. However, densely utilized railways networks are particularly vulnerable to disturbances and disruptions (Vromans, 2005). Due to the scarcity of buffer time, perturbations tend to rapidly propagate through a line, especially when demand is high. This causes a mismatch between the planned and the delivered service, which translates into unreliability.

In terms of passenger experience, unreliability in a public transport system is one of the main causes of dissatisfaction (Cacchiani et al., 2014; Levinson, 2005). Unreliability leads to longer waiting times, higher and uneven vehicle crowding and increases the distribution of the arrival time (Oort, Brands, Romph, & Flores, 2015). Addressing this problem smartly and efficiently would increase the attractiveness of public transport and improve cost efficiency for the operator.

It is for these reasons that one of the works being done at the Rail department at Royal HaskoningDHV aims at solutions to avoid the bunching of railway vehicles and thus maintain stability and reliability in peak hours. The present research has been performed in collaboration with both Royal HaskoningDHV and TU Delft. The remainder of this introductory chapter consists of the description of the problem statement, the definition of the research objective and the corresponding questions. Furthermore, the societal and scientific contributions of the research are presented. Finally, the research approach is outlined briefly to provide an overview of the whole study and the present document.

1.1. Problem statement

One of the tools that can be used to mitigate unreliability in real-time is the rescheduling of services. In most cases, this nowadays still relies on predefined contingency plans or human judgement. The inherent complexity of the problem makes it common for traffic controllers to take sub-optimal or adverse decisions. In particular, it is hard to accurately predict and manage the growth of delays due to the impact of demand in dwell times. This phenomena, denominated here as the bunching effect, and its impact on reliability, will be further discussed in Chapter 2 of this document. Although research has been done to find optimal rescheduling strategies to cope with disturbances in railway networks, the gap between theoretical knowledge and applied methods is still considerable.

1.1.1. Research objective

The main goal of this research is to develop models and algorithms that mitigate the impact of disturbances on passengers through the rescheduling of the timetable whilst considering the dynamic variation of demand and its effect on train operations. In this context, the aim of this research can be considered to be twofold. The models and algorithms to be developed have to accurately represent the impact that real-time variation of demand has on reliability on the one hand and optimize the set of rescheduling measures on the other.

1.1.2. Research questions

To fulfil the research objective, the following research question has been posed:

Considering a disturbance in a metro network, what is the effect of passenger demand on the performance of the timetable and what is the recommended rescheduling strategy for passengers and operator?

Since this research question encompasses multiple aspects, it is necessary to formulate a set of sub-questions. These are intended to guide the research towards an answer to the main research question:

1. What is the effect of incorporating passengers in traffic modelling of metro lines on the development of delays?
2. How does the trade-off between passenger and operator perspective influence the recommended rescheduling strategy?
3. How does dynamic passenger allocation impact the effectiveness of a rescheduling strategy?

The first research sub-question focuses on the effect that passenger demand has on the dwell time and ultimately, on the reliability of a service. Logically, higher demand in absolute terms would lead to higher dwell time. This could be tackled at a tactical level by increasing frequency or capacity. However, the focus in this research is on the side of the variability of the demand along a short period. In other words, this question addresses dynamic changes in demand considering a frame of hours, rather than the substantial growth of the demand over the years. This question is crucial to understand the feedback loop between headway growth, passenger demand and dwell time, to be further explained in Chapter 2. The effect of passenger flows in delays is often neglected in literature. This study integrates passenger flows in a train simulation tool to evaluate their effect on delays and, in turn, how these affect the passenger's perceived travel time.

The second research sub-question aims to elucidate what is important for each of the considered stakeholders, namely the passenger and the operator. The objective is that the recommended rescheduling measure includes passenger perspective, which is often ignored. To this aim, it is essential to define the most relevant needs and desires of both stakeholders in the first place. The main objective of the rescheduling is towards passenger's benefit. However, the operator's point of view is also taken into account. Furthermore, the applicability might limit the choice of a rescheduling strategy. Some strategies might yield a substantial passenger or operators benefit but be excessively intricate, or inconvenient to be employed in real life.

The third research sub-question deals with the effect that passenger allocation has on the implementation of a rescheduling strategy. When a change is made in the arrival or departure time of a train, the number of passengers boarding differs. Furthermore, this change impacts the passenger exchange of the following train as well. This is expected to affect the crowding and dwell time of the vehicles, which may alter the expected benefits of applying such a strategy.

1.2. Research scope

This research is focused on real-time rescheduling to cope with disturbances in metro networks, considering dynamic variation in passenger demand. To define the boundaries of this research, its scope is outlined in this section. For a deeper understanding of the placement of this research within the related work, please refer to Chapter 2. The assumptions and choices that characterize this research can be summarized as follows:

- The focus of this research is restricted to metro networks. This implies that the resulting models should not be lightly utilized in railway networks in general without careful consideration. Metropolitan railways are defined by the International Association of Public Transport as urban, electric transport systems with high capacity and high frequency of service that run separately from other traffic (UITP, 2012). Some transit networks fulfil the technical and service standards of metro systems but are not considered metros because, for instance, they reach far out of the city. Examples of these systems are suburban, commuter or regional rail and S-trains. For this thesis, these networks are still within the scope as long as they are high capacity, high frequency, they have dedicated infrastructure, and are used exclusively for passenger transport. The reason why the scope of this thesis is not extended to all railway networks is that heavy rail differs from urban rail-bound transit in areas such as disturbance and disruption probability of occurrence, common strategies of real-time management utilized by the traffic controllers, network density and redundancy (Roelofsen D., Cats O., van Oort N., & Hoogendoorn S., 2018). Not only are the control measures more restricted in the case of metro systems, but in general, the dynamics are different from those of a heavy rail system. Metros are more densely used but do not have any interaction with other transport modes (particularly when they are underground). As a result, the probability of a disturbance happening is higher on metros, but the probability of disruption is higher on heavy rails. Another difference is that metros tend to be more homogeneous with regards to traffic type and vehicles, and freight traffic does not make use of this network (Luan et al., 2018). Although this research focuses on metros in particular, there are concepts and knowledge that can be acquired from public transport in general and railway management in particular.
- The tools to deal with unreliability are confined to the realm of real-time management and more specifically real-time rescheduling. However, notes on how a rescheduling measure translates into a strategical or tactical requirement may be found throughout the document.
- The stakeholders considered in this research are limited to the passengers and the operator. Other actors such as authorities and non-users are not explicitly taken into account. However, constraints imposed by authorities to the operator, for instance, will be considered as restrictions of the operator itself.
- One of the main characteristics of a model is the level of detail with which the infrastructure is represented. In a microscopic model, infrastructure is represented with a high degree of accuracy. For instance, nodes may indicate signals, points, etc. and links contain detailed information such as speed limit, gradient, the radius of a curve. Conversely, a macroscopic model contains no details about track characteristics or signalling, and information in links and nodes is far more aggregated. Sahin, Ricci, and Vasic-Franklin (2013) state that a microscopic model is required for calculating running times, creating timetables and simulations. In this work, infrastructure will be considered in relative detail, including blocking sections and signals through the use of a simulation tool. This microscopic approach is needed to compute headway and running times and thus evaluate the application of different control measures. However, the rescheduling is done through a macroscopic optimization. The feasibility of the resulting timetable at a microscopic level is then verified by a run in the microscopic simulation.
- Passengers are handled with a rather disaggregated perspective for the input of the model. However, aggregated data may be used to support the design of disaggregated passenger demand profiles.

1.3. Relevance

This section discusses the contribution of this research both in the scientific and the societal area. The outcome of this thesis is a model that can obtain control measures to mitigate the dynamic propagation of delays due to the inevitable disturbances inherent to an unstable, densely utilized metro network.

1.3.1. Societal Relevance

Equity with regards to accessibility and resource efficiency are societal goals that closely relate to public transport in general. With the growth in population and urbanization, accessibility is increasingly under pressure over all modes of transport in cities. As authorities begin to be aware of this, the importance of achieving efficient and accessible transport gets higher in their agendas. Goal 11 of United Nation's Sustainable Development Goals, "Sustainable Cities and Communities" explicitly states the need to provide access to safe, affordable and sustainable transport systems for everyone in cities (UN News Centre, 2015). Additionally, one of the Horizon 2020 societal challenges of the European Commission is to attain smart, green and integrated transport (European Commission, 2014).

It is known that unreliability is a key quality aspect of public transport service for passengers (van Oort, 2014). Its improvement would, therefore, increase passenger satisfaction, and in turn ridership. Potentially, this could draw passengers from modes such as cars, which would be environmentally favourable. However, improving reliability is often done by means of increasing the robustness of the timetable. This usually implies increasing buffer times, thus decreasing the capacity utilization. In this way, there is a trade-off between reliability and frequency. The development of a model that improves the performance of the metro service efficiently, adapting to everyday disturbances and their demand dependent dynamics, is therefore in line with current and future societal challenges. By adequately choosing a rescheduling strategy, reliability can be improved without adding more buffer time to the timetable at a tactical level. Therefore, the models and algorithms developed allow to increase the efficiency of the system while preserving reliability, or maintain efficiency while improving reliability, by considering the current passenger demand.

Furthermore, one of the aims of this research is to explicitly include passenger perspective into the objective of the measures taken. This implies that the rescheduling strategy suggested as a result will take into consideration passenger benefits and not solely the operator's perspective. Although research has been carried out on this matter before, it is still a relatively new angle to solve the problem of real-time rescheduling in metro systems

Finally, the models and algorithms developed would aid dispatchers in their day to day complex decision making. Suggested solutions derived from this model will have a stronger scientific basis than solely human experience. Moreover, dispatchers may feel less stressed since pressure on decision making is partially relieved of them.

1.3.2. Scientific Relevance

The research conducted in this thesis, as well as the developed models, have contributed to the scientific field in several aspects, which are discussed more deeply in chapter 2. The three main scientific contributions can be summarized as follows:

Firstly, the accuracy and level of detail in the modelling of the dwell time of vehicles is higher than in most of the previous research. Most literature related to disturbances in metro networks directly do not mention how the issue of dwell time depending with the arrival of passenger and headway of the vehicle is treated. The focus is often in other areas of disturbance management. On the contrary, the modelling of dwell time as dependent on dynamic passenger arrival rate and its influence in the spread of delays is a central part of this research.

Secondly, this research aims to produce a simulation-based optimization model. OpenTrack, a commercial simulation software, is used to model the network and assess the decisions taken by an optimization module. Using this tool, RoyalHaskoningDHV has been working towards the representation of the bunching effect in the railway simulation software OpenTrack. This work in progress is extended and refined in the course of this research to make it fully functional. The optimization model exchanges information with the simulation in OpenTrack and derives a strategy that aims at minimizing the impact of disturbances in both passengers and operator.

Thirdly, this research aims to employ a more balanced approach by including passenger perspective as well as the operator. Traditionally, research has focused primarily on delays affecting trains, disregarding the impact on passengers, or at least not explicitly addressing it.

As a conclusion, it has to be noted that, in spite of the vast research done on the subject of real-time rescheduling, not much of it has been applied in practice. This may be due to not only the interests of the industry but also the lack of applicability in some of the developed models. The approach taken in many of the papers encloses them to the theoretical realm, due to their rather simplistic representation of railway operations. Indeed, although there have been recent technological developments in the field of railway dynamic traffic management, in practice, service control still relies heavily on human judgement (Caimi, Fuchsberger, Laumanns, & Lüthi, 2012) or pre-designed contingency plans. Due to the inherent complexity of the problem, mostly sub-optimal or even adverse decisions are taken. It is not reasonable to expect controllers to make decisions that minimize the impact of disturbances on the diverse stakeholders in such a short time and without appropriate aiding tools. The fact that different perspectives may not be aligned makes this task more cumbersome. For instance, waiting time is an important parameter for the passenger, but this does not necessarily require schedule adherence. However, for the operator, schedule adherence might be the most relevant criterion (Carrel, Mishalani, Wilson, Attanucci, & Rahbee, 2010). This study intends to be a step towards closing this gap between research and practice.

1.4. Outline of the report

Figure 1.1 presents an outline of the remaining of the report. The numbers in brackets indicate the chapter in which the corresponding part of the research is detailed. The literature review in Chapter 2 provides background knowledge to better understand the problem at hand and the research gap that is being tackled. Chapter 3 explains the theoretical framework and the development of the models and algorithms. This chapter describes the methodology in general terms with sufficient details to ensure reproducibility. Chapter 4 introduces the case study, which is an application of the model to two lines in Rotterdam metro. The implementation of the sub-models is exemplified via the case study in separated subsections within that chapter. This chapter also presents and discusses the results obtained through the case study. Finally, Chapter 5 presents the conclusions derived and further recommendations for future research.

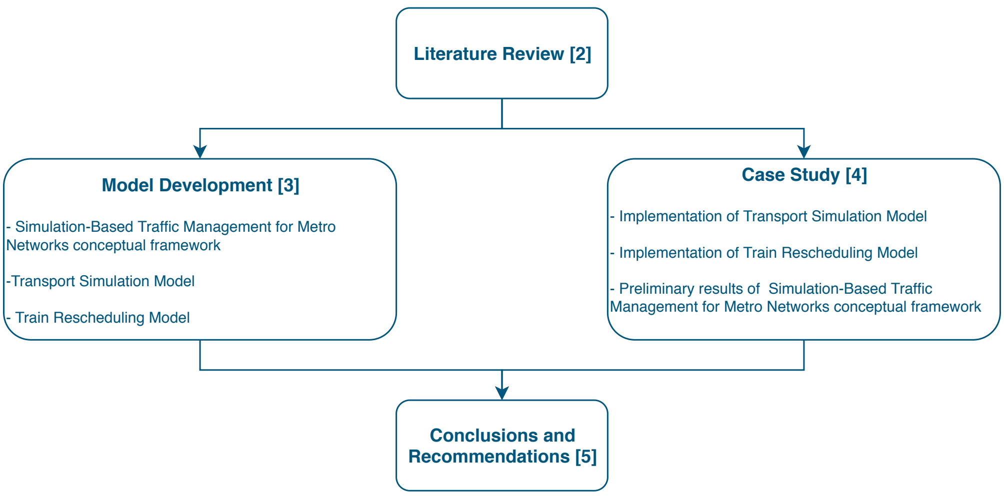


Figure 1.1: Outline

2

Background knowledge and related work

This chapter provides the background information necessary to understand the motivation for this research and the field in which it takes place. Firstly, an overview of railway planning and management, as well as their inference in reliability, is supplied to indicate the stage in which this research intends to intervene. Secondly, the problem at hand in general and the phenomena of vehicle bunching, in particular, are discussed. Thirdly, the factors that affect the dwell time of a vehicle are discussed, and background information of the dwell time function is provided. The following section reviews the related work available in this field. Furthermore, the research gap that this research intends to fill, is specified.

2.1. Railway traffic management

The planning of railway services is done in four stages or levels depending on the time frame and impact (Huisman et al., 2005). The *strategic level* refers to long term, generally capital intensive planning such as construction and design of new infrastructure. In the *tactical level*, the medium-term planning is done. In this stage, the basic conflict-free timetables, schedules and plans are developed. The *operational level* implies the planning that takes place around every two months, in which plans are adjusted to specific demands or patterns. Furthermore, the *short-term planning* encompasses the decisions taken for a short horizon, on a daily basis.

The resulting planned services can be either *schedule* based or *frequency* based (Gentile, Florian, Hamdouch, & Cats, 2016). Although there is usually a timetable for management reasons, this can be published or not. Especially in services with low frequency, it is of interest to the traveller to know at what exact time a train will depart. In these cases, a schedule presenting the arrival and departure of each train is commonly made public. This form of displaying information and the consequent decision making correspond to a *schedule* based service. In cases in which the frequency is high, passengers may not plan their trip based on the departure of the train. Therefore, they may not care about the actual time at which the train departs. In this scenario, the headway (or frequency) is of relevance to the passenger and the scheduled times at stops may not be published. This corresponds to a *frequency* based service.

Railway planning also involves sequential planning steps (Leung, Kuo, & Lai, 2016; Maroti, 2006). *Network planning* implies determining the location of tracks and stations. *Line planning* deals with the origin/destination of route lines and the corresponding frequencies. *Timetabling* aims at producing the exact time at which trains should be dispatched, and when each event (for instance departure or arrival) should take place. The *rolling stock scheduling* assigns vehicles to specific trips. Finally, in the *crew scheduling*, the duties and rosters of drivers are derived.

Unfortunately, it is inevitable for real-time operations to sometimes deviate from the original, conflict-free timetable due to anomalies that affect everyday operation. In this case, controllers may have to take decisions in a period of minutes to regain the desired level of service. Perturbations that may affect the reliability of a public transport system can be catalogued as *disturbances* or *disruptions*. A *disturbance* differs from a *disruption* in that its probability of occurrence is higher, but the severity of its impact is smaller (Cacchiani et al., 2014). *Disturbances* occur because a certain process takes longer than what was scheduled. For instance, dwell time might take longer due to an unexpected peak of demand, or run time might extend because adverse weather imposes lower speeds. *Disruptions* happen due to incidents that have a relatively large repercussion in the performance of the service. Causes of disruption can be a signal failure, or a collision with an object, among others. As a result, *disturbances* can be resolved by rescheduling the timetable, whereas *disruptions* require to also reschedule vehicles or/and crew.

Several real-time rescheduling measures to mitigate disturbances can be found in literature and practice. Galviz (2016) mentions the following common strategies to manage disturbances in metro networks: holding of trains, deadheading, cancelling a service, short-turning, termination of a train, stop skipping, rerouting trains, reordering trains, using a stand-by or back-up train set, and exchanging stop patterns. According to Eberlein, Wilson, and Bernstein (1999), real-time rescheduling can be classified into station control, inter-station control, and others. Station control includes skipping stops, applying boarding restrictions, and holding trains at stations. Inter-station control consists of speed control, traffic signal preemption and other measures, whereas the third category implies strategies such as adding a vehicle or splitting a train. Note that here, measures such as deadheading and short turning can be considered special cases within stop skipping.In this work, small disturbances and their propagation in a densely utilized urban rail bounded network are considered. The focus is on the employment of real-time rescheduling tools that mitigate the consequences of these disturbances. In this scenario, the phenomenon of railway bunching becomes relevant, as it is directly related to the dynamic growth of delays when disturbances occur. Since this work is limited to small disturbances, the rescheduling of vehicles or crews is out of the scope.

2.2. Disturbances and Vehicle Bunching

As mentioned in the previous section, the possible triggers of disturbances are innumerable. Adverse weather, a passenger holding the door, a malfunction of a system, or a medical emergency in a coach are examples of what could cause a deviation in the planned timetable. Particularly in cases in which vehicle headways are rather short, the primary disturbance could degenerate into what is known as vehicle bunching. The bunching of vehicles is a common problem faced by public transport operators, particularly during peak hours in urban areas. Operators in the bus sector have been trying to end the problem of bus bunching for years (Fonzone, Schmöcker, & Liu, 2015).

This phenomena is illustrated in figure 2.1. The undisturbed scenario, represented in the first row, has even headways between the three vehicles. An initial delay in vehicle B increases its headway with its predecessor, vehicle A. This leads to a larger number of passengers waiting to board at the next stop. The dwelling time of a vehicle is a function of the number of passengers boarding and alighting (Aashtiani & Iravani, 2007). Since there are more passengers at the stop than the expected, the dwell time may be higher than the scheduled dwell time. This large dwell time increases the headway between A and B. At the same time, the headway between B and C reduces because C has fewer passengers to pick and is therefore on schedule, or even ahead of it if allowed by regulations. Eventually, the bunching of B and C occurs. It can also be seen how vehicle B tends to be overcrowded whereas vehicle C is likely to be far less crowded than planned.

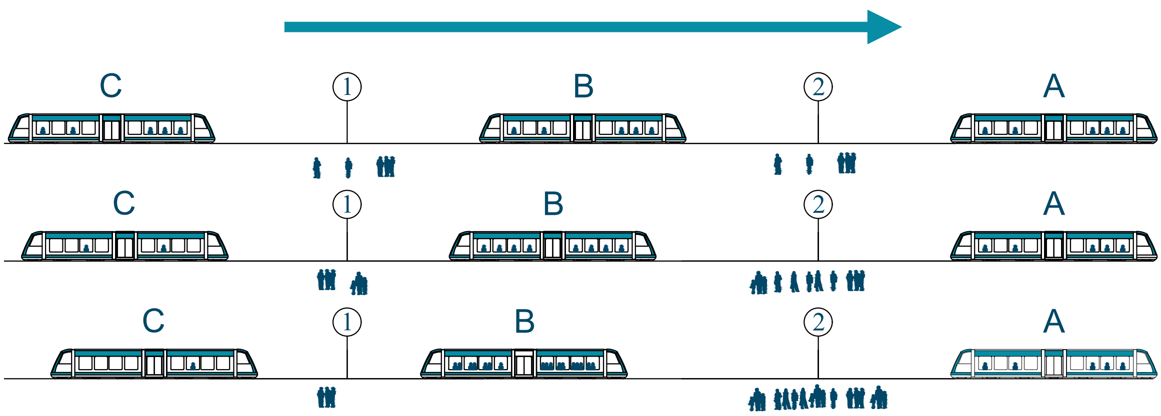


Figure 2.1: Illustration of bunching in a rail bounded line

The underlying cause of vehicle bunching is that densely utilized systems, where headways are shorter, are inherently unstable. This means that, as long as no initial perturbation occurs, services run smoothly. However, as soon as a vehicle incurs in a delay, this tends to grow dynamically and affect other vehicles if no control measure is taken. This harmful positive feedback loop causes uneven headways and vehicle bunching. The result is a decrease in the reliability of the service and uneven crowding of the vehicles, which makes this phenomenon a highly undesirable one.

Although literature in vehicle bunching commonly refers to the case of bus bunching, this problem is not unique to that particular public transport mode. Railway bunching has been observed in dense networks with high demand and frequency, such as metros and trams in cities. Nevertheless, there are some differences between the two mentioned modes of transport that call for specifically designed rescheduling strategies.

Firstly, the fact that railways are bound by their track, impose limitations to the overtaking and rerouting possibilities when compared to busses. This is more noticeable when comparing metros to buses. Since busses have in general the freedom to change lanes in most places along the route, the overtaking is far easier than in the case of railways. Furthermore, busses have in general way more available routes, and therefore more rerouting alternatives than rail bounded vehicles.

Secondly, the shared rail infrastructure leads to higher safety constraints that require the use of blocking systems, signals and interlocking. All of these are elements that are non-existent in bus networks. This increases the complexity in the deployment of rescheduling measures in the case of rail bounded transport systems, as there are more variables regarding safety in place.

Thirdly, in particular for metro systems, passengers waiting at a stop are unable to see whether the delayed train that has just stopped at the station is bunched with the following one or not. Usually, information panels indicate the expected arrival time of the next train. However, the lack of visual certainty may lead passengers to board the overcrowded, delayed train instead of waiting for the following vehicle. In other words, an overcrowded, late train that is already at the platform, may be perceived as a better alternative than the potential of a less crowded train coming after. This increase the delay of the train even more. In the case of busses, passengers are sometimes able to see the bunched vehicles and may opt not to board the first one that arrives at the stop.

2.3. Dwell time function

This section provides background information on the dwell time function and describes how the dwell time of a vehicle relates to the passenger demand. This is helpful to identify the dwell time functions that can be used in the model. Firstly, the variables that are relevant to the derivation of the dwell time need to be established. Cornet et al. (2019) presents an overview of the factors affecting the dwell time in railway networks. They mention that trains dwell times in stations are affected by the following factors:

- Technical features of the rolling stock. Particularly the required time for opening and closing the doors.
- Boarding and alighting of passengers. According to Daamen, Lee, and Wiggenraad (2008), the time required for this process to take place is, in turn, a function of factors such as:
  - The number of passengers alighting and boarding
  - The load in the train
  - The level of crowding in the platform
  - The train and station longitudinal configuration.

  Furthermore, passenger behaviour has an impact on dwell time as well. It is not uncommon for passengers to block the doors while they are closing, causing an extended dwell time that cannot be predicted.
- Timetable. In general, operators intend to stick to a schedule, which means that trains are forbidden to depart early from a station. If a train arrives ahead of schedule, it may have to wait longer to depart, even if the passenger exchange has concluded.
- Signaling. In most countries, for safety reasons, a train at a station should not depart until the track ahead is cleared. This is indicated by a signal, usually located at the end of the platform.

- Driver behaviour. Depending on the case, there might be some variability in the driving behaviour that can affect the dwell time. For instance, some drivers may rush the closing of the doors after the passenger exchange is done, whereas others may wait longer.

Literature provides several dwell time functions that consider some or all of the aforementioned predictors. However, a function might be more suited for one case than for another. To provide some flexibility in the modelling of dwell time, the derived model should allow adjusting or changing the default dwell time function to better suit the study case. As an example, Hao, Song, He, and Lan (2019) uses a dwell time function with the number of boarding and alighting passengers, load at the station and number of doors of the train as independent variables. The parameters of the function are determined through the usage of historical data. However, this function does not consider the crowding inside the train. If, for instance, the crowding inside the train has more influence in the dwell time than the crowding in the platform, this function may not be the best suited. When a case study is undertaken, it is advised to perform some statistical analysis to evaluate which predictors are most relevant for the case at hand. This enhances the accuracy with which the dwell time is represented as a function of the predictors for a particular case study.

2.4. Literature Review

This section presents background information on the related work that has been done on the field of this research. Furthermore, table 2.1 shows a brief perspective on the scientific context in which this thesis is located, and provides an overview of the related work done in the past. Due to the extensive research that has been done in real-time management in trains, the table is restricted to rescheduling problems in small disturbance scenarios. The three main topics explored in this section are rescheduling models, simulation, and integrated approaches, which combine simulation and optimization.

According to Cacchiani et al. (2014), most papers on rescheduling models in railways seem to consider the system at a microscopic level and aim at solving disturbances. Within this specific topic, the control measures evaluated, the objective, the application and approach differs from one paper to another. Mathematical models are the most commonly used approach for optimization in railway rescheduling. For instance, Schanzenbacher, Farhi, Leurent, and Gabrie (2018b) propose a dwell time and running time control to minimize headway variance in metros. Shen and Wilson (2001) derive a mixed-integer programming model that uses holding, skipping stops and short turning as measures to minimize passenger delays.

An alternative approach to the mitigation of delays due to disturbances by rescheduling is that of Hao et al. (2019). They present a running time train control combined with a passenger control model to minimize the total delay of disturbed trains with minimal impact on operation costs and service quality. Indeed, the combination of train regulation and passenger flow control is a fairly new concept that is first introduced by Li, Dessouky, Yang, and Gao (2017). In these studies, the relationship between dwell time, passenger flow, and the impact on growing delays is carefully elaborated. Conversely, most rescheduling models introduced in literature simplify greatly the relationship between dwell time and passenger flow. Many papers consider a statistical distribution of dwell time (Corman, D'Ariano, Pacciarelli, & Pranzo, 2010). Other assume that dwell time varies according to a given constant arrival rate of passengers at the station (Schanzenbacher, Farhi, Leurent, & Gabrie, 2018a). Few papers consider the dwell time-passenger arrival relation in further depth or with a more disaggregated approach. Exceptions include Hassannayebi, Sajedinejad, and Mardani (2014) and Grube, Núñez, and Cipriano (2011)

Traditionally, real-time rescheduling models aim to minimize delays of trains by sticking to the schedule as much as possible. In that sense, the emphasis is in the train oriented perspective rather than in a passenger one (Cacchiani et al., 2014). Nevertheless, there is an increasing number of papers taking into consideration the negative effects on passengers in their optimization objective. This reflects a change in the target of research, in which a more balanced approach is pursued.

In terms of application, many rescheduling models described in papers specifically concern stations and junction areas. These are thoroughly studied because they tend to act as bottlenecks in the system (Mannino & Mascis, 2009; Pelledrini, Marliere, & Rodriguez, 2013). For instance, Caimi et al. (2012) propose a dispatching decision tool for a complex railway station area based on discrete-time model predictive control. A forecasting module predicts the evolution of the system and a rescheduling model computes new disposition schedules. Once the dispatcher takes a decision, this is forwarded to the infrastructure, trains and the intended commercial offer is changed. This closes the control loop since the forecast model uses the updated output of the dispatcher decision. Thus, trains are rescheduled in discrete time steps.

Fernandez, Cucala, Vitoriano, and De Cuadra (2006) propose a rescheduling model based on a predictive control approach to minimize train time-headway variance and maximize the schedule adherence by run time and stop time control in railways. Their use of predictive control would be interesting considering the dynamic characteristics of delay growth due to the bunching effect. However, their mathematical model simplified the representation of the system to reach a feasible computational time. The assumptions made in their research prevents a deeper exploration of the dwell time-passenger flow relation and their impact on reliability.

It is remarkable that the vast majority of the papers do not make use of a simulation model but rather rely solely on mathematical models. This limits the complexity of the network that can be studied. Moreover, it is harder to obtain representativity in a mathematical model when trying to portray a real network with sufficient level of detail. A set of simplifying assumptions is often needed to develop a mathematical model. Sometimes simplifications are extended for the sake of computational time, further constraining the representativity of the model. As a result, it is unlikely that mathematical models capture the desired patterns and effects for this research. The level of accuracy attainable by using a simulation is considered to be more appropriate to evaluate the implications of rescheduling measures in disturbed scenarios.

Regarding the availability of these simulation tools, some of the research that has been done in railway microscopic simulation lead to the launching of simulation software that are currently available in the market. Hürlimann (2002) developed OpenTrack, the simulation tool used in this research. It uses a mixed discrete-continuous process and object-oriented programming to simulate rail system operations. This simulation tool is widely used by industry and researchers. Another successful railway simulation tool is RailSys, which integrates a timetable and infrastructure manager with synchronous microscopic simulation. However, neither of these simulation tools are suitable to evaluate control measures that include passengers. To partially overcome this issue, Krause (2014) introduces dynamic delays in station dwell times given passenger arrival rates in a simulation using OpenTrack and its API. His study serves as a basis for the development of this research. Furthermore, Grube et al. (2011) designed an event-driven dynamic simulator for multi-line metro systems that allows for passenger arrival rate to be used as an input. This simulator is based on object-oriented programming and can be used to design and evaluate real-time control strategies. Nevertheless, the focus on the research is on the simulation and evaluation of measures, without the aim of improving them.

Finally, some researchers integrate a simulation module with optimization to find optimal or sub-optimal rescheduling measures. Altazin (2017) propose an iterative approach that uses stop skipping to minimize the recovery time when disturbances happen in a railway rapid transit system. Their solution combines an optimization module to propose decisions and a macroscopic simulation module to evaluate these decisions. Corman and Quaglietta (2015) developed a traffic control framework by coupling a conflict detection and resolution system (ROMA) with railway simulation model (EGTRAIN). In this framework, EGTRAIN feeds ROMA with current traffic information at regular time intervals. ROMA then predicts conflicts and derives (sub) optimal strategies to minimize the maximum consecutive delay in the network. Another research with a simulation-based approach is the PhD thesis from Toletti (2018). Her research extends the work done by Fuchsberger (2012), who developed a rescheduling algorithm for complex station areas based on the resource conflict graph formulation. Toletti (2018) integrates a simulation-based approach to derive the blocking time stairways linked to the decision variables of the resource conflict graph formulation, among other contributions. She uses the microscopic simulation tool OpenTrack through its Application Programming Interface (API) to build the blocking time stairway patterns to be used by the rescheduling algorithms.

Reference	Perspective	Evaluation criteria	Modelling approach	Decision variables	Solution method	Dwell time	Application
Hao et al. (2019)	Train and passenger	Operation costs and passenger loss	Markov decision model	Running time and passenger control	Approximate dynamic programming	Function of dynamic arrival rate	Yizhuangxian line
Schanzenbacher et al. (2018b)	Train	Headway variance	Discrete event	Dwell and run time	-	Average passenger arrival rate	Metro loop line
Luan et al. (2018)	Train	Sum of train delays at all stations	MINLP and MILP	Retiming and rerouting	MATLAB and IBM ILOG PLEX	Not treated	Network (Ut to Ht)
Khosravi, Bennell, and Potts (2012)	Train	Tardiness of trains	Job shop - MILP	Scheduling	Shifting bottleneck	Not treated	Network (London bridge)
Altazin (2017)	Train and passenger	Recovery and passenger waiting time	Event graph activity	Skipping stops	Heuristics	Statistically distributed	SNCF Transilien line
Vázquez-Abad and Zubieta (2005)	Train and passenger	Train waiting cost, average passenger waiting time	Discrete event simulation	Headway	Gradient-based methods	Function of static arrival rate	No
Grube et al. (2011)	Train and passenger	Passenger waiting time	Object oriented and event driven dynamic simulator	Dispatching time and train speed	Control algorithms modelled in MATLAB	Function of dynamic arrival rate	Network (Santiago de Chile)
Fernandez et al. (2006)	Train	Train time headway variance	Quadratic programming	Run time and stop time	GAMS and CPLEX	Linearly dependent on headway	Metro loop line
Hassannayebi et al. (2014)	Passenger	Average waiting time per passenger	Object oriented DES	Headway	Simulation based optimization using GA	Function of dynamic arrival rate	Metro line
Li, De Schutter, Yang, and Gao (2016)	Train	Deviations from schedule and control force	Convex optimization involving linear matrix inequalities	Running time	Model Predictive Control	Function of average passenger arrival rate	Metro loop line
Corman, D'Ariano, Marra, Pacciarelli, and Samà (2017)	Passenger	Time passengers spend n a system	MILP	Scheduling and passenger routing	Heuristics	Statistically distributed	Parts of Dutch railway network
Caimi et al. (2012)	Passenger	Passenger satisfaction	LP	Rescheduling and rerouting	Model Predictive Control	Not treated	Complex station area
Corman and Quaglietta (2015)	Train	Maximum consecutive delay	ROMA and EGTRAIN	Retiming and reordering	Automatic rescheduling tool (ROMA)	Statistically distributed dwell times	Corridor Utrecht-Den Bosch
This research	**Train and passenger**	**Passenger and operator cost**	**Object oriented mixed discrete-continuous simulation tool, LP**	**Train holding, speed adjustment**	**Python and PuLP**	**Variable dwell time with dynamic arrival rate**	**Rotterdam metro network**

Table 2.1: Thesis within the scientific context

2.5. Scientific gap

Within the research done on rescheduling to mitigate delays due to disturbances in railway systems, there is a scarcity of passenger orientation, detailed modelling of dwell time variation, and the integration of simulation model. Note that these statements are regarding railway systems in particular and not necessarily true for a bus network, in which bunching has been more thoroughly studied. Furthermore, most of the research is focused on railway networks in general and not in dense urban metros in particular. Finally, the gap between scientific research and application seems to be widened by the fact that virtually all papers disregard the complexity of applying the optimal rescheduling measure. Each of these issues has been tackled by researchers separately. However, this is, to the best of the author's knowledge, the first research combining a passenger-oriented rescheduling module with a simulation that describes dwell as a function of passenger demand in higher detail. Moreover, this is the first study that integrates passenger flows with a train simulation in order to keep track of passenger allocation and their effect on the application of rescheduling measures.

3

Simulation-Based Traffic Management for Metro Networks (SBTM-MN) Development

To answer the main research question, and as an objective of this thesis, a framework, to be referred to as the Simulation-Based Traffic Management for Metro Network (SBTM-MN), is developed. The SBTM-MN itself consists of two interacting models: namely the Transport Simulation Model (TSM) and the Train Rescheduling Model (TRM). The TSM encompasses the Train module and the Passenger module, which exchange information with one another in an iterative process. Furthermore, a simulation that mimics real-world operations, which is referred to as Transport Simulation model of the Real World (TSM-RW), is coupled with the SBTM-MN to evaluate its performance under different scenarios. This chapter describes the methodology undertaken in general terms to ensure the possibility of reproducing it in the future. Firstly, the modelling framework is presented in Section 3.1, as well as a brief explanation of how each component works. Secondly, the assumptions made are specified in Section 3.2. Thirdly, the input of the SBTM-MN is discussed in Section 3.3. After, the modules, their components and the interactions between them are explained in detail in Sections 3.4, 3.5 and 3.6. Then, the modelling of the real world operations and its coupling with the SBTM-MN are described in section 3.7. The offline pre-processing and parameter calibration is presented in section 3.8. Finally, a small example of the algorithm in the TSM-RW and the data exchange in SBTM-MN is provided in section 3.9.

3.1. The SBTM-MN Framework

The modelling framework developed in this thesis and its interaction with the simulated real world is presented in Figure 3.1. In this representation, the parallelogram represents data (either input data or data exchanged between modules), the rectangle with rounded edges represents models and their modules. The arrows show the direction in which information is delivered. At different points in time, the SBTM-MN is triggered by the TSM-RW, which sends real-time data to the SBTM-MN, and retrieves a rescheduled timetable, as shown in Figure 3.2. The SBTM-MN itself contains two models that interact with one another, and their components, inputs and outputs. The passenger module and the train module constitute the Transport Simulation Model (TSM. These modules exchange information in an event-based inner loop. Furthermore, the TSM sends and receives information to and from the Train Rescheduling Model (TRM) in what is defined as an outer loop. Considering this, the SBTM-MN can be split into two main components:

- Transport Simulation Model (Section 3.4)
- Train Rescheduling Model (Section 3.5)

The aforementioned components can be briefly described as follows :

Offline pre-processing and scenario setup: This involves the calibration of dwell time parameters and the estimation of other parameters such as arrival rate of passengers for a given time frame. This process is performed off line and it is necessary to set up a case-specific scenario.

Input: This is the data that the user of the module has to define in accordance with the case under study. The external input includes data on the passenger demand profile, dwell time functions and estimated parameters, and information on the metro system to design the network and its restrictions. This serves to represent, on one hand, the state of the system itself and on the other the constraints that limit the solution space.

Transport Simulation Model: This component predicts passenger demand and distribution, as well as train movements for a given horizon. It is comprised of the train module and the passenger module.

The train module takes place via a simulation in OpenTrack (Hürlimann, 2002). The railway network is represented at a microscopic level in what is called a double vertex graph. In this graph, vertices mark the point on the railway network in which a route attribute changes or a signal is located. The edges of the graph represent sections of the railroad track.

The passenger module computes boarding and alighting passengers at each train stop, as well as the load in the train after departure. The dwell time at a station is calculated based on these values. The passenger demand is calculated based on historical data as well as real-time data obtained from the modelled real world. Neither the individual passenger's actual flow nor their underlying process of choice behaviour is modelled or analyzed in depth. Since no microscopic simulation of each passenger movement is performed, the determination of the dwell time as a function of passenger allocation is based on regression models. The representation of the dwell as a function of the passenger arrival at the station and train headway is achieved by the interaction between the passenger and the train module. This enables the introduction of the dynamic growth of delays.

Train Rescheduling Model: This component interacts iteratively with the TSM to reschedule the timetable for the benefit of passengers. In each iteration, the TRM comes up with a tentative solution that is evaluated through a run in the simulation. Only passengers and operator are considered as stakeholders in the objective function. The quality of the tentative solution is thus measured in terms of perceived travel time of passengers and schedule adherence at stations. Since the variables are the arrival and departure times of trains at stations, and they are continuous, this is considered to be a Linear Programming Problem.Limitations imposed by the layout, authorities or the operator act as constraints of the problem.

Output: After a solution has been found, the output of the model is stored. This includes details such as the preferred rescheduled timetable and the objective value. The considered measures include adjusting the speed of trains, modifying the departure times at starting stations, and increasing dwell time at a station. Previous solutions are also stored in case a subsequent evaluation is required and to provide insights on what the possible measures are.

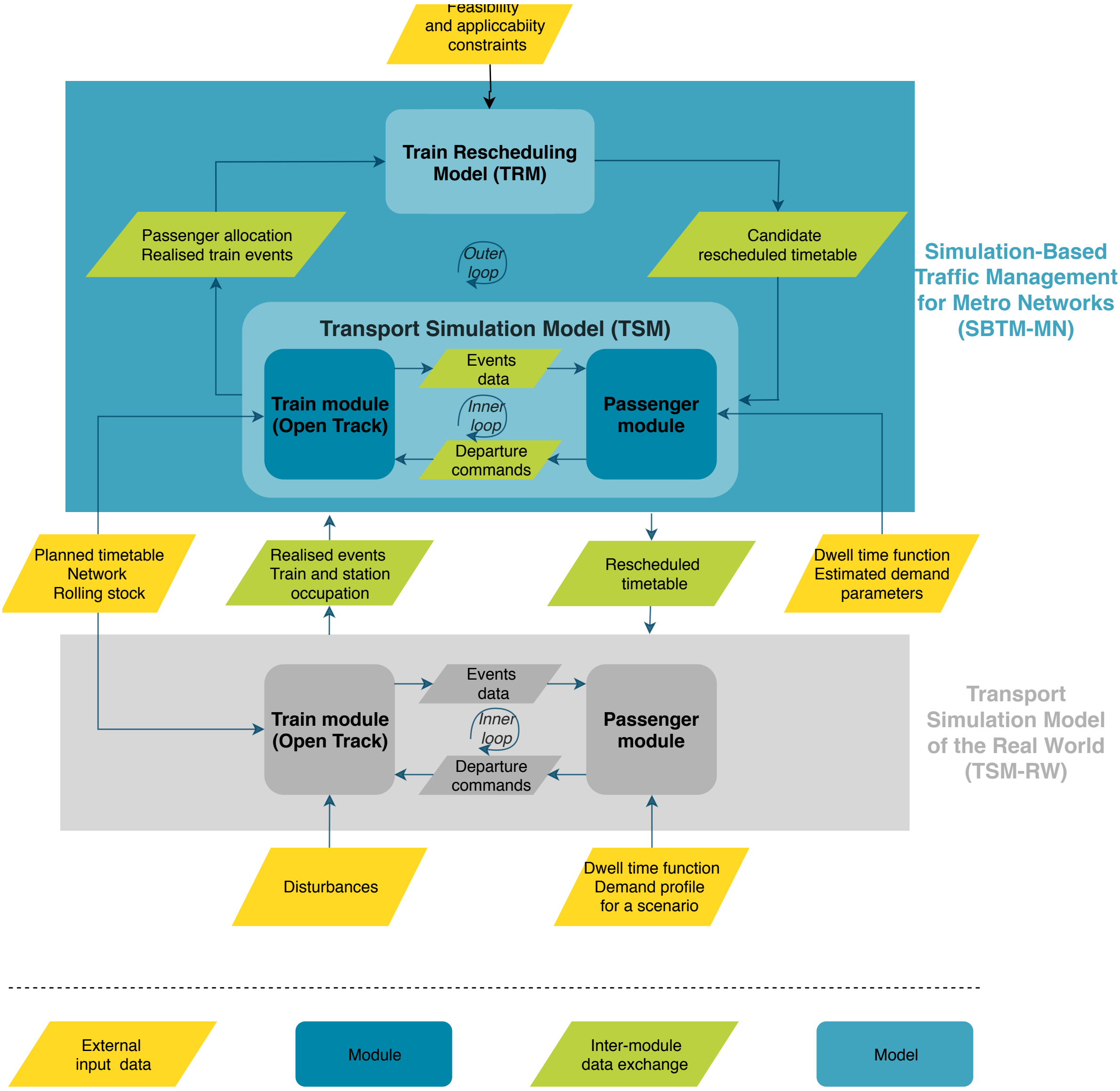


Figure 3.1: Representation of the Simulation-based traffic management for metro network framework

The process works as follows: the TSM-RW mimics the operations in the real world, acting as a field test for the functioning of the SBTM-MN. This simulation includes train movements, passenger rides and disturbances for a given scenario. The SBTM-MN is triggered by the TSM-RW at different points in time, as shown in figure 3.2. When this occurs, the TSM-RW provides the SBTM-MN with data on the realised train movements and the occupation of trains and stations. For a given timetable and an estimated demand for the prediction horizon, the TSM calculates the passenger allocation and sends it to the TRM. This allows the latter to estimate the cost of the timetable and modify it to reduce the perceived travel time of passengers. However, this calculation is done based on the allocation of passengers as a result of implementing the timetable corresponding to the last iteration. Each time a timetable simulated in the TSM, the passenger allocation changes accordingly. This passenger allocation acts as weights for the rescheduling decisions in the optimization environment. The TRM and the TSM exchange information iteratively until a suitable solution is found, or after the resulting timetable starts to deteriorate. If a timetable provided by the TRM performs worse than the corresponding to the previous iteration in terms of total costs as defined by the objective function, three more iterations are run. If no fluctuation is observed in the cost of the new iterations, the process is stopped. Then, the best performing timetable on the set of iterations is selected.

As shown in Figure 3.2, the architecture of the TSM is similar to that of the TSM-RW. However, the input of the TSM-RW is the actual demand pattern and any disturbances in the network for a given scenario, whereas the TSM estimates the demand for a horizon based on current and historical data. This means that the TSM-RW is fed detailed passenger rides and train delays to mimic a real-world situation, and the TSM is only able to estimate a prediction of passenger movements in a time horizon. In both simulations, the train module notifies the passenger module every time a train arrives at a station. Then, the passenger module updates the departure time of said train based on the passenger demand.

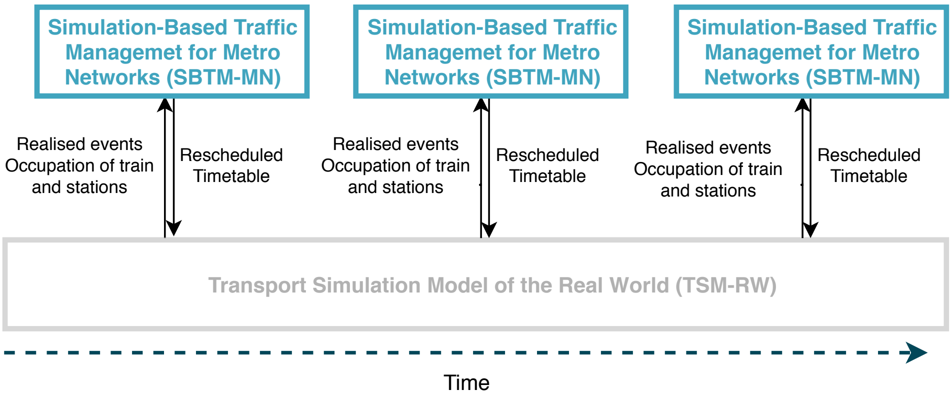


Figure 3.2: Representation of the interaction between simulated real world and the SBTM-MN

3.2. Assumptions

The general scope of the project is discussed in 1.2 to give the reader an indication of the boundaries of this research. This section outlines the assumptions of the SBTM-MN in further detail:

- Resource constraints (such as crew scheduling) are disregarded.
- No major disruption is modelled in order to keep the study bounded to disturbances which are solvable by rescheduling measures and without modifying rolling stock or crew scheduling.
- The selection of destination, mode and route by a passenger is considered to be fixed. This means that, although in real life a passenger might change the transport mode, the route or even his/her destination when a disturbance occurs, this is neglected by the model.
- Passengers are considered to board the first train that would take them to their destination. This assumption implies that the spare time within their journey is spent once they alight from the vehicle and not before boarding it. This is done so that each time a train arrives at a station, it can pick up all passengers that tapped in, disregarding the time at which they exit the system, which is not known at the moment in which the train arrives.
- The effect of stochasticity in the processes is omitted. This implies that the simulations performed are deterministic.
- Denied boarding is not considered. This means that, although crowding is penalized, it is considered that passengers can board even when capacity has been reached. Therefore, every passenger at the station whose destination is a station served by the arriving train will board it regardless of how crowded it is. The relevance of this assumption highly depends on the case study considered. There are limited cases around the world in which trains are too busy to be boarded.
- Passengers that get to the platform once the train has already arrived cannot board said train, even if it has not departed yet. This is because no internal iteration between departure time and passenger arrival is modelled. Instead, it is assumed that the train collects only passengers getting to the platform during the inter-arrival headway. According to Daganzo (2009), this approach leads to simpler models.

3.3. SBTM-MN: Input

The SBTM-MN requires two types of input for its initialization: external input provided by the user, and data imported from the simulated real world at the time in which the SBTM-MN is triggered. This section explains the external input for each module in the SBTM-MN, whereas the data exchange with the simulated real-world is further explained in the following sub-chapters.

3.3.1. Input for the passenger module

The passenger module estimates the demand of passengers for a given horizon and the dwell time at each station as a consequence of this demand. To do so, the passenger module requires the following two external inputs:

Estimated demand parameters

To estimate the passenger demand for the desired horizon, the passenger module uses an arrival rate of passengers at each station and their destination split. These are derived from historical data and are specific to the timeframe in which the prediction horizon takes place. Furthermore, the number of passengers in trains and stations when the SBTM-MN is triggered is an input from the TSM-RW. However, their destination is not known, since passengers have not yet exit the system. To predict the destination of passengers, the fraction of passengers in a train with a given destination is derived from historical data. Therefore, the estimated demand parameters can be defined as:

λ_s^y The arrival rate of passengers to station s per second for timeframe y

$\delta_{s,d}^y$ The fraction of passengers in station s that have station d as destination in timeframe y

$\chi_{r,s,d}^y$ The fraction of passengers with destination d on a train in route r after departing from station s for timeframe y

These parameters allow to derive the destination of passengers, besides their origin. This increases the detail in the assignment to trains according to the stations that they serve, which improves the estimation of loads in the trains and passengers alighting at their destination stop.

Dwell time functions

The passenger module updates the departure time of trains according to the calculated dwell time. The factors that affect the dwell time of vehicles have been discussed in 2.3. From these factors, the number of passengers boarding and alighting, the load in the train and the level of crowding in the platform are known each time a train arrives at a station. Given a dwell time function and its parameters, the dwell time of a vehicle is calculated based on these variables. The dwell time functions and its parameters are case specific and need to be calibrated before feeding them as an input to the passenger module.

The passenger module has been designed with a default function with parameters from technical specifications and parameters to be derived via regression using historical data. If technical specification data is lacking, or the model fit is insufficient, an alternative dwell time function and its parameters can be provided as an input. For an explanation of the default dwell time function used and the derivation of an alternative one, the reader is referred to section 3.4.

The parameters required as input for the use of the default dwell time function can be found in Table 3.1.

Table 3.1: Parameters of the default dwell time function

Parameter	Explanation	Derivation
e^f	Constant time needed to open and close the doors	Technical specifications
τ^b	Minimum time needed for a passenger to board	Technical specifications
τ^a	Minimum time needed for a passenger to alight	Technical specifications
α^b	Coefficients of extra boarding time per passenger according to the degree of vehicle congestion	Regression
α^a	Coefficients of extra alighting time per passenger according to the degree of vehicle congestion	Regression
v	Number of vehicles per transit unit	Technical specifications
d	Number of doors per vehicles	Technical specifications
p	Space capacity of a vehicle	Technical specifications

3.3.2. Input for the train module

The train module simulates train movements using OpenTrack. As shown in Figure 3.1, this simulation tool uses three types of input data: rolling stock, network infrastructure and timetable. Figure 3.3 represents the simulation process when using OpenTrack. Although the developed module includes interaction with the simulation through the API, the input requirements for OpenTrack do not change. The user must define the input data prior to the simulation run. In this way, predefined trains move on a provided track layout on the conditions of the timetable data. This section describes the three types of data required for the train module as described by Huerlimann and Nash (2010).

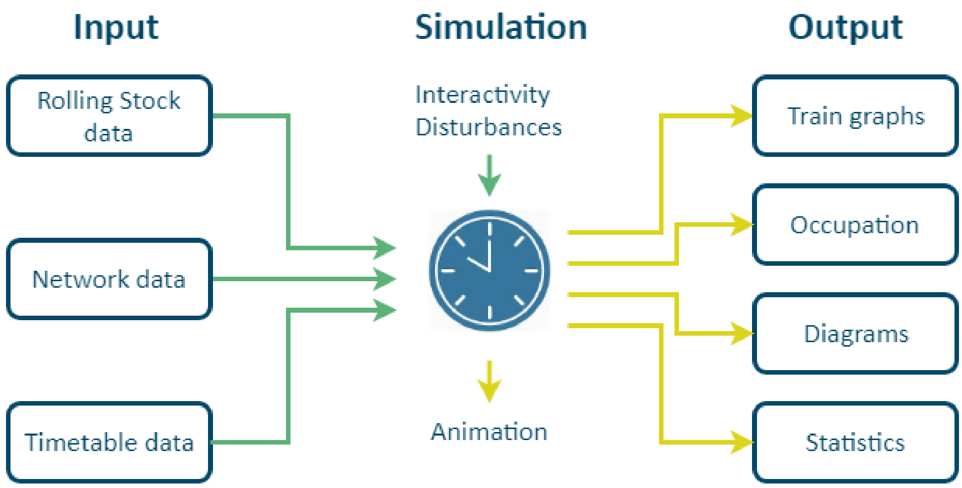


Figure 3.3: OpenTrack Process: Input-Simulation-Output (adapted from Huerlimann and Nash (2010))

Rolling stock data

The rolling stock consists of locomotive and wagons that are combined to form trains. The technical specifications of different types of locomotives are stored in a database called Depot. The user can select one of these predefined locomotives or define a particular locomotive by adding new data. Wagons do not need to be defined, because the simulation only requires the length and load of a complete train. This is obtained by combining the corresponding locomotive/s of a train with length and weight data. These defined trains are then stored in a train database.

Network data
The network layout data enables OpenTrack to describe the physical infrastructure that is being simulated using double vertex graphs. This representation includes actual infrastructure (track segments, signals, stations), and virtual elements (points and routes). Each edge of the graph represents a track segment, whereas vertices mark places where at least one route attribute changes or a signal is located. Every element of the graph holds various representative attributes. The user can modified and manage these attributes or create and delete new elements to accurately represent the topology of the study case. Figure 3.4 presents an example of the track topology in a station area as represented in OpenTrack.

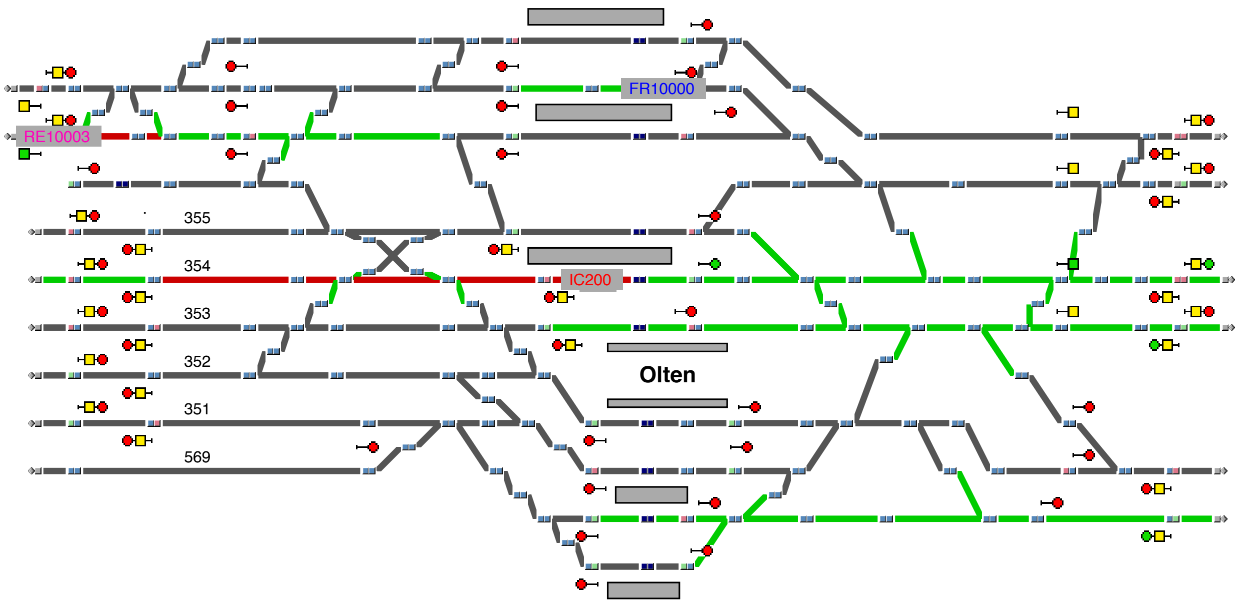


Figure 3.4: Example of a station layout in OpenTrack (Huerlimann & Nash, 2010)

Timetable data
The timetable data provides information on the movement of trains. This information includes the desired arrival and departure times of each train at every station, the required connections between trains, the minimum dwell times at a station and other stop information that might be relevant for the simulation.

3.3.3. Input for the TRM
Although the objective of the optimization and the decision variables may be general, the parameters and constraints of the LP utilized can be case-specific. This means that the user needs to calibrate the parameters to accurately represent the relevance of each variable and the limitations imposed by the system and the stakeholders. This section describes what the user needs to provide as an input for the TRM.

Parameters and constraints
A constraint is an inequality or equality that defines a limitation in the model. These limitations can arise from the layout of the network, conditions imposed by operator or authorities, or restrictions required by passengers. As such, these constraints may vary for a particular study case. To represent the new conditions, the user may have to adjust the parameters of the constraints or even add or remove a constraint. These constraints include limitations such as maximum dwell time, maximum and minimum speed allowed for trains, minimum headways or turn around times. Determining the value of the parameters is a crucial and challenging part of the optimization modelling (Hillier & Lieberman, 2015). These parameters are the coefficients that can be found in the objective function and the constraints. In the constraints, parameters located in the right-hand side indicate the limiting factor. For instance, they indicate the required minimum dwell or running time. In the objective function, the parameters indicate the relative weight of each term in the objective value. In this particular case, this indicates the relative relevance of waiting time, in-vehicle time, or schedule adherence in the objective.

3.4. SBTM-MN: Transport Simulation Model

The objective of the simulation is to represent the metro system including dynamic train and passenger interactions, in an attempt to answer the first research sub-question. The passenger module is used to calculate the dwell time of a train once it arrives at a station, as a function of the passenger demand and the train headway, and retrieve the corresponding departure time to the train module. The latter consists of a simulation carried out in OpenTrack.The software uses a mixed discrete-continuous simulation process that calculates both the continuous numerical solution of the differential motion equations for the vehicles (trains) and the discrete processes of signal box states. This is considered to be a suitable approach for the modelling given the accuracy required by the problem at hand. The OpenTrack simulation is coupled to the passenger module to overcome the fact that OpenTrack is unable to deal with passenger flows on its own. The information flow between the two modules that constitute the simulation module can be seen in Figure 3.1.

In the iterative exchange of information between modules, the train module sends events data to the passenger module, whereas the latter retrieves commands to the train module. The types of events that OpenTrack can report through the API include: starting of the simulation, status messages, departure of a train from a station and arrival of a train to a station. The most important command that the passenger module sends to the train module is the departure command, which represents the actual update of the dwell time of a train. In brief, the passenger module calculates the actual dwell time of a train based on passenger data and the train arrival data provided by the train module. Since the dwell time directly conditions the departure time of a train, the updated departure time is returned to the train module. This leads to an iterative flow of information between the two modules that influence each other in a loop through the API of OpenTrack. During these iterations, data is dynamically stored in two matrices:

- Station matrix, denominated Π. Each station has a matrix that indicates the passengers remaining at the platform and their destination after a train stops. The matrix is updated by adding a row with the corresponding timestamp, each time a train arrives at the station.
- Train matrix, denominated Υ. Each train has a matrix that indicates the passenger load and their corresponding destination. This matrix is updated by adding a row each time a train departs from a station.

Before starting the simulation in the SBTM-MN, this needs to be initialized using the current data obtained from the simulated real world to improve the representativity. Figure 3.5 shows a flowchart of the processes that the passenger module carries out after the initialization, starting with the interpretation of the message from OpenTrack, to the derivation of messages that are retrieved to it. The departure of a train from a station and the arrival of a train to a station are the relevant messages that can be sent online from the train module to the passenger module. These messages trigger processes in which passenger allocation data is stored and dwell times are adjusted. In the remaining of this section, the initialization of the TSMis described. Then, each of the main processes in Figure 3.5 and their components are explained. For the sake of clarity, the notation that is used in those sections is summarized in table 3.2. After this, an example of the procedure with a short trip is explained. Finally, the calculations behind the dwell time estimation are further elaborated. For the interested reader, a pseudocode of the passenger module is included in Appendix A.

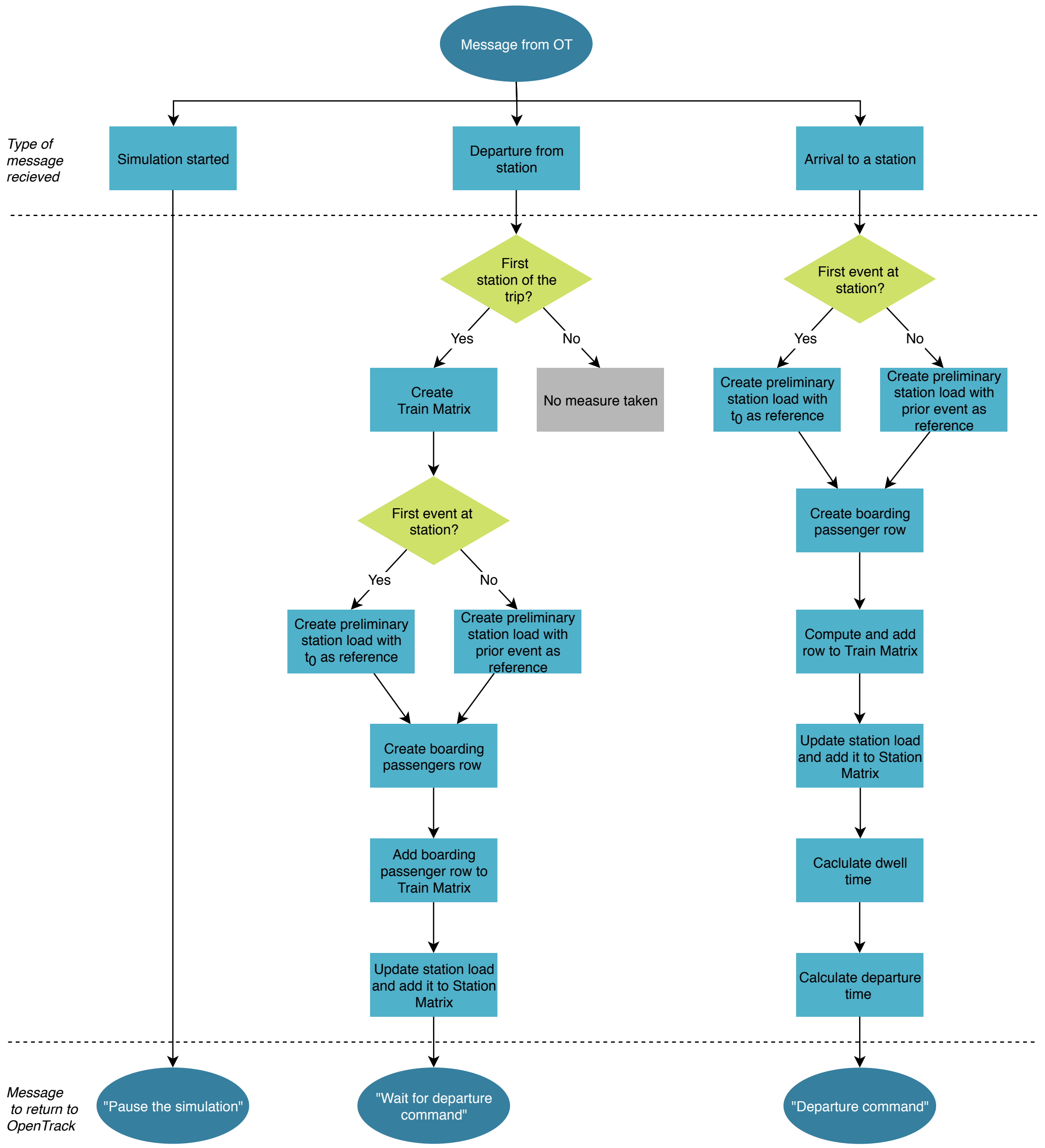


Figure 3.5: Process of dwell time update

3.4.1. Initialization

When the SBTM-MN is started, three main data is provided by the simulated real world: the station occupation, the train occupation and the realised last departures of all trains in the network. The underlying assumption is that it is possible to obtain or infer this real-time data from a system in the real world. This information allows improving the estimation of demand and passenger movements for the desired horizon. In the initialization of the SBTM-MN, all trains are set to start in the last known time-position point, i.e. the last detected departure in the TSM-RW. In this way, the starting point of the TSM and the TSM-RW is the same.

Furthermore, the Π and the Υ are updated with the actual passenger load obtained from the simulated real world. Although it is assumed that the loads are available data, it is not reasonable to assume that the SBTM-MN can know the destination of passengers in the station or on board of the train. In most metro systems, the destination of passengers is not known until they tap out at their exit station. The passenger split is calculated using the estimated demand parameters previously fed as input to the SBTM-MN for the corresponding timeframe.

The Υ of all trains that are already in the network when the simulation is started are updated as:

$$\Upsilon m(\dot{s}, d) = \hat{l}_{m,\dot{s}} * \chi^{y}_{r,\dot{s},d} \tag{3.1}$$

Where $\Upsilon_{m(\dot{s},d)}$ is the passengers in train m with destination d after train m has departed from the last registered station $\dot{s}$. $\hat{l}_{\dot{s},m}$ is the known passenger load in train m after the last registered departure at station $\dot{s}$. $\chi^{y}_{r,\dot{s},d}$ is the estimated fraction of passengers with destination d on a train in route r after it has departed from station s for the timeframe y.

The Π of all stations is updated by:

$$\Pi s,(0,d) = \hat{w}_s * \delta^{y}_{s,d} \tag{3.2}$$

Where $\Pi_{s,(0,d)}$ is the number of passengers waiting at station s with destination d at the start of the simulation. $\hat{w}_s$ is the known number of passengers in station s at the start of the simulation, and $\delta^{y}_{s,d}$ is the estimated fraction of passengers in station s going to d in the timeframe under study y.

Table 3.2: Notation for the Υ and Π derivation

Parameter	**Explanation**
$event$	A departure of a train from the first station of a trip, or an arrival to any station
S	Set of stations in the network
s	Current station station $s \in S$
d	Destination station $d \in S$
M	set of vehicles
λ^{y}_{s}	The arrival rate of passengers to station s per second for timeframe y
$\delta^{y}_{s,d}$	The fraction of passengers in station s that have station d as destination in timeframe y
$\chi^{y}_{r,s,d}$	The fraction of passengers with destination d on a train in route r after departing from station s for timeframe y
$w_{s,d,m}$	Passengers waiting at station s with destination d right before an event of vehicle m takes place
$r_{s,d,m}$	Remaining passengers at station s with destination d after vehicle m departs
$b_{s,d,m}$	Passengers boarding vehicle m at station s with destination d
$t_{s,m}$	Timestamp at which the event of vehicle m at station s takes place
$b_{s,m}$	Total passengers at station s boarding vehicle m
$a_{s,m}$	Total passengers alighting from vehicle m at station s
$l_{s,m}$	Total passenger load in vehicle m after departing from station s
$\hat{l}_{\dot{s},m}$	Real time passenger load in vehicle m after departing from station $\dot{s}$ when the SBTM-MN is triggered
$\hat{w}_s$	Real-time number of passengers waiting at station s when the SBTM-MN is triggered

3.4.2. Departure of a train from a station

As a standard practice, trains do not wait for a departure command in OpenTrack. They must, however, fulfil preset restrictions such as connections with other trains and minimum dwell time at a station before departing. This is why, when a train departs from its first station, the algorithm sends a message to OpenTrack indicating that every time said train arrives at a station, it has to wait for a command to depart.

The algorithm only acts if the departure station corresponds to the start of a trip. In this case, besides sending instructions to wait for a departure command at future stations, the algorithm creates a Υ for the train and updates the status of both aforementioned data matrices. The Υ created by the algorithm is an empty matrix with the names of the stations to be served as columns. After building this matrix, the number of passengers waiting at the platform at the time of the event is computed and a 'preliminary station load row' is created.

- If this is the first event in the simulation for station s, the number of passengers at the platform is the passengers at the station at the beginning of the simulation t_0 plus the estimated number of passengers that arrived at the station station from t_0 to the time in which the event takes place. For a station s, this is computed as:

$$w_{s,d,m} = \Pi_{s,(0,d)} + \lambda_s^y * \delta_{s,m}^y * (t_{s,m} - t_0) \tag{3.3}$$

  Where $w_{s,d,m}$ is the number of passengers waiting at station s with destination d right before the event (in this case a departure) of vehicle m takes place. $\lambda_s^y * \delta_{s,m}^y$ gives the arrival rate of passengers to station s with destination d for the timeframe y. Multiplying this term by the time elapsed from the start of the simulation to the current event provides the number of passengers that arrived at station s from he start of the simulation.

- If this is not the first event in the simulation at the station, the number of passengers is those remaining at the platform after the preceding train departed $r_{s,d,m-1}$, plus all the passengers that arrived between both trains. For station s this is calculated as:

$$w_{s,d,m} = r_{s,d,m-1} + +\lambda_s^y * \delta_{s,m}^y * (t_{s,m} - t_{s,m-1}) \tag{3.4}$$

The following step is to compute a 'boarding passengers row'. This consists of all the passengers in the last row of the Π whose destination is a station yet to be served by the train. Since this event is the start of a trip, the train is empty when it arrives at the station. Therefore, the 'boarding passengers row' equals the train load after departure. The first row in the Υ is then the 'boarding passengers row' computed at the first departure of a train's journey.

Finally the preliminary station load row is updated by subtracting the passengers that boarded the train m. For a station s this is represented by Equation 3.5. The resulting row is appended to the Π, and it represents the passengers that remained at the station after the event occurred.

$$r_{s,d,m} = w_{s,d,m} - b_{s,d,m} \tag{3.5}$$

Where $b_{s,d,m}$ are the passengers boarding train m a station s with destination d. In the case of a train departure, no dwell time is computed or updated. At the first station, there is no dwell time but the departure of the train is assumed to be depending on other factors that are not passenger related (such as signalling and timetable). At other stations, dwell time is determined at the arrival of a train.

3.4.3. Arrival of a train

When a train arrives at a station, the algorithm updates the load at the station and in the train by adding a row to the Π and Υ respectively. Furthermore, the dwell time is calculated and the departure command indicating the calculated departure time of the train is sent to the train module.

The process starts by checking whether this is the first event at the station in the simulation. Exactly as explained in the previous section, the preliminary station load is computed by either taking t_0 or the previous event as a reference point. After this, the "boarding passenger row" is created by selecting, from the preliminary station load, all those passengers waiting at the station with a destination to be served by the train.

In this case, the event is not the start of a trip, and therefore, the train may have a previous load when arriving at the station. Therefore, the new row of the Υ is a result of adding the boarding passengers to the previous row of the Υ. Subsequently, a row calculated by subtracting the boarding passengers from the preliminary station load is appended to the Π. Hereafter, the variables necessary for deriving the dwell time are extracted from the ϒ and the Π.

- The total number of passengers b boarding train m at station s is computed by adding all the passengers in the 'boarding passengers row', as in:

$$b_{s,m} = \sum_{d} b_{s,d,m} \tag{3.6}$$

- The number of passengers alighting a from vehicle m at station s equals to the value in the cell of ϒ of train m corresponding to the last row and the current station column. This means, where the index and the column equal the current station. For station s, this is indicated in:

$$a_{s,m} = \Pi_{m,(s,s)} \tag{3.7}$$

- The total load $l_{s,m}$ in the train m after departing from station s can be found by adding all of the passengers in the last row of the ϒ that do not correspond to the current station:

$$l_{s,m} = \sum_{d \neq s \in S} \Pi_{m,(s,d)} \tag{3.8}$$

- The level of crowding in the platform can be determined by adding all passengers waiting at the platform when a train arrives:

$$w_{s,m} = \sum_{d \in S} w_{s,d,m} \tag{3.9}$$

The dwell time of the train at the station can be calculated based on the number of boarding passengers, the number of alighting passengers, the load in the train and the crowding in the platform. The equations used for this process are detailed further on in the dwell time function section. The departure time is calculated by adding the dwell time to the time in which the train arrived at the station. Finally, a departure command is sent to the train module, indicating that the train should leave the station at the calculated departure time, provided that all of the pre-set requirements are also fulfilled.

3.4.4. Dwell time calculations

For the calculation of dwell times, two approaches are taken. Firstly, a default function, adapted from literature, is proposed and introduced in the module. The parameters of this function can be obtained from regression using realised data, technical measurements, or literature. A second approach is to perform statistical analysis on realised data to evaluate the impact of different dwell time predictors and either choose a suitable function from literature or derive an ad-hoc function. It is advised that the user selects the most suitable approach for the case study at hand, according to the data availability and model fit.

Section 2.3 outlines the factors that influence the dwell time of vehicles in passenger railways. In this case, the timetable and signalling restrictions are taken into account by the simulation tool, whereas the driver behaviour is out of scope. The dwell time function only accounts for the required dwell time to open the doors, exchange passengers, and close the doors, as shown in Figure 3.6. It is assumed that the level of crowding in the train and platform may influence the duration of the passenger exchange component. To use these predictors, the passenger module computes the number of boarding and alighting passengers, as well as the passenger load at the train and platform every time a train arrives at a station.

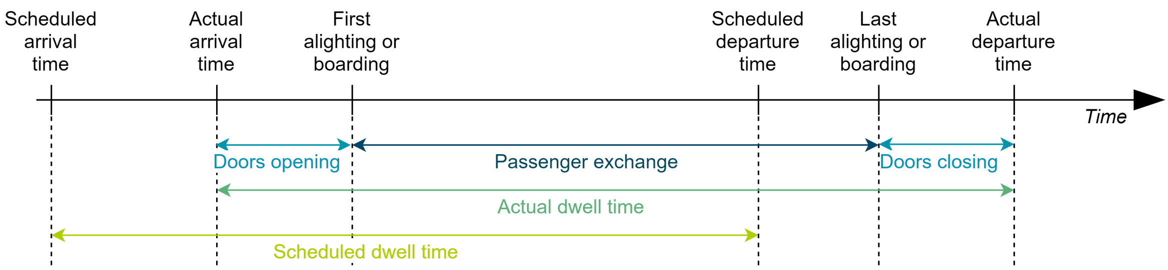


Figure 3.6: Dwell time components (Adapted from Cornet et al. (2019))

The chosen default dwell time function of the passenger module is adapted from Jiang, Xie, Ji, and Zou (2015), one of the most complete studies on dwell time modelling in crowded rail transit. The development of the default dwell time function arises from the assumption that the dwell time is the sum of the time it takes to open and close the doors, and the duration of the passenger exchange. In this case, the extra time caused by doors being unable to close due to an intentional or unintentional incident such as a passenger holding a door or malfunctioning of any kind is not considered.

$$e^{AD} = e^{f} + e^{p} \tag{3.10}$$

Where, e^{AD} is the actual dwell time, e^{f} is the fixed operational time that takes to close and open the doors of the train. This constant can be known in advance or be obtained through the regression. e^{p} is the duration of the passenger alighting and boarding process. It is assumed that alighting and boarding are sequential processes. Furthermore, the duration of each of the processes is affected by the crowding in the vehicles. To represent this, the minimum time needed by a person to board or alight is increased by a coefficient for extra boarding or alighting passenger due to congestion times the level of congestion. It is assumed that, although congestion increases boarding time and discomfort on passengers, capacity does not limit the boarding of passengers. This means that denied boarding is not considered. Under these assumptions, e^{p} can be calculated as:

$$e^{p} = e^{b} + e^{a} \tag{3.11}$$

$$e^{b} = (\tau^{b} + \alpha^{b} * \beta^{b}) * b^{n} \tag{3.12}$$

$$e^{a} = (\tau^{a} + \alpha^{a} * \beta^{a}) * a^{n} \tag{3.13}$$

Where e^{b} and e^{a} are the time necessary for passengers to board and alight the vehicle. τ^{b} and τ^{a} are the minimum boarding and alighting time per passenger, respectively. α^{b} and α^{a} are the coefficients of extra boarding and alighting time per passenger according to the degree of vehicle congestion, respectively. β^{b} and β^{a} are the average degree of congestion during alighting and boarding, calculated through equations 3.14 and 3.15 $b^{n}_{s,m}$ and $a^{n}_{s,m}$ are the number of passengers boarding and alighting at each door for a train m arriving at a station s.

$$\beta^{b} = \frac{\frac{n^{OBT}_{s,m} - a_{s,m}}{v*d} + \frac{b^{n}_{s,m}}{2}}{p} \tag{3.14}$$

$$\beta^{a} = \frac{\frac{n^{OBT}_{s,m}}{v*d} - \frac{a^{n}_{s,m}}{2}}{p} \tag{3.15}$$

Where m is a train in the collection of all trains M, and s is a station in the collection of all stations S. $n^{OBT}_{s,m}$ is the number of on-board passengers for arriving train m at station s. $a_{s,m}$ is the total number of alighting passengers for train m at station s. v is the number of vehicles per transit unit, d is the number of doors of each vehicle and p is the space capacity of a vehicle. Considering that $n^{OBT}_{s,m}$ is the passenger load at train m after departing from the previous station $l_{s-1,m}$, and as a result of replacing terms, equation 3.16 is obtained.

$$e^{AD} = e_{f} + (\tau^{b} + \alpha^{b} * \frac{\frac{l_{s-1,m} - a_{s,m}}{v*d} + \frac{b^{n}_{s,m}}{2}}{p}) * b^{n}_{s,m} + (\tau^{a} + \alpha^{a} * \frac{\frac{l_{s-1,m}}{v*d} - \frac{a^{n}_{s,m}}{2}}{p}) * a^{n}_{s,m} \tag{3.16}$$

To use equation 3.16, it is necessary to obtain several parameters before the initialization of the SBTM-MN. In some cases, these parameters are not available in the technical specifications and have to be derived by regression on historical data. In this case, the fit of the model can vary widely depending on the study case and the data characteristics. The second approach provides an alternative to improve the model fit, based on statistical analysis on the realised data. Studying how the different predictors affected the dwell time provides an idea of how the dwell time function should look. Based on this, an ad-hoc function can be developed and tested, or an existing function from literature can be selected and provided as input.

3.5. SBTM-MN: Train Rescheduling Model

The TRM interacts with the TSM in an attempt to reschedule the timetable for the benefit of passengers and operator. The TRM is explained in this section, addressing sub-questions 2 and 3. This model considers the infrastructure and operations at a macroscopic level. The feasibility of the derived timetable at a microscopic level is guaranteed by running the derived timetable in the TSM. A two-way line with a track for each direction is considered. The directions are referred to as *"inbound"* and *"outbound"*. Furthermore, it is assumed that overtaking is not allowed and that there are not alternative tracks, even at stations. This implies that each train must stop at the predefined platform at each station. Moreover, the capacity of terminal stations is not considered as a constraint. The TRM considers the following strategies:

- Increasing the dwell time of a train at a station
- Increasing the speed of a train in a segment between two stations
- Decreasing the speed of a train in a segment between two stations.

In essence, this means that the arrival and departure events can be retimed as long as the chronological order in each station per direction is preserved. A core assumption is that passenger allocation is static within the TRM, and does not change when arrival and departure times of trains are modified. This implies that passenger movements are not modelled in the TRM, but they are provided as an input from the TSM. Other rescheduling strategies such as stop skipping or short-turning are excluded.Furthermore, the assumptions mentioned in 3.2 remain in use. In this context, the TRM can be described as a linear programming problem.

3.5.1. Mathematical formulation, sets and parameters

This section describes the mathematical formulation of the optimization problem. Firstly, the mathematical formulation is presented. After that, its components, parameters and constraints are explained. Finally, table 3.1 presents a summary of the variables, sets and parameters used in the optimization.

Consider a line with a set of stations S, where each station is denoted as $s \in S$. A set of trains M serves the network (M^+ is the subset of inbound trains and M^- is the subset of outbound trains), and a single train in this set is called $m \in M$. Each train m has a subset of stations to be served, denoted as S^m, whereas each station s has a subset of trains that will serve it, M^s. This formulation allows considering trains serving different stations according to the schedule and the line to which they belong. The decision variables considered are the arrival and departure time of a train m at a station s ($t^{arr}_{s,m}$ and $t^{dep}_{s,m}$ respectively). The objective and constraints of the TRM can be formulated as:

$$\min \quad \beta_w * Wt + \beta_i * Ivt + \beta_a * \sum_{m \in M} \sum_{s \in S^m} Y_{s,m} + \beta_t * \sum_{m \in M} X_m \tag{3.17}$$

$Subject\ to:$

$$t^{dep}_{s,m} - t^{arr}_{s,m} \geq e^{min}_s \qquad \forall s \in S^m, m \in M \tag{3.18}$$

$$t^{arr}_{s+1,m} - t^{dep}_{s,m} \geq q^{min}_{s,s+1} \qquad \forall s \in S^m, m \in M \tag{3.19}$$

$$t^{dep}_{s,m+1} - t^{arr}_{s,m} \geq h^{out}_s \qquad \forall m \in M^{-,s}, s \in S \tag{3.20}$$

$$t^{dep}_{s,m+1} - t^{dep}_{s,m} \geq h^{in}_s \qquad \forall m \in M^{+,s}, s \in S \tag{3.21}$$

$$t^{dep}_{s,n} - t^{arr}_{s,m} \geq c^{min}_{m,n,s} \qquad \forall (m,n,s) \in V \tag{3.22}$$

$$t^{arr}_{l,m} - t^{arrs}_{m} \leq x_m \qquad \forall m \in M \tag{3.23}$$

$$t^{arrs}_{m} - t^{arr}_{l,m} \leq x_m \qquad \forall m \in M \tag{3.24}$$

$$t^{deps}_{s,m} - t^{dep}_{s,m} \leq Y_{s,m} \qquad \forall m \in M, s \in S^m \tag{3.25}$$

$$t^{dep}_{s,m} - t^{deps}_{s,m} \leq Y_{s,m} \qquad \forall m \in M, s \in S^m \tag{3.26}$$

$$t^{dep}_{s,m} - t^{depo}_{s,m} \leq u \qquad \forall S \in S, m \in M \tag{3.27}$$

$$t^{depo}_{s,m} - t^{dep}_{s,m} \leq u \qquad \forall S \in S, m \in M \tag{3.28}$$

This optimization has more than one term in the objective function. Primarily, it seeks to minimize waiting time and perceived in-vehicle time for passengers, weighted by their corresponding factors. Furthermore, it aims at minimizing the deviation from train departures at all stations, and the deviations from the scheduled arrival time of a train to its terminal. The first two terms of the objective function refer to the perceived waiting and in-vehicle time respectively, whereas the third term indicates the deviation from the departures at all stations, and the third term presents the deviation from arrival to a terminal, to reduce the impact on the rolling stock and crew scheduling of the operator. The relative weight of each term is given by the values of the β parameters in the function.

The waiting and in-vehicle time is calculated using the passenger allocation data provided by the TSM. The latter provides the number of passengers waiting at each station when the optimization is triggered ($\hat{w}_s$), the number of passengers left behind each time a train departs from a station ($r_{s,m}$), and the passengers waiting at the station when a train arrives ($w_{s,m}$). Moreover, the passenger load at the time a train departs from a station, $l_{s,m}$ is provided. Knowing the train seating capacity, k_m, this allows to compute the number of passengers sitting $l^{sit}_{s,m}$ and standing $l^{stand}_{s,m}$ after a train m departs from station s.

The evolution of passengers waiting at a station s can be visualized in Figure 3.7. The green shade represents the number of passengers that are left behind by a train that does not serve their destination, and have to wait for a train that does. Blue represents the passengers that enter the platform between two consecutive arrivals of trains. Note that this formulation accounts for all passengers waiting at station s with any final destination.

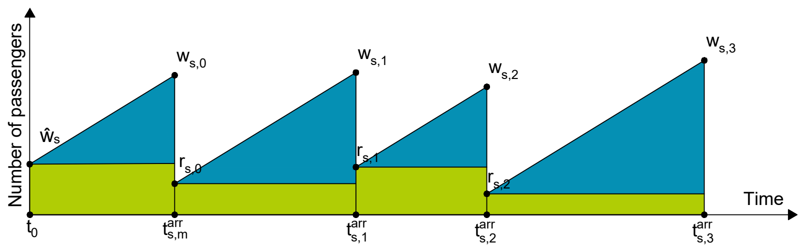


Figure 3.7: Evolution of passengers waiting at a station

It is assumed that the number of passengers waiting at a station remains the same regardless of changing $t^{arr}_{s,m}$, because $w_{s,m}$ and $r_{s,m}$ are fixed within the TRM. Changing $t^{arr}_{s,m}$ only affects the duration of the waiting time. In this way, the total waiting time between two consecutive train arrivals at a station can be calculated as the average number of passengers over time waiting at a station (average between $w_{s,m}$ and $r_{s,m-1}$), multiplied by the time elapsed between arrivals. This is calculated for the set of trains serving each station and then added up across stations to calculate the total waiting time. Assuming static passenger allocation in the TRM avoids quadratic terms in the calculation of total waiting times. However, in reality, once $t^{arr}_{s,m}$ is modified, the allocation of passengers changes. This is modified by the TSM in each iteration. Under these assumptions, the waiting time for all passengers at stations can be defined as:

$$Wt = \sum_{s \in S}((t^{arr}_{s,0} - t_0) * \frac{(w_{s,0} + \hat{w}_s)}{2}) + \sum_{s \in S}\sum_{m \in M^s}((t^{arr}_{s,m} - t^{arr}_{s,m-1}) * \frac{(w_{s,m} + r_{s,m-1})}{2}) \tag{3.29}$$

Figure 3.8 presents the development of in-vehicle time based on the number of passengers on board of a train in each segment between two stations, and the running time of the train for that segment. The blue shade represents the passengers that have to travel standing due to the occupation of a train exceeding the seating capacity.

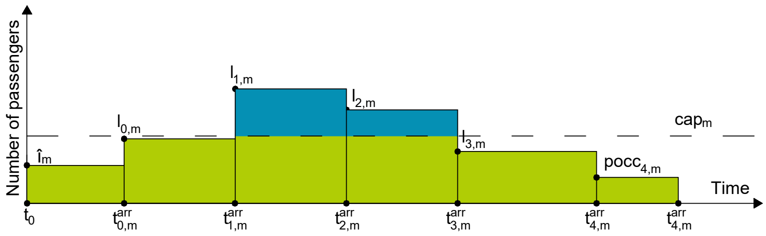


Figure 3.8: Evolution of passengers in a train

Similarly to the case of the waiting time calculation, the fact that the occupation depends on the headways between trains and therefore on their arrival and departure, is accounted for by the TSM in each iteration. Assuming that passengers standing have a more negative perception of the in vehicle time, the total perceived in vehicle time can be calculated as:

$$Ivt = \sum_{m \in M}\sum_{s \in S^m}(l^{sit}_{s,m} * \gamma_{Sit} + l^{stand}_{s,m} * \gamma_{Stand}) * (t^{arr}_{s+1,m} - t^{arr}_{s,m}) \tag{3.30}$$

The in-vehicle time is, then, the weighted load of passengers in train multiplied by the runtime in each segment served by a train. Then this value is summed across all trains.

The train departure delays are calculated by summing the difference between the realized and scheduled departures through all stations and trains. The deviation from scheduled arrival of a train to its terminal is calculated as the difference between the rescheduled and originally scheduled arrival of a train to the last station of the trip, summed across all trains. Since these are absolute values, it is necessary to linearize them before including them in the formulation. This is done by adding a variable denoted as $S_{s,m}$ and constraints 3.25 and 3.26 for the deviations at all stations. For the deviations at the terminal station, variable X_m and constraints 3.24 and 3.24 are added.

Constraint 3.18 indicates that the time spent by the train at a station has to be at least the required minimum dwell time at that station. This minimum is the maximum between the originally scheduled dwell time and the time required for passenger exchange in the last iteration. This is done to avoid systematically underestimating the dwell time by using the scheduled dwell time, which tends to be too short during peak hours.

Constraints 3.19, 3.20 and 3.21 are the train traffic constraints. Constrain 3.19 states that the time a train takes to traverse a segment between stations cannot be smaller than the minimum running time for that segment. Constraint 3.20 ensures the minimum safety headway that two outbound trains must have at a station. It states that all outbound trains serving a station s must arrive at least h^{out}_s later than the departure time of its predecessor. Constraint 3.21 is the corresponding of 3.20 for inbound trains.

Constraint 3.22 is the rolling stock circulation constraint, and it ensures the minimum connection time between two trains. This is needed for instance in terminal stations when two trains use the same rolling stock unit. In this constraint, train n can only depart from station s tc_s^{min} after train n has arrived to the same station.

Constraints 3.23, 3.24, 3.25 and 3.26 are necessary for the linearization of the schedule adherence terms in the objective function.

Constraints 3.27 and 3.28 indicate boundaries for the difference between variables and their realised value in the last iteration to avoid extreme fluctuations between consecutive iterations. It states that departure events cannot differ more than a value of u from the realised departure event of the last simulation. In this way, the step size is limited from one iteration to the other.

Table 3.3: Variables, sets and parameters of the TRM

Indices and sets	
s	Index for stations $s \in S$
m	Index for vehicle $m \in M$
S	Set of all stations in the network
M	Set of trains that run in the network in the considered horizon
S^m	Subset of stations to be served by vehicle m [0...l]
M^s	Subset of vehicles that will serve station s
M^+	Subset of inbound vehicles
M^-	Subset of outbound vehicles
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 vehicle m 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 maximum between the originally scheduled dwell time and the time needed for passenger exchange in the last iteration.
$t_{s,m}^{depo}$	Realised departure time of train m from station s in the last simulation
t_m^{arrs}	Originally scheduled time of arrival of train m at its destination station
$t_{s,m}^{deps}$	Originally scheduled time of departure of train m from station s
General parameters	
γ_{Sit}	Crowding multiplier for sitting passengers
γ_{Stand}	Crowding multiplier for standing passengers
β_w	Cost coefficient multiplier for waiting time
β_I	Cost coefficient multiplier for in vehicle time
β_O	Cost coefficient multiplier 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 trains m and n at station s

3.6. SBTM-MN: Coupling TSM and TRM

This section explains the information exchange between the TSM and the TRM. In the first iteration, the simulation runs with the original schedule as an input. This run serves as a benchmark for the performance of the optimization. In subsequent iterations, the timetable provided by the TRM is run. However, the realised timetable may differ from the scheduled one due to passenger-train interactions. This means that, although a timetable is given as an input to the simulation in each iteration, dwell times may be longer than expected due to the number of passengers boarding and alighting. This leads to variations in arrival and departure times.

The result from the TRM is a timetable that indicates the planned departure and arrival times of trains. These events define the running time of trains between stations. However, in OpenTrack, the software used for the train module, the opposite occurs. Here, arrival events are subject to the running time and the departure from the previous station. Furthermore, departure events are constrained by the arrival time and dwell time. The latter, as explained before, cannot be predicted, as it is affected by the number of passengers at the station. In other words, the simulation can only attempt to implement the provided timetable, but it is constrained by the external process of passenger exchange. To increase the accuracy in the implementation of the timetable, the running time of each train at a segment is adjusted to achieve the scheduled arrival times. This is done by tuning the performance parameter of a train for the next segment every time it departs from a station. This performance parameter modifies the speed profile of a train, having a direct effect on the runtime. The process is done as follows: the optimization sends a table with the arrival and departure times for each train stopping at a station. When executing the timetable, each time a train arrives at a station, the departure time is calculated as a result of passenger exchange. This implies that the departure time might not be the scheduled one. This has a direct impact in the next arrival unless the runtime of the train in the following stretch is modified. For instance, if a train departs later than scheduled, it should increase its speed (if possible), to avoid arriving late at the next station. This is done by calculating the required runtime to achieve the next arrival on time, and deriving the performance parameter that would lead to it. Note that the performance parameter has a limit (100%), in which the train goes at is fastest allowed speed with the best acceleration curve. If this value does not reduce the running time sufficiently, the train will arrive late to the next station.

Running the timetable in the TSM has two main objectives: to verify the feasibility of the timetable at a microscopic level under the influence of passenger movements, and to reallocate passengers according to this new timetable. Furthermore, it is only after having run it in the simulation that the actual cost of the new timetable can be known. This is because the timetable calculated in the TRM is optimal for a passenger allocation that is not its own.

3.7. Simulated real world

The architecture of the simulated real world is almost identical to that of the TSM. It is comprised of a train module and a simulation module that interact to represent passenger allocation and train movements in real operations, exactly like explained in section3.4. The key difference is that the simulated real-world has detailed input of the demand and train disturbances for a simulated scenario, whereas the TSM predicts the passenger demand for a horizon. Although it is assumed that some real-time data can be obtained from the simulated real world to improve the prediction in the TSM, the latter still uses a prediction and is thus unable to perfectly represent operations and passenger movements yet to take place at the time the SBTM-MN is triggered. The remainder of this section briefly describes the main differences between the TSM-RW and the TSM. Furthermore, the information exchange between the TSM-RW and the SBTM-MN is explained.

3.7.1. Passenger input

The simulated real-world utilizes a profile of passenger demand throughout a day as an input. This is provided as a matrix with passenger rides throughout the day. It is considered that a dynamic profile of demand is more representative of reality than the most commonly used arrival rate. If an arrival of passengers that is evenly spread in time, for instance, is assumed, the impact of a disturbance would be easier to predict and therefore, easier to deal with than what it is in real life. A variable arrival of passengers, on the other hand, has peaks of travellers arriving at the platform. This contributes to further destabilize the system, and it might worsen the bunching process (Fonzone et al., 2015). The flexibility of this data structure allows the user to include variations in the demand in both intensity and directionality.

The effect of this non-uniform passenger arrival has been commonly ignored in previous studies and public transport planning in general. It is commonly accepted that with headways shorter than 10 minutes, uniform passenger arrival patterns can be expected. However, Luethi (2006) found that passengers consult schedules even when the headway is as short as 5 minutes.An important remark is that the matrix should contain passenger rides and not trips since the simulation cannot account for transfers. A ride is the movement of a traveller in a single vehicle. This implies that there is no transfer involved. If a trip originally includes a transfer, it needs to be divided into legs, where each of them is a ride.

3.7.2. Train input

Besides the rolling stock data, the network data and the timetable data explained in section 3.3.2, the train simulation in the simulated real-world can include disturbances corresponding to a specific scenario. These disturbances can be operational failures or problems. Examples include signal failures, slow orders or unplanned delays. Disturbances have a starting and ending time and a given impact in operations. Logically, these disturbances cannot be an input to the SBTM-MN unless they are planned or expected. Otherwise, the SBTM-MN would be able to predict future unexpected disturbances.

3.7.3. Simulation

The simulated real-world starts from the beginning of daily operations, in order to keep track of passenger movements. Therefore, at the start of the simulation, there is no pre-load in trains or stations, but they are empty. The process of updating train dwell times is as depicted in figure 3.5. However, t_0 is now a predefined time before the start of the daily operations. Furthermore, the equations used to calculate preliminary station loads are slightly different, since the passenger input structure is not the same as in the SBTM-MN:

- If the Π is empty, this is the first event in the day at the station. The number of passengers at the platform is computed by adding every passenger that tapped in at the station from t_0 to the time in which the event takes place. For a station s, this is computed as:

$$w_{s,d,m} = \sum_{t=t_0}^{e_{s,m}} p_{s,d,t} \tag{3.31}$$

  Where $w_{s,d,i}$ is the number of passengers waiting at station s with destination d right before the event e (in this case a departure) of vehicle m takes place, and $p_{s,d,t}$ is a passenger at the platform of station s at time t and wanting to go to d.

- If the Π is not empty, this is not the first event in the day at the station. The number of passengers is those remaining at the platform after the preceding train departed $r_{s,d,m-1}$, plus all the passengers that arrived between both trains. For station s this is calculated as:

$$w_{s,d,m} = r_{s,d,m-1} + \sum_{t=e_{s,m-1}}^{t=e_{s,m}} p_{s,d,t} \tag{3.32}$$

Once the number of waiting passengers at a station is computed, the rest of the calculations and the derivation of the Π and Υ remain as described in 3.4.

3.8. Calibration process

Besides the calibration of the train model in the OpenTrack simulation, the parameters of the dwell time functions need to be adjusted for the case under study. If the default dwell time function is used, the parameters to be calibrated may include the technical time to open and close the vehicle doors (e^f), the minimum time needed for a passenger to board an alight(τ^b and τ^a), and the coefficients of extra boarding and alighting time per passenger according to the degree of congestion (a^b and a^a). A summary of all parameters in the default dwell time function can be found in table 3.1.

To perform a regression model and derive the value of these parameters, historical data on the number of passengers boarding and alighting, loads in trains and realised dwell times are needed. As can be seen in table 3.1, some of the parameters refer to vehicle characteristics, whereas the remaining are coefficients of the passenger exchange process. The latter could be defined as general variables or station-specific. In general, it is convenient to perform a regression analysis to find station-specific parameters (Martínez, Vitoriano, Fernández, & Cucala, 2007). The TSM-RW scenario is defined by its train and passenger input. Table 3.4 presents an example of the passenger input data structure. The first column of this matrix is the identification number of the passenger. The second column, *"In_time"* is the time in which the passenger is ready to board at the platform. This time value is provided in seconds, to be in line with the format in which OpenTrack receives and sends messages through the API. The third column, named *"In_station"* is the origin station for the passenger trip. The fourth column, *"Out_time"* is the time in seconds in which the passenger taps out at the end station. The fifth column, *"Out_station"*, is the destination station of the trip. In practice, the module only uses columns two, three and five of the matrix, since the trip is identified by the starting time and its OD pair. The *"ID"* and *"Out_time"* columns aid traceability of errors. As an example, the first row in Table 3.4 indicates that passenger 26 is waiting at the platform of station A at 7:30 in the morning (27000 seconds) and taps out at station B half an hour later.

Table 3.4: Example of the passenger input format

ID	In_time	In_station	Out_time	Out_station
25	27000	A	28800	B
26	30000	C	31440	A

The way in which the input data is derived varies according to the case under study and the analysis to be performed. If available, empirical tap in and out data of a particular day could be used. For instance, a representative weekday could be used as an input to evaluate which rescheduling measures would be helpful in regular situations if a disturbance occurs. Historical tap in data of a specific day could be used to find optimal strategies in, for instance, an event day. Furthermore, this data could be simulated based on historical data to assess the effect of demand in several scenarios, including an increase in demand or a change in mobility patterns.

3.9. Simple example of the algorithm in the TSM-RW and the data exchange in SBTM-MN

The functioning of the algorithm in the TSM-RW is exemplified by using a line with four stations and a train starting its journey at station B, illustrated by Figure 3.9. In this example, the train, depicted in green, started its journey at station A, arrived at B and will serve C and D. This is not the first event in station B.

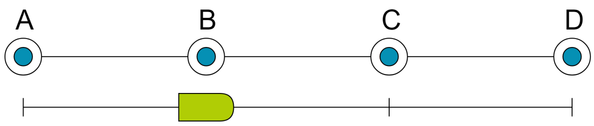


Figure 3.9: Illustration of a train service from stations A to D

The algorithm receives a message from OpenTrack with the ID of the train, the location of the departure, and the time of departure in seconds, in the following format:

<trainDeparture trainID="T-001" stationID="B" time="36000" />

The existing Π can be seen in table 3.5. This indicates that after the previous train left, a total of 15 passengers remained at the platform. 10 of them waiting for a train that would get them to station C, and 5 with destination D.

Table 3.5: Υ for station B right before event 1 occurs

R	Timestamp	A	C	D
0	35000	0	10	5

The number of passengers arriving at the platform of station B between 09:43:20 (35000 seconds) and 10:00:00 (36000 seconds) is taken from the passenger demand profile. If between the previous and the current event at station B, 5 passengers with destination A, 3 with destination C and 6 going to D arrived, the updated preliminary row at station B is as shown in table 3.6.

Table 3.6: Preliminary row at station B for event 1

W	A	C	D
1	5	13	11

The train picks up all of the passengers at station B with destination C and D. The second row of the Π is the number of boarding passengers row plus the previous row at the Π, as shown in Table 3.7.

Table 3.7: Train matrix at station B

Station	A	B	C	D
A	0	4	2	5
B	NAN	4	15	16

The preliminary load row for the station is updated by subtracting the boarding passengers, and this new row is added to the Π, as shown in Table 3.8.

Table 3.8: Station matrix for station B after event 1 took place

R	Timestamp	A	C	D
0	35000	0	10	5
1	36000	5	0	0

For this event, the values of the variables for function 3.16 are:
$b_{B,T-001} = 13 + 11 = 24$
$a_{B,T-001} = 4$
$l_{B,T-001} = 15 + 16 = 31$
$w_{B,T-001} = 5 + 13 + 11 = 29$

If equation 3.16 indicates that the dwell time is 22 seconds, the passenger module sends the following message to the train module:

<setDepartureTime trainID="T-001" stationID="B" time="36022" />

If the SBTM-MN is triggered, the occupation of trains and stations, as well as the realised train events, are provided by the TSM-RW, and the iteration process starts. The TSM estimates passenger's destination according predefined split parameters. Furthermore, it estimates passengers movements for a horizon, similarly as explained for the TSM-RW, but using arrival rates based on historical data instead of a rides database. In each iteration, the data exported from one module to another is structured in a single matrix, as represented in Figure 3.10.

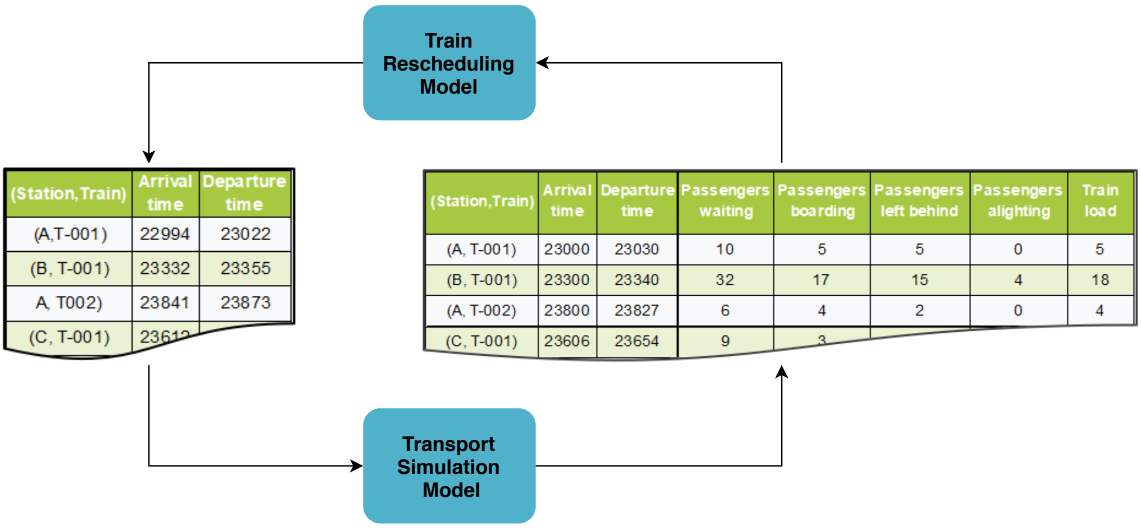


Figure 3.10: Example of the information exchange between simulation and optimization

4

Case study

In this chapter, the implementation of the developed model in a real-world case is explained. The lines E and D from the Metro of Rotterdam with direction north are chosen to evaluate the applicability of parts of the model. This case study is chosen because the segment in which both lines overlap is the busiest part of the Rotterdam metro network, and is thus prone to suffer from disturbances. The application of the TSM, the TRM and the SBTM-MN are evaluated in three different sets of experiments.

The remaining of the chapter is structured as follows: firstly, an overview of the Rotterdam metro network, along with an introduction to the case study, is presented in Section 4.1. This includes an analysis of the demand and supply of the network in Sections 4.1.1 and 4.1.2 respectively, which leads to the scoping of the case study. Secondly, the model specifications and assumptions of the case study are discussed in Section 4.2. This section contains the pre-processing of the input required in the passenger side, for both TSM and TSM-RW in Section 4.2.1. The pre-processing of the input required for the TRM discussed in Section 4.2.2. Finally, Section 4.3 describes the tests performed on the case study and presents the results obtained. Three types of experiments are performed. Firstly, the TSM is run for different delay scenarios. These delay scenarios are also run excluding passenger-train interactions, to observe the value of adding passengers in the microscopic modelling of trains and how this, in turn, affects passengers travel time. The experiment settings and the results are presented in Section 4.3.1. Secondly, the TRM is analysed for alternative objectives in the optimization in Section 4.3.2. The rescheduled timetables are compared in terms of waiting time, in-vehicle time and train delays to see how the rescheduling for one perspective affects others. This provides an overview of the trade-offs done in the multi-objective optimization. Finally, in Section 4.3.3, the SBTM-MN is tested for a small set of iterations on two disturbance scenarios, as a preliminary test on how the framework would perform.

4.1. Overview of the case study

The metro of Rotterdam was the first metro system to operate in the Netherlands. The line connecting Rotterdam Centraal with Zuidplein was the first one to open in 1968, and it is, to this day, the busiest segment of the network. Figure 4.1 presents a map of the metro network including the recent extension of line B to Hoek van Holland Strand.

The metro network currently consists of five lines labelled with the letters A to E, and 62 stations and it is the largest metro system in the Netherlands. The system is operated by Rotterdamse Elektrische Tram (RET) and has a total extension of 78.3 km. Both the ridership and the passenger-km have been consistently growing during the last years. Figure 4.2 presents the development in both parameters for the past five years, as stated officially by RET. This puts pressure on the capacity of the network. To exploit the capacity more efficiently, headways are shortened. This threatens the stability of the system, leading to unreliability problems.

To evaluate the model, two sets of automatically-collected data corresponding to two weeks in 2019, from the 4th to the 17th of March are provided by RET. The first set consists of all the trips that took place in the network during the said time frame. This is referred to as the Passenger matrix. Each trip is characterized by its spatial and temporal origin and its destination. There is no information regarding the time and station in which transfers between lines are made. The second matrix comprises AVL data for all train rides in the two weeks. This includes the scheduled and realised arrival and departure times of each train to the visited stops in the network. Both matrices correspond to the same time frame.

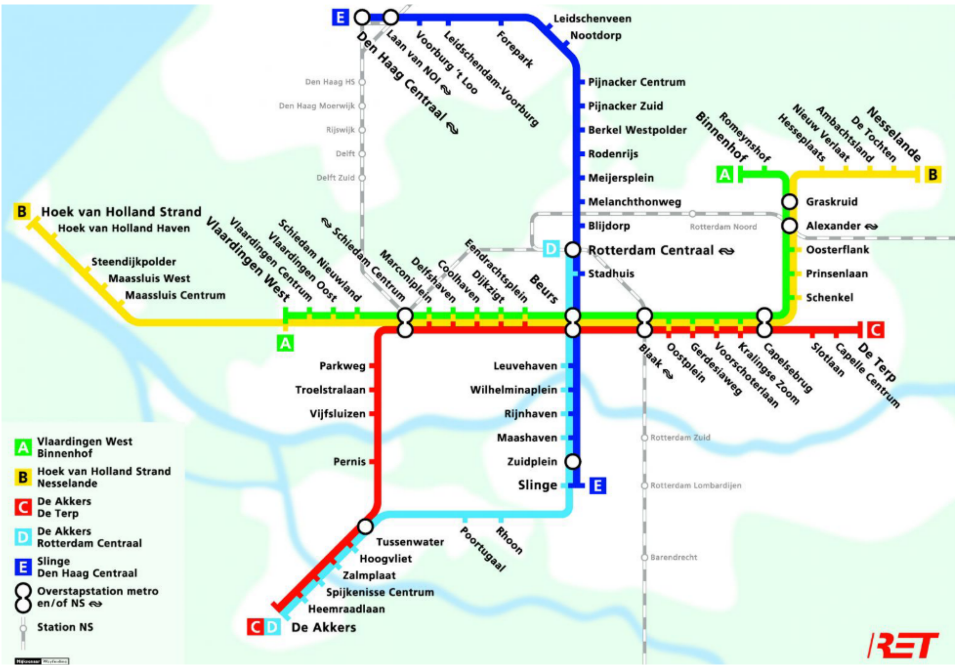


Figure 4.1: A map of the Rotterdam metro network including the extension planned (RET)

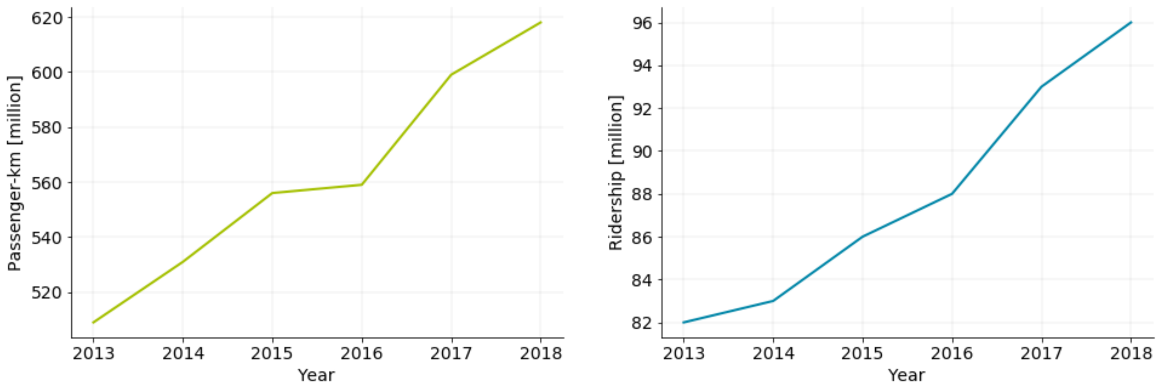


Figure 4.2: Passenger-km and ridership during for last five years (RET)

To keep computational time feasible and due to model limitations, it is decided to narrow the scope of the simulation both in spatial and in time instead of modelling the whole network for a full day. This is done based on the characteristics of passenger movements and observed disturbances in the data. For this study, it is interesting to consider a corridor with high demand and short headways, particularly at the busiest time of the day. According to data analysts at RET, the corridor between Slinge and Rotterdam Centraal seems to be a suitable candidate for the application of the SBTM-MN. In this corridor, two metro lines (E and D) overlap, sharing the tracks for around 7 km and serving some of the busiest stations in the centre of Rotterdam. This leads to headways between consecutive trains as short as three minutes during the morning peak. This suggests that the morning peak during weekdays is a suitable time scope for the analysis. To evaluate the validity of choosing a study case containing the mentioned stretch, both datasets are analysed. As a result, both lines E and D are selected as a study case. The segment runs from De Akkers to Den Haag Centraal and contains the stretch from Slinge to Rotterdam Centraal.

4.1.1. Demand analysis

The demand as represented by the passenger matrix is studied to evaluate which time frame and area of the network have a higher impact on passengers. Choosing the busiest time and segment has two major advantages. Firstly, with more passenger movements, the chances of observing disturbances and their propagation in real-life increase. This is desirable because having evidence of the problem is the first step in attempting to solve it. Secondly, improving the service in a busy segment would yield benefits to a larger number of passengers. The statistical analysis is carried out in two weeks in March, which is considered a representative month for public transport in the Netherlands.

The distribution of trips in time is in line with the general shape of daily profile typically observed in literature (Courchamp, Hoffmann, Russell, Leclerc, & Bellard, 2014; Festin, 1996). This means that the weekend and the weekday profile are significantly different, and the latter presents the characteristic morning and evening peak. Figure 4.3 presents a histogram of the average number of trips of the weekdays in the dataset aggregated every ten minutes. With regards to the shape of the peak periods, it can be seen that the morning peak is sharper and higher than the evening peak. This abrupt and high peak of demand motivates the choice of morning peak, from 7:00 to 9:00 as a time frame for the application of the SBTM-MN. The demand profiles of all weekdays are available in Appendix B.

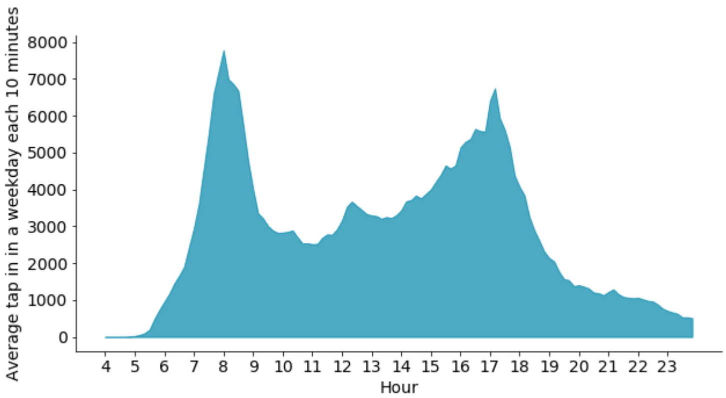
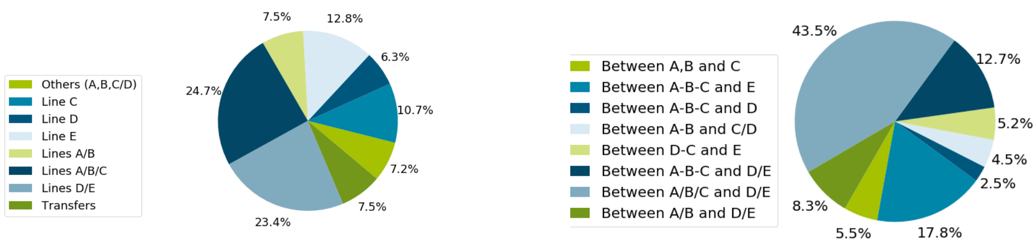


Figure 4.3: Histogram of the demand pattern in an average weekday

Figure 4.4 presents a chord diagram of the 100 Origin-Destination pairs with the highest demand during the selected time frame. Those trips that start or end in a station on lines E or D are highlighted in blue. The average Origin-Destination pairs per hour in the morning peak on a weekday can be found in appendix C.
As can be seen, Beurs, Rotterdam Centraal and Zuidplein are among the stations with the highest passenger movement. Furthermore, the majority of the trips are between stations within the stretches Rotterdam Centraal-Slinge and Schiedam Centrum-Capelsbrug. The first segment is served by lines E and D, whereas lines A, B and C overlap in the second segment. This suggests that most of the trips in the network were done without the need for a transfer, which is confirmed by the chart in Figure 4.5a. This is an important observation since trips with a transfer have to be divided into rides with the necessary assumptions. Figure 4.5a presents the share of trips according to the line or lines that serve them. The backslash indicates that the OD is served by more than one line and the passenger is most likely indifferent between them. In these cases, passengers are likely to board the first train that arrives at their station with the desired direction. The use of a hyphen means an 'or' statement and it is used in Figure 4.5b to group trips that have too few occurrences to be accounted for on their own. Figure 4.5a shows that only 7.5% of the trips made during these two weeks required to transfer. Moreover, at least 42.5% (12.8%+6.3%+23.4%) of the studied trips are done between origins and destinations in lines E and D, whereas 23.5% of all trips in the network are between ODs within the stretch Rotterdam Centraal-Slinge. The most interesting insight from Figure 4.5b is that the majority of transfer trips (43.5%) are between the mentioned busiest stretches. This preliminary statistical analysis of demand highlights the importance of Rotterdam Centraal-Slinge and Schiedam Centrum-Capelsbrug segments. In terms of spatial scoping, it is suggested that either of them are suitable candidates for this study.

Figure 4.4: 100 OD pairs with highest demand in the network



(a) Trip distributions per service

(b) Transfer trips

Figure 4.5: Trip distribution per service

4.1.2. Supply analysis

This section describes the realised train data provided by RET, its limitations and how they are handled. The AVL data matrix was recorded using the VerKeersLeider system (VKL). This is a traffic management system that registers all arrivals and departures from a station each day. The following observations need to be made regarding the accuracy of the data registered by this system:

- Some entries in the data were not registered correctly, or are missing. The rows that have missing or incomplete data are excluded from this study.
- Only part of line E has ZUB installed and is able to record the actual arrival and departure of a train in the platform. Therefore, the dwell time of a train at these stations can be calculated with a higher degree of accuracy. For all other stations, only the time at which the last wheelset of a train enters the section linked to the station and the time in which said wheelset leaves the section are recorded. This

means that the dwell time is not directly measured. A correction is made to derive the dwell time, in which 11 seconds are added to the entrance time and 13 seconds are subtracted from the leaving time. The same procedure is done for all stations with the same correction factor.

- The dataset contains entries in which it is not possible to calculate the required dwell time due to passenger exchange. For instance, in early arrivals or when the train is forbidden to depart by a signal ahead. These data points are excluded for the calculation of dwell times.
- The dataset includes entries in which the dwell time resulted from subtracting the arrival time from the departure time is irrationally small or even negative. Entries with dwell times smaller than 10 seconds are excluded as it is considered that there was an error in the measurement and therefore the record is not reliable. Also, occurrences of dwell times larger than 5 minutes are excluded since it is considered to be an exceptional event and not representative for this study.
- Some entries in the dataset correspond to trains reversing at an end station. Since longer time is needed for this task, it is not possible to derive the dwell time from these entries. These data points are also excluded from the dwell time distribution analysis.

  To evaluate the distribution of dwell times due to passenger exchanges in the network, it is necessary to filter out data points that do not add information. First, the incomplete records, such as entries with no available number in the time cell, are excluded. Secondly, events with early arrivals whose dwell time is dictated by schedule adherence are eliminated. Thirdly, the cases in which the dwell time of a train was extended because it was forbidden to depart by a signal are removed. Finally, events corresponding to the start or end of a trip, and those dwell times that are too short or large to be related to passenger exchange are eliminated. After filtering out the entries that are not useful for the calculation of dwell times, only 58% of the data points remained. An overview of the data points filtered can be seen in Table 4.1.

Table 4.1: Filtering of data points to find the distribution of dwell times in the network

Description	Total number of visits at stations
All registered events	260500
Excluding incomplete records	256294
Excluding early arrivals	168073
Excluding waiting signalling	160456
Excluding start and end of trips	150385
Excluding dwell times larger than 5 minutes or smaller than 10 seconds	150343
Excluding dwell times larger than 5 minutes or smaller than 10 seconds	148627

The distribution of the dwell times for each stop can be found in Figure 4.6. This figure shows that the average dwell time is below 50 seconds for all station, and the highest average dwell times correspond to stations Schenkel (A/B), Rotterdam Centraal(E/D), Hesseplaats(B), Oosterflank(A/B), De Tochten(B), Beurs(A, B, C, D, E) and Prinselaan(A/B). Most of those stations are located in the stretch Schenkel-Nesselande on line B, which does not have high passenger demand. Stations with the highest dwell time variability, on the other hand, are mostly located in lines D or E. These include Blijdorp, Zuidplein, Rotterdam Centraal and Rijnhaven. The high variability in dwell time could indicate that the bunching effect, among other disturbances, occurs relatively often. Since the stations with highest dwell time variability are also some of the busiest stations, it is reasonable to choose the stretch containing them as a case study. Both lines E and D are chosen, to have a segment sufficiently long to evaluate different measures and their impact.

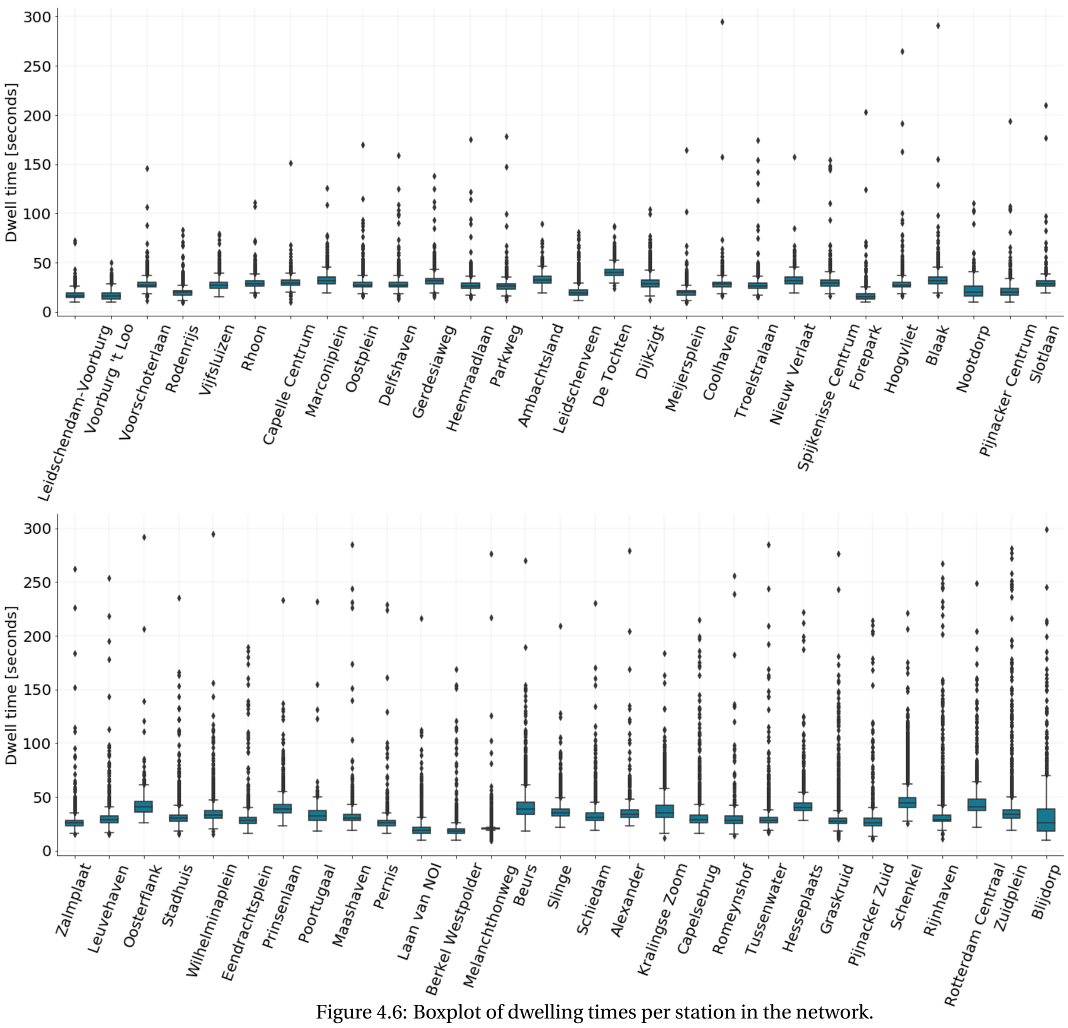


Figure 4.6: Boxplot of dwelling times per station in the network.

To evaluate the variation of dwell time as dependent on the headway, boxplot charts are made for each station in lines E and D. The plots, which can be found in Appendix D, depict the distribution of dwell time realization according to the headway grouped in ten-second blocks. For the development of these boxplots, the data is filtered as shown in section 4.1.2. Furthermore, only the stations in lines E and D are considered. Weekends and events outside the range from 7:00 to 19:00 are also excluded from the dataset. No visible strong correlation can be found between headways and dwell times, which would be logical to observe, as supported by the literature. The lack of evidence for the dwell time-headway relation can be due to more than one factor. Firstly, there are rather few datapoints remaining for the analysis once they have been filtered. Around 2000 data points are used per station. To avoid downsizing the dataset even more, the timeframe is kept between 7 A.M. and 7 P.M. This leads to the second possible reason behind the lack of dwell time-headway representation. The dwell time of a vehicle does not depend solely with the headway, but there are multiple variables playing a role. One of the most important is the arrival of passengers. If a headway increases but the arrival rate of passengers decreases, the dwell time might remain the same. By including data points in a range of 14 hours in a day, it is assumed that a variation in the headway has the same effect on the dwell time throughout the timeframe. This implicitly disregards the role that passenger arrival rate has in the dwell time. As shown in Figure 4.3, passenger demand varies notably through the day. This means that a headway of 10 minutes on a certain station probably leads to a dwell time larger at 8 in the morning than at 11.

As an example of the disturbances that occur along lines D and E, Figure 4.7 presents the realised and planned trajectories for lines D and E in the morning peak of Monday the 4th March 2019. This time-distance diagram presents the planned trajectories in grey and the realised trajectories in dark blue. The colouring of the data points represents whether the operations are delayed, bunching, or none. Since there is no consensus in the literature regarding the characterization of a bunched state, for the sake of visualization, the following was considered: vehicles are delayed if the increase of actual versus planned headway with the previous vehicle is 70% higher than with the following vehicle. In this case, the data points are coloured red. A vehicle is considered bunched if the increase of actual versus planned headway with the following vehicle is 70% higher than with the previous vehicle. In this case, the dots are coloured green. This approach takes into consideration the deviation with the planned headway rather than punctuality. Figure 4.8 shows the trajectories of two trips that presented bunching on the 4th of March 2019. The lightly coloured trajectories correspond to the planned trajectories, whereas the opaque lines are the realised trajectories. The trajectory depicted in green shows a vehicle that falls behind schedule. A headway of ten minutes is planned between trains. However, once the second train starts falling behind schedule, its headway with the predecessor keeps on increasing. The third vehicle, whose trajectory is depicted in teal, manages to stick to the schedule. The result is that the headway between the first and second trains increased to almost 15 minutes, even when the first train was also delayed. Furthermore, the headway between the second and third train decreased to less than three minutes. The fact that the total time spent in stations by the second train is significantly higher than that of the first and third trains undoubtedly contributed to the headway variability.

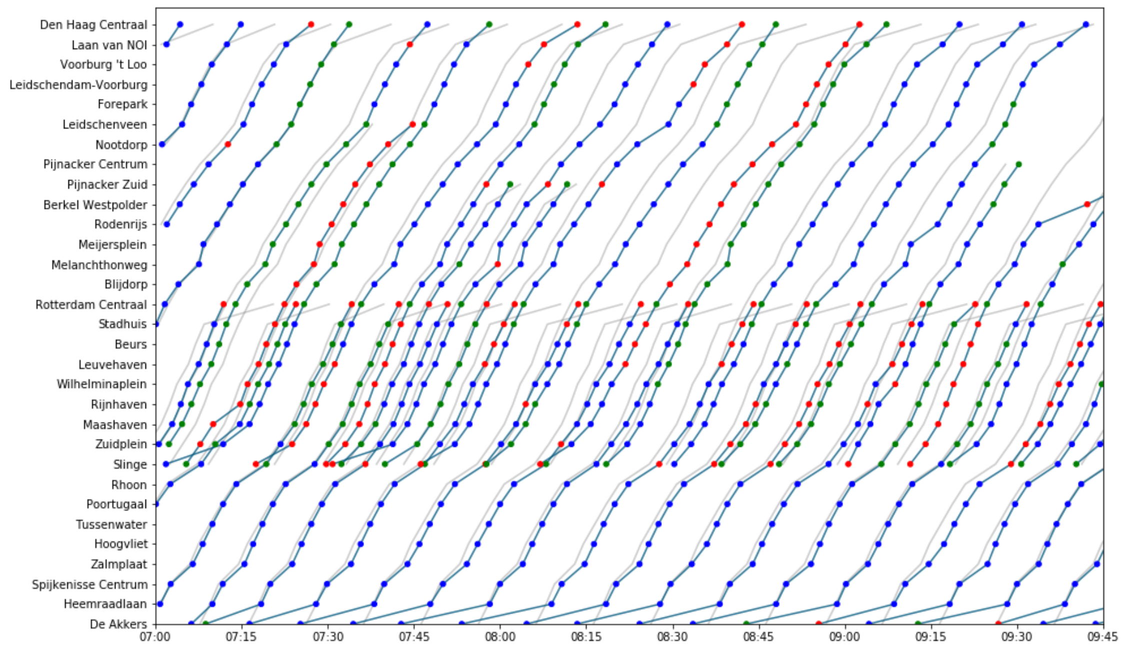


Figure 4.7: Trajectories of metro trips in corridor De Akkers-Den Haag Centraal on the morning peak of Monday 4th March, 2019

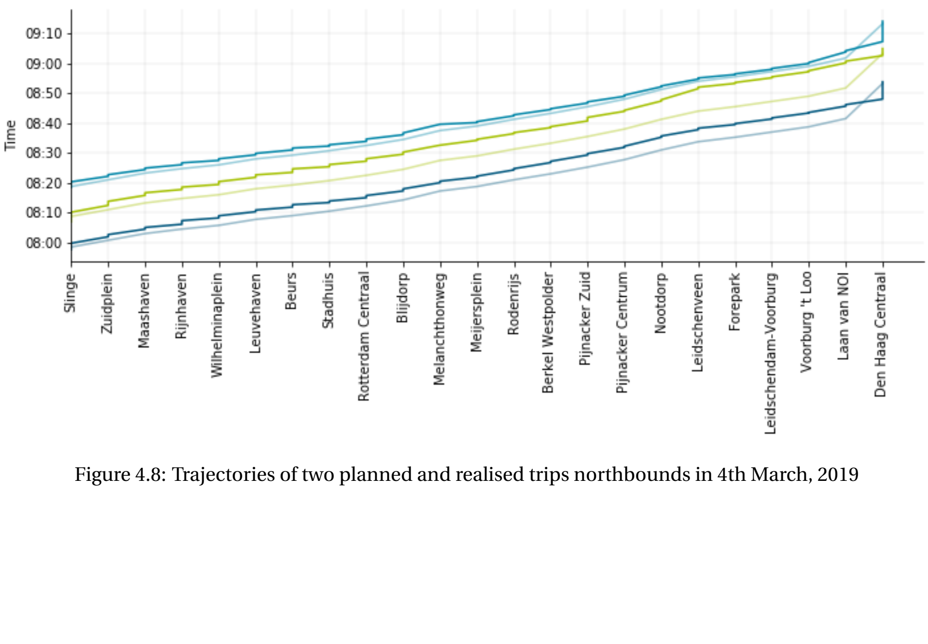


Figure 4.8: Trajectories of two planned and realised trips northbounds in 4th March, 2019

4.2. Case study specifications

The case study and simulated network represent lines E and D in the metro of Rotterdam during the morning peak of a regular weekday. The operations are simulated in the north direction and for both lines. Line D consists of 17 stations and runs from De Akkers to Rotterdam Centraal, whereas line E serves 23 stations from Slinge to Den Haag Centraal. Both lines overlap in the stretch from Slinge to Rotterdam Centraal, serving a total of 8 stations in that stretch, which is the busiest section of both lines.

This section explains how the input for the SBTM-MN is designed for this specific case study. The shaping of passenger data and calibration of dwell time parameters is discussed in section 4.2.1. The files for the input of the train model are supplied by RET. They include the timetable corresponding to the realised passenger data provided. Although data on the full network is available, only trains in line E and D are run. Since the files provided by RET include the model of the train simulation in OpenTrack, the input for the train module is not further discussed. Section 4.2.2 describes the input used for the TRM, including the calibration of parameters and weights of all functions.

Figure 4.9: A map of the segment under study

4.2.1. Passenger input data

The passenger and AVL data provided by RET is used to design the passenger demand for the TSM-RW, the statistical arrival rates and distribution for TSM and the calibration of dwell time parameters. However, this data consists of passenger information for the whole network, presenting tap in and out locations and time. The SBTM-MN requires rides with the time at which a passenger arrives at the platform, instead of trips, as explained in 3.3. Moreover, not all of the network is modelled, but the case study is restricted to two lines. Therefore, all trips outside the lines under study are excluded, and the trips are reshaped into rides between stations. This required a series of assumptions.

Firstly, passengers are assumed to be in the platform and ready to board a train exactly one minute after having tapped in at the gates. The same assumption is valid for all stations and is performed by simply off-setting the tap in time by a minute in all rows. Although different station layouts and crowding may influence the time it takes for a passenger to get from the gates to the platform, a minute is believed to be a relatively representative average.

Secondly, an assumption has to be made regarding transfer points and times. Although the vast majority of trips do not require transfer and are therefore equivalent to rides, transfer trips might be of relevance when studying dwell time variations. This is because transfers cause a characteristic type of passenger inflow in the platform of the transfer station. It can be considered that the latter experience two types of passenger inflow: passengers that enter the station at any given time and passengers transferring, who enter the platform at discrete moments in time when their first ride gets to the transfer station. The following assumptions were made with regards to transfers:

- Passengers do not transfer unless it is exclusively necessary to reach their destination. This implies that transferring has a higher penalty in the utility of travellers, which has been corroborated by literature. Therefore, passengers are willing to travel longer if it means that they do not need to transfer. This is considered a valid assumption because in this particular network there are no large travel time gains by transferring.
- Passengers whose trip requires a transfer between E and D, do so in the first available station. For instance, if a traveller has to go from Den Haag Centraal to De Akkers, it is assumed to transfer in Rotterdam Centraal and not in any other station in the segment in which lines E and D overlap. In reality, there is certain stochasticity when it comes to transferring choices. However, it is reasonable to assume that most passengers would rather transfer at the line start station of their second trip leg, hoping to get an empty seat. Figure 4.10 shows the main transfer points between lines. Transfers between E and D make up for 1% of all transfers trips in the network for the period analysed.
- Passengers transferring from lines A, B or C to lines D or E, do so in station Beurs, as shown in Figure 4.10. Exceptions are passengers from Vijfsluizen or Pernis to Poortugaal, Rhoon, Slinge or Zuidplein. These passengers transfer from line C to D or vice-versa through station Tussenwater. This choice was made based on travel times provided by RET.

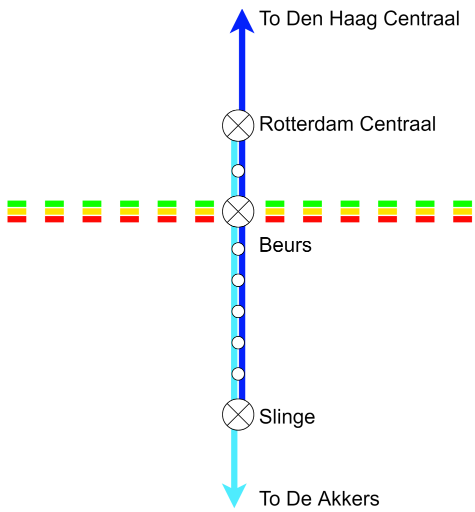


Figure 4.10: Illustration of main transfer points

- When a transfer is required to carry out a trip, the latter is divided in its legs (at most two in this network) according to the following:
  - If the first leg of a trip is in lines E or D, the destination of the trip is modified to match the transfer station. Then, the second leg of the trip is discarded if it takes place outside lines D or E.
  - For all second legs within lines D or E, it is assumed that the passenger took the first train that takes him or her to the transfer station. The time at which a train picks the passenger up is picked

from the realised AVL data for the corresponding time and day. From the same data, the time at which the passenger would get to the transfer station is picked. A minute is added to said time for the passenger to switch platforms. The resulting time replaces the original time of arrival for the passenger, and the location is changed to the transfer station.

As an example, if a passenger taps in at Den Haag Centraal at 7:09:10 in the morning with destination De Akkers, the trip is split in two. Both legs are kept because they take place in lines D and E. For the first leg, the destination station is changed to Rotterdam Centraal. For the second leg, the next train going to Rotterdam Centraal is picked from the AVL database. Assuming that the earliest train was at 7:11:05 and got to Rotterdam Centraal at 7:44:02, the time of arrival of the passenger is changed to 7:45:02 and the tap in location is changed to Rotterdam Centraal. Table 4.2 shows the original trip and the two rides as an example. The timestamps need to be changed to seconds prior feeding the input to the passenger module.

Table 4.2: Example of a trip division in its constituent rides

	In_time	In_station	Out_time	Out_station
Original trip	7:09:10	Den Haag Centraal	8:21:22	De Akkers
First ride	7:09:10	Den Haag Centraal	-	Rotterdam Centraal
Second ride	7:45:02	Rotterdam Centraal	-	De Akkers

The passenger data is adjusted to rides for the two considered weeks through these sets of assumptions and used for the following:

TSM Estimated demand parameters

The passenger ride matrices are filtered to those rides carried out in the morning peaks of weekdays. Then, the arrival rate of passengers per second, $\lambda_s^{morning}$, and their destination split $\delta_{s,d}^{morning}$ is calculated. Based on these values, the fraction of passengers with destination d, $\chi_{r,s,d}^{morning}$ is estimated for each route and station.

TSM-RW demand

The passenger ride matrix corresponding to Tuesday the 5th of March 2019 in northerly direction is used as a demand profile for the TSM-RW. This is considered to be a regular day for public transport demand in the Netherlands, and no disruption was registered in the realised data. Therefore, the matrix is used as an input without further processing. Figure 4.11 shows the histogram of the rides on the morning of Tuesday the 5th of March, which is the specific time frame of the study case. Furthermore, Figure 4.12 presents a chord diagram of the rides that took place on the mentioned space and time frame. The cyan ribbons correspond to rides that use line D. Conversely, the dark blue ribbons correspond to rides using line E. Finally, the teal coloured ribbons correspond to rides that can take place using either line E or D indifferently.

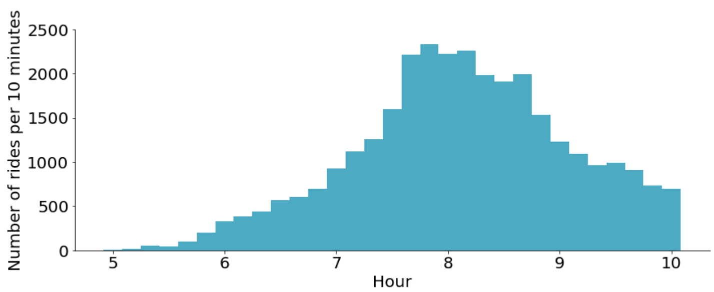


Figure 4.11: Histogram of the ride pattern for the morning peak of the 5th March, 2019

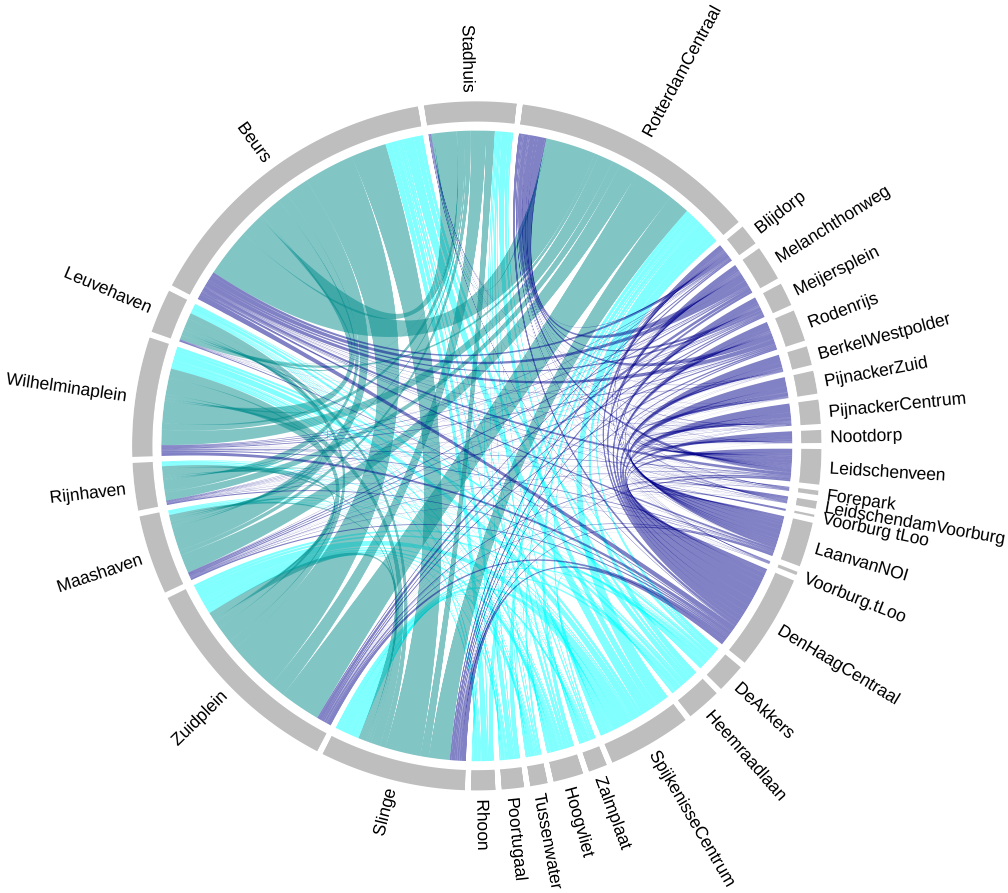


Figure 4.12: OD rides for the morning peak of the 5th of March, 2019

TSM Estimated dwell time parameters

To estimate the dwell time functions for each station, the ride matrices are matched with the complete AVL data. This provides, at each event, the passengers boarding, alighting, inside the train and in the platform and the realised dwell time. Only after this, is the AVL data filtered as explained in 4.1.2. This is because although many train entries are not useful to fit a dwell time function, excluding them from the passenger assignment would mean eliminating segments of trips that actually took place.

Finally, the regression with equation 3.16 is performed. The parameters obtained from technical specifications are the space capacity of each vehicle, p (270 passengers), the number of doors per vehicle d (7), the number of vehicles per transit unit v (2).

To minimize the influence of different types of passenger trips on the resulting dwell time, the data points were restricted to weekdays between 7:00 and 19:00. Equation 3.16 can be considered a sum of boarding passengers and alighting passengers weighted with, among other parameters, the load of the train. Logically, and according to literature, there should be a correlation between dwell time and the sum of passengers alighting and boarding. To evaluate this, realised dwell time was plotted against the number of passengers boarding, alighting and their sum.

Figure 4.13 shows that, although there is significant variability in the data points, there is still a visible correlation between predictors and dwell time. Since it was not possible to observe a strong correlation between headway and dwell time in section 4.1.2, figure 4.13 highlights the relevance of the passenger flow characteristics on the dwell time derivation. If the boarding and alighting of passengers had the same rate throughout the day for each station, there would be a direct correlation between headway and dwell time. Since the arrival of passenger and their destination, which affects their alighting location, changes through time, deeper data analysis was necessary to find the relation between dwell time and headway. Nevertheless, figure 4.13 shows entries with a low number of passenger exchange but a long realised dwell time. This indicates that the dwell time of those entries is not due to the passenger exchange, but owing to an unknown factor. For this reason, dwell times that are inexplicably long for the volume of passenger exchange are excluded. The threshold considers a 35 second fixed time for opening and closing doors plus the time that passenger exchange would take if each person would take 4 seconds to board, assuming passengers are equally distributed along the platform and train. These values are higher than those that can be found in literature, and they are meant as a roof for the validity of the data points. After this step, the regression model was performed to obtain the station parameters for equation 3.16.

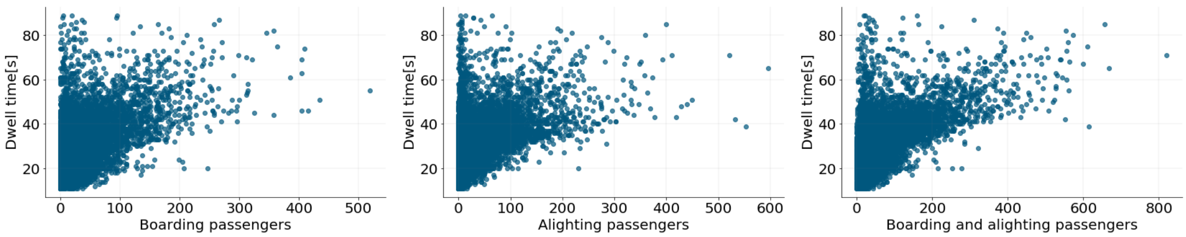


Figure 4.13: Scatterplots of dwell time vs. predictors

The goodness of fit is estimated through the adjusted R^2. This indicates that the proportion of the variation in the dwell time explained by the variables is 69%. Regression analysis is performed in alternative functions using the same predictors, but they are discarded because the resulting model fit is lower. Figure 4.14 provides a visualization of the model fit. The data points used to perform the regression analysis are depicted in blue, whereas the calculated points are depicted in green. Note that regression analysis is performed for each station using equation 3.16 which yields station-specific parameters.

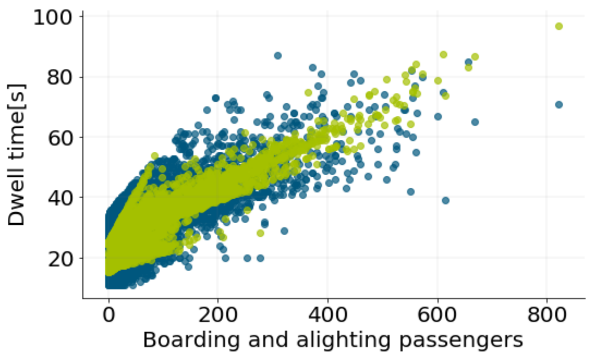


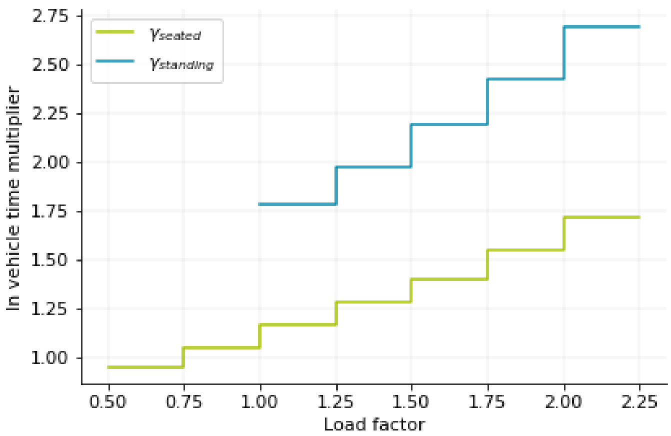
Figure 4.14: Scatterplot of data and calculated points

4.2.2. TRM input data

The TRM retrieves the passenger allocation parameters from the simulation in each iteration. Conversely, the general parameters for this model need to be supplied as inputs before the start of the simulation.

The technical parameters that limit the headway, connection and running times are derived from the OpenTrack model provided by RET. The minimum headways h_s^{out} and h_s^{in} are derived as the difference between arrival and departure of two consecutive trains with the minimum headway as indicated by the headway calculator of the simulation software. This is performed for each station and both directions. It should be noted that, although the minimum headway between two trains changes with their performance, this is disregarded in the current research. For this study, the headways are calculated considering a train performance of 100%. The minimum running times $q_{s,h}^{min}$ are calculated as the time it takes a train to traverse each segment in the north direction, running at its best performance and speed limit. The minimal connection time between two trains at a station, $c_{m,n,s}^{min}$, is taken from the original timetable provided by RET. Furthermore, considering that each vehicle has 104 seats, and each transit unit consists of two vehicles, the sitting capacity of a train, k_m, is 208. With regards to the stepwise limitation, the allowed margin of difference between the times of events in the input and the output of the optimization, u, is set to 60 seconds.

The weights of the objective function are obtained through literature studies. Waiting time weights twice the in-vehicle travel time, as found for commuting trips in metros (Wardman, 2004). Since the main objective of the optimization is passenger-oriented, the weight for schedule deviation β_a is set to be half of β_I. These values can be adjusted easily to steer the rescheduling towards passenger or operator. Furthermore, the crowding multipliers that account for passenger perception of the in-vehicle travel time according to the vehicle load (γ_{Seated} and $\gamma_{Standing}$), are derived from the meta-study by Wardman and Whelan (2011). Figure 4.15 presents a visualization of the multipliers used. The meta-study by Wardman and Whelan (2011), provides multipliers for discrete load factor values, as presented in the table in figure 4.15. For this research, a stepwise transition between those values is assumed.



Load factor ($l_{s,m}/k_m$)	Seated in-vehicle multiplier (γ_{Seated})	Standing in-vehicle multiplier ($\gamma_{Standing}$)
50%	0.95	
75%	1.05	
100%	1.16	1.78
125%	1.28	1.97
150%	1.4	2.19
175%	1.55	2.42
200%	1.71	2.69

Figure 4.15: Crowding multipliers derived from Wardman and Whelan (2011)

4.3. Experiments

Three sets of tests are carried out to evaluate the applicability of the SBTM-MN. Firstly, the performance of the TSM is assessed for different delay scenarios. Secondly, the TRM is analysed for alternative objectives in the optimization of a single scenario. Finally, the SBTM-MN is tested for one scenario. The remainder of this section further describes each set of experiments and their corresponding results.

4.3.1. Transport Simulation Model (TSM) experiments

One of the main contributions of this research is the modelling of passenger movements in conjunction with the train simulation performed in OpenTrack. This allows exploring the effect of passenger-train interaction in the execution of the timetable and how this, in turn, impacts passengers. Additionally, the TSM enables to evaluate how different disturbances in the railway system undermines passenger's travel time and level of comfort.

To prove the functionality of the TSM, a series of experiments are performed for different disturbances in the network and their combinations. These tests are done including the train-passenger interaction, and excluding it. Excluding train-passenger interactions implies that the dwell time considered does not respond to the actual passenger exchange, but it is always the scheduled one. Passenger allocation is still calculated for all scenarios to compare the effect of delays on travel time and congestion. Therefore, when excluding passenger-train interactions, this is done by running the TRM disabling the messages from the passenger module to the train module. If only the train module is run, the passenger flow modelling is neglected and passenger allocation is untraceable. In the scenarios that include passenger-train interaction, train dwell times depend on the passenger exchange. Therefore, these scenarios are named S^p. In scenarios that are clear of passenger-train interaction, from now on named S^c, the dwell time is set by the schedule. Table 4.3 presents an overview of the tested scenarios. Two disturbance locations with three different intensities and their combinations are tested. The disturbances are modelled as a breakdown of the edge at the entrance of a station, which blocks train movements. They take place at 7:00:00 in Heemraadlaan (close to the start of the D line northbound), or/and at 7:30:00 in Zuidplein (in the segment in which both lines overlap). The duration of these disturbances is of 5, 10 or 15 minutes.

Table 4.3: Overview of scenarios tested with TSM

(a) With passenger-train interaction (S^p)

		Disturbance in Zuidplein			
		0 min	5 min	10 min	15 min
Disturbance in Heemraadlaan	0 min	$S^p_{(0,0)}$	$S^p_{(5,0)}$	$S^p_{(10,0)}$	$S^p_{(15,0)}$
	5 min	$S^p_{(0,5)}$	$S^p_{(5,5)}$	$S^p_{(10,5)}$	$S^p_{(15,5)}$
	10 min	$S^p_{(0,10)}$	$S^p_{(5,10)}$	$S^p_{(10,10)}$	$S^p_{(15,10)}$
	15 min	$S^p_{(0,15)}$	$S^p_{(5,15)}$	$S^p_{(10,15)}$	$S^p_{(15,15)}$

(b) Without passenger-train interaction (S^c)

		Disturbance in Zuidplein			
		0 min	5 min	10 min	15 min
Disturbance in Heemraadlaan	0 min	$S^c_{(0,0)}$	$S^c_{(5,0)}$	$S^c_{(10,0)}$	$S^c_{(15,0)}$
	5 min	$S^c_{(0,5)}$	$S^c_{(5,5)}$	$S^c_{(10,5)}$	$S^c_{(15,5)}$
	10 min	$S^c_{(0,10)}$	$S^c_{(5,10)}$	$S^c_{(10,10)}$	$S^c_{(15,10)}$
	15 min	$S^c_{(0,15)}$	$S^c_{(5,15)}$	$S^c_{(10,15)}$	$S^c_{(15,15)}$

The number of scenarios is limited to 32 because, due to issues in the communication speed through the API, the simulations have to be run at a time step of 10:1. These simulations are run from the start of daily operations to the end of the morning peak (9:00:00). However, only the events that take place in the morning peak (7:00:00 - 9:00:00) are taken into account in further analysis. The previous simulation hours considered a necessary initialization process for the running of trains and passenger allocation. The results obtained from these simulation runs are compared in two main aspects. The first pertains to the schedule adherence and delay of trains. The second, passenger-oriented, analyses in-vehicle time, waiting time, and the level of congestion in trains.

Train Delays

The train delays for each scenario, measured as the total sum of the differences between realised and scheduled departures in hours, can be seen in table 4.4. Here, the cells coloured in darker red illustrate a higher total delay. The average departure delay, maximum delay and standard deviation of delays per scenario can be found in table 4.5. When including passenger-train interactions, the delays are significantly higher for the same delay scenario. Indeed, even the scenario without externally imposed disturbances has delays when passenger-train interactions are included. This is because the dwell time due to passenger exchange often exceeds the scheduled dwell time during peak hours, causing delays in trains. The minor delays observed in $S^C_{(0,0)}$ are due to two extra trains in line E, scheduled during the morning peak, running from Slinge to Nootdorp. These trains depart 75 seconds after their predecessors, which proves to be insufficient for the extra trains to run without conflicts. As a consequence, there is an inherent delay in the planned timetable. For the interested reader, time-distance diagrams for S^p plotted over the corresponding S^c scenarios some sets of disturbances, can be found in appendix E. In each plot, the time-distance diagram of a S^c scenario is plotted in orange in the background of the image, whereas the diagram of the corresponding S^p is plotted on top for comparison.

Table 4.4: Total train delays of scenarios tested with TSM in hours

(a) Without passenger-train interaction (S^c)

		Disturbance in Zuidplein			
		0 min	5 min	10 min	15 min
Disturbance in Heemraadlaan	0 min	0.57	1.56	5.28	11.85
	5 min	0.65	1.63	5.36	11.92
	10 min	1.77	3.72	7.44	14.01
	15 min	6.55	8.9	15.54	24.77

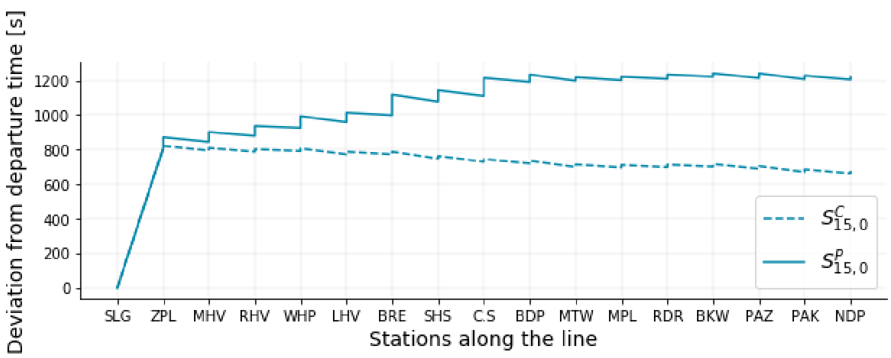
(b) With passenger-train interaction (S^p)

		Disturbance in Zuidplein			
		0 min	5 min	10 min	15 min
Disturbance in Heemraadlaan	0 min	8.67	9.70	15.48	27.23
	5 min	8.79	9.80	15.89	28.32
	10 min	15.90	16.09	23.13	35.49
	15 min	19.07	20.55	28.42	42.45

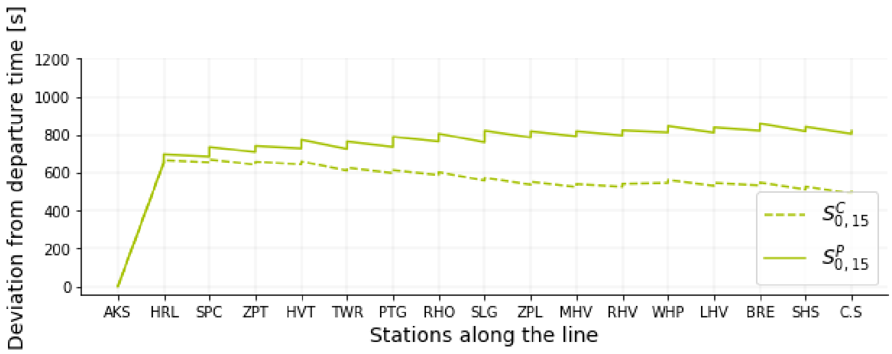
Table 4.5: Summary of the results obtained for each scenario

	S^p				S^c			
	Disturbance in Zuidplein							
	0	**5**	**10**	**15**	**0**	**5**	**10**	**15**
Disturbance in Heemraadlaan	**Average delay [s]**							
0	43.4	48.5	77.4	136.1	2.9	7.8	26.4	59.2
5	44.0	49.0	79.4	141.6	3.3	8.2	26.8	59.6
10	79.5	80.4	115.7	177.4	13.8	18.6	37.2	70.1
15	95.4	102.8	142.1	212.2	32.8	44.5	77.7	123.9
	Maximum delay [s]							
0	197	307	751	1241	94	222	522	822
5	187	308	755	1243	94	222	522	822
10	706	708	1040	1452	369	369	522	822
15	858	846	1234	1653	669	758	1058	1358
	Standard deviation [s]							
0	43.8	57.9	143.1	267.5	12.0	31.0	94.7	175.5
5	42.8	57.1	143.4	266.2	12.9	31.3	94.7	175.4
10	123.3	124.9	188.6	300.5	54.1	60.2	105.6	179.3
15	170.0	169.8	247.6	364.2	119.4	144.5	205.7	288.1

The timetable of RET allocates all buffer time in the stop at stations. This implies that, in the model, trains run at 100% performance and at top speed in the stretches between stations. Trains are expected to make up for their delays by using the slack time at stations. However, if the passenger exchange takes longer than the scheduled dwell time plus the buffer time, the delay of trains increases along their trip. This directly affects the recovery of schedule adherence. Unless the demand is low, the first train affected by a disturbance is unlikely to recover when passenger-train interaction is considered. As an example, figure 4.16 presents the deviations from scheduled departure for the first trains affected by disturbances in Heemraadlaan and Zuidplein. These graphs show how, in S^p scenarios, delays decline along the trajectory of the train, whereas the opposite happens in S^c scenarios. Furthermore, it can be seen that the growth in the delays is sharper in figure 4.16a than in figure 4.16b. This is because the dwell time at stations, visible as steps in the graphs, are larger in 4.16a than in figure 4.16b. There are three main reasons for this: firstly, the northbounds demand is higher in the stretch from Slinge to Rotterdam Centraal. This is evident in Figure 4.12, where the ribbons corresponding to the demand between stations in the stretch Slinge-Rotterdam are coloured in teal. Secondly, the disturbance in Zuidplein is introduced at 7:30:00, half an hour later than the one in Heemraadlaan. At this time, the absolute demand in the network is higher, as can be seen in figure 4.11. Thirdly, the nature of the bunching effect, that reinforces itself in a feedback loop. The process depends on the headway and the arrival of passengers. Although the initial headway of train M009-007 07.03 AKS C.S is larger than that of train M010-043 07.29.45 SLG NDP, the higher demand of the second train induces a sharper deterioration of punctuality. Figure 4.16 also shows that the demand, translated in a longer dwell time, is higher at the beginning of lines. This means that a disturbance at the beginning of the line is more prone to degenerate into bunching in S^p scenarios.



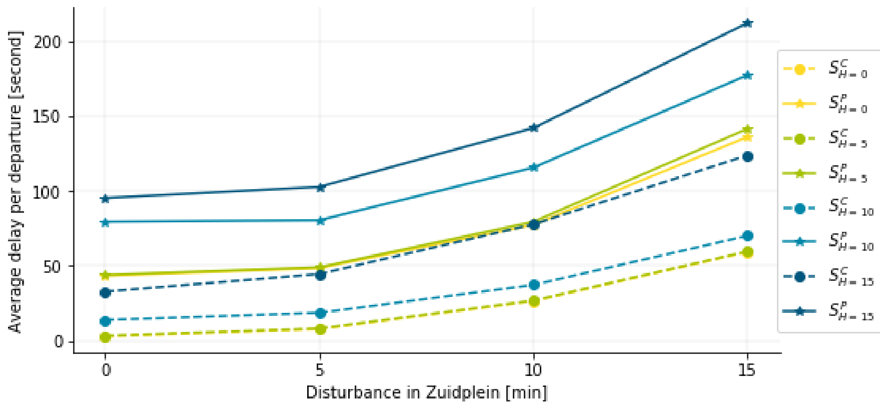
(a) Train M010-043 07.29.45 SLG NDP for scenarios $S^C_{15,0}$ and $S^P_{15,0}$



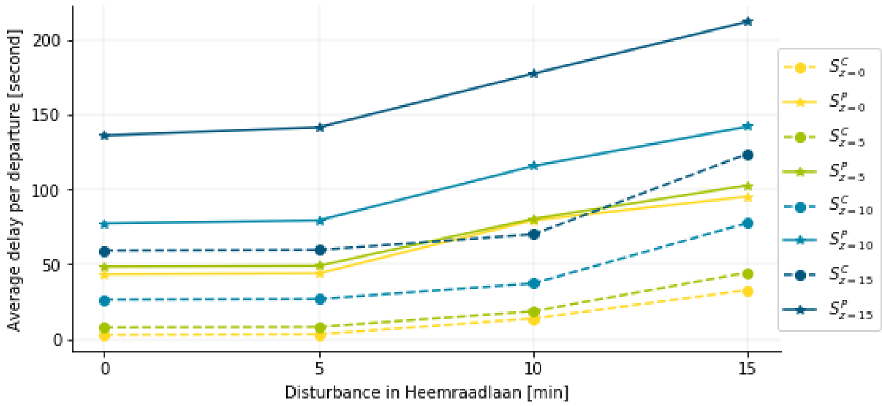
(b) Train M009-007 07.03.00 AKS C.S for scenarios $S^C_{0,15}$ and $S^P_{0,15}$

Figure 4.16: Deviation from departure along the line for the first train affected by a disturbance

Further exploration of the results reveals that in all cases, disturbances in Zuidplein causes more deterioration in punctuality than disturbances in Heemraadlaan. When combined, an increase in the duration of the disturbance in Zuidplein still has a higher impact. This can be seen in figure 4.17b, which presents the average delay per departure as a function of the duration of a disturbance in one station, for different levels of disturbance in the other station and with or without passenger-train interaction. Trains affected in Heemraadlaan can recover some of their delays before inducing secondary delays in other trains. This is not the case when a delay is induced in Zuidplein, due to the higher demand in the time and location. Furthermore, headways are shorter in Zuidplein, since lines E and D overlap. This reinforces the spread of delays in the timetable. Finally, the impact of a disturbance depends on the headway between trains. For instance, figure 4.17b shows that including a disturbance of 5 minutes in Heemraadlaan hardly impacts the average delays. This is because the first train affected gets to Heemraadlaan when the disturbance is almost over. This train arrives at the station with just a minute of delay. Since the headway with the following train is 150 seconds, there is no secondary delay. By the time the affected train arrives at Slinge, any consequences of the disturbance have faded without perceivable impact in $S^c_{0,5}$. For the case of $S^p_{0,5}$, the delay is not recovered due to passenger demand, and some secondary delay is caused in the following train. However, this delay is not further spread to a third train due to the large enough headways. Secondary delays become far more evident when the 10-minute disturbance is included, because all train headways are smaller than this value. As a matter of fact, there is usually at least two trains per ten minute span in peak hours. This means that a ten minute delay has a high probability of causing a secondary delay.



(a) Duration of a disturbance in Zuidplein vs. average delay per departure for different disturbances in Heemraadlaan



(b) Duration of a disturbance in Heemraadlaan vs. average delay per departure for different disturbances in Zuidplein

Figure 4.17: Average delay per departure

The variation of dwell time as a function of passenger exchange increases not only the total delays but also the largest delay and the standard deviation. Figure 4.18 presents the cumulative distribution function of the delays for all the scenarios tested. The full lines represent the scenarios in which passenger-train interaction is modelled, whereas the dashed lines represent the scenarios in which it is neglected. As an example, for the worse case in terms of delay, $S^P_{(15,15)}$, the largest delay is 1653 seconds (around 55 minutes), whereas the largest delay for $S^C_{(15,15)}$ is 1358 (around 45 minutes). Moreover, the standard deviation for $S^C_{(15,15}$ is 288 seconds, whereas the corresponding to $S^P_{(15,15)}$ is 76 seconds larger. Similar behaviour is present in all cases when comparing the S^p scenarios and S^c scenarios. This can be observed in table 4.5. Another interesting fact is that, although the average delay of $S^p_{(0,5)}$ is higher than that of $S^p_{(0,5)}$, the opposite occurs with the maximum delay and the standard deviation (see table 4.5). This is because the maximum delay in both scenarios corresponds to train M010-043 07.29.45 SLG NDP at station Pijnacker Zuid. When a disturbance is included in Heemraadlaan, in $S^p_{(0,5)}$, two trains from De Akkers reach their final destination in Rotterdam Centraal with a minute of delay. This minute is sufficient for these train to capture passengers that would otherwise board train M010-042 07.28.30 SLG GVC, which precedes M010-043 07.29.45 SLG NDP. Given the short headway between these trains, as explained, there is an inherent conflict in the timetable. As a result, in $S^p_{(0,5)}$, fewer passengers board M010-042 07.28.30 SLG GVC, which translates into a smaller delay of this train and the following.

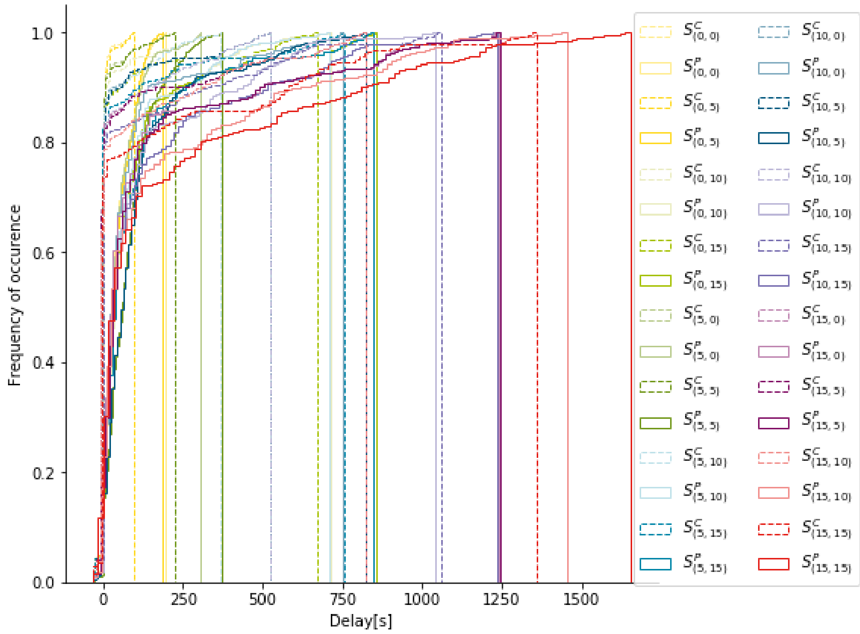


Figure 4.18: Cumulative distribution function of the delays for each scenario

Passenger impact

This section discusses the different aspects in which train delays caused by disturbances affect the travel experience of passengers. The integrated modelling of trains and passenger movements is used to evaluate the waiting time of passengers, their perceived in-vehicle time, and the level of crowding in trains. These three areas are expected to be influenced negatively by an increase in the disturbances and the inclusion of train-passenger interactions.

Figure 4.19 presents a bar chart with the difference in the average travel time, using $S^C_{(0,0)}$ as a benchmark. This figure shows scenarios clustered by the magnitude and the combination of the disturbance induced. For all cases, the in-vehicle time is significantly higher in S^p scenarios than in S^c scenarios. This is because the bunching effect that takes place in S^p increases both the delay of trains initially affected by the disturbance and their load. Since the delayed train is more crowded, travel time is higher penalized as depicted in figure 4.15. The waiting time, on the other hand, presents less intuitive results. The average waiting time for S^p and a S^c scenarios with the same disturbance is rather similar. When a train is delayed, passengers waiting for the next train can board the present one, which reduces their expected waiting time. If passengers arrived at a station at a fixed arrival rate, this would still yield a higher average waiting time. However, in this case, a demand profile is used rather than a steady arrival rate. This includes peaks of demands. In this way, for instance, the discrete influx of transfer passengers at transfer stations is modelled. If this shorter waiting time benefits sufficient passengers, it can out weight the increase in waiting time for others when calculating the average. Moreover, extremely long waiting times are not penalized in the way in which extremely crowded in-vehicle time is. This means that even if the standard deviation of waiting time was higher, the average would remain the same.

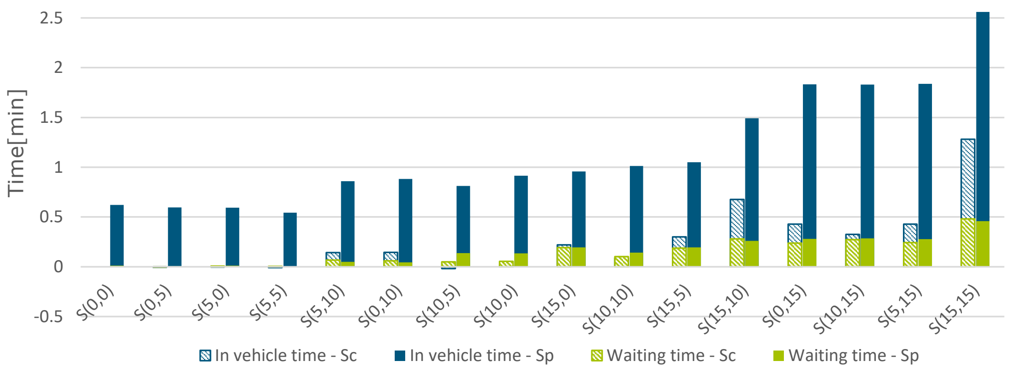
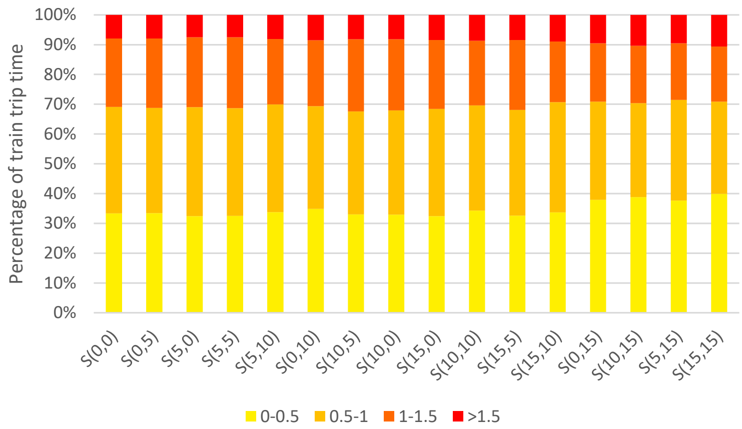
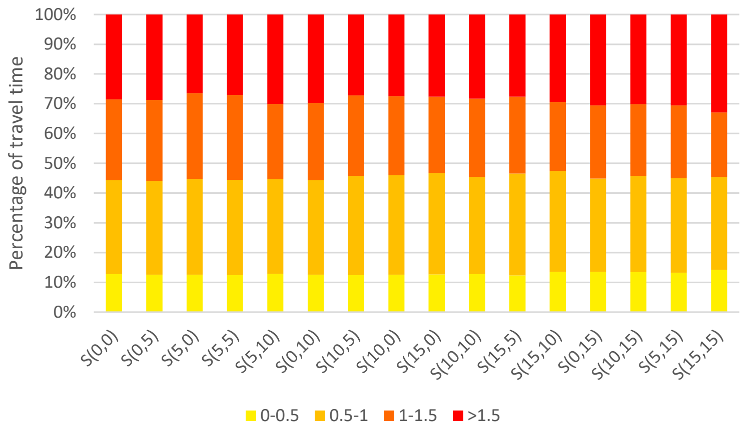


Figure 4.19: Travel time per scenario

The crowding levels, partly responsible for the differences in the in-vehicle time between S^p and S^c scenarios, are represented in figure 4.20b. These bar charts show the percentage of the total passenger travel time corresponding to different crowding levels. As can be seen, passengers in S^p scenarios travel in more congested conditions, which impacts directly the total perceived in-vehicle time. This is in line with the concept that vehicle bunching leads to a more uneven distribution of vehicle load, in which more people travel in crowded vehicles and fewer travellers board trains that are almost empty.



(a) S^c scenarios



(b) S^p scenarios

Figure 4.20: Percentage of total travel time in different crowding conditions according to the load factor for each scenario

4.3.2. Train Rescheduling Model (TRM) experiments

The train rescheduling model includes both passenger and operator perspective. The weights of its multi-objective function indicate where the emphasis lies when rescheduling the timetable. To explore the impact of different types of objectives, 20 experiments, summarized in table 4.6, are performed. These experiments consist in alternatively modifying the parameters, β_w, β_i, β_a and β_t (corresponding to the waiting time, the in-vehicle time, the train delay at all stations and the train delay at the terminal station). Simulation scenario $S^p_{(10,0)}$, described in section 4.3.1, is run until 7:40, time in which the imposed disturbance ends. This delay scenario is chosen because in scenarios with smaller disturbances, train headways allow recovering most of the delays without incurring into secondary delays, even without a rescheduling strategy. Scenarios with more severe disturbances, on the other hand, cause a bunching of vehicles such that it may over restrict rescheduling possibilities. After running $S^p_{(10,0)}$ until 7:40, the timetable is rescheduled with a horizon of 1 hour and 20 minutes (from 7:40 to 9:00).

As a benchmark, simulation scenario $S^p_{(10,0)}$ is run for the horizon, using RET strategy to deal with disturbances. This consists of running trains at 100% performance and top speed in an attempt to regain schedule adherence, and it is named R_{RET}. The rescheduling scenarios are named according to the relative importance of the weights in the objective function, being w the waiting time, i the in-vehicle time, a the train delays at all stations and t the train delays at the terminal station. For instance, R_i is the rescheduling objective that only considers in-vehicle time. The weights in $R_{w,i,t}$, on the other hand, consider the descendent order of priority to be waiting time, in-vehicle time and train delays at the terminal station.

Table 4.6: Weights specification per rescheduling objective

	Weights			
Objective label	Waiting time β_w	In-vehicle time β_i	Train delays at all stations β_a	Train delays at terminal β_t
R_t	0	0	0	1
R_a	0	0	1	0
R_i	0	1	0	0
R_w	1	0	0	0
$R_{w,i,a}$	1	2/3	1/3	0
$R_{w,a,i}$	1	1/3	2/3	0
$R_{w,i,t}$	1	2/3	0	1/3
$R_{w,a,t}$	1	0	2/3	1/3
$R_{w,i}$	1	2/3	0	0
$R_{i,w,a}$	2/3	1	1/3	0
$R_{i,a,w}$	1/3	1	2/3	0
$R_{i,t,w}$	1/3	1	0	2/3
$R_{a,w,i}$	2/3	1/3	1	0
$R_{a,i,w}$	1/3	2/3	1	0
$R_{a,w,t}$	2/3	0	1	1/3
$R_{a,i,t}$	0	2/3	1	1/3
$R_{t,w,i}$	2/3	1/3	0	1
$R_{t,a,w}$	1/3	0	2/3	1
$R_{t,i,w}$	1/3	2/3	0	1
$R_{t,a,i}$	0	1/3	2/3	1

The schedule obtained for each objective is evaluated by comparing its performance with that of the benchmark case in four performance indicators:

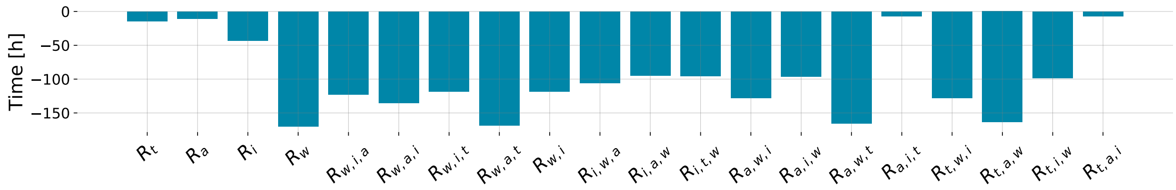
- The total passenger waiting time
- The total perceived in-vehicle time of passengers
- The total train delays at all stations
- The total train delay at terminal stations

These indicators are calculated for each rescheduled timetable. The results are summarized in table 4.7.

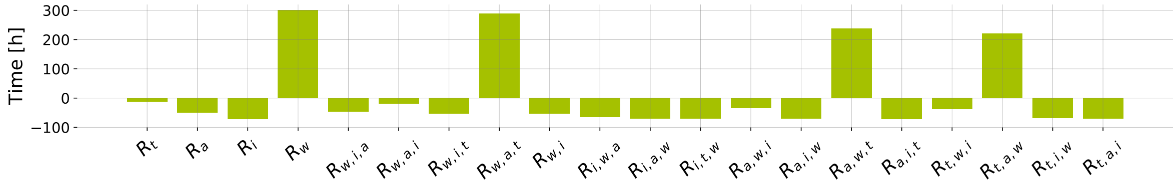
Table 4.7: Results of the TRM experiments

	Waiting time [h]	**In-vehicle time [h]**	**Delays at all stations [h]**	**Deviations at terminal [min]**	**Objective value [h]**	**Benchmark value [h]**
R_{RET}	671.3	4091.1	13.3	1.1	-	-
R_t	656.9	4079.7	3.9	1.0	0.017	0.019
R_a	660.9	4040.8	3.7	1.4	3.717	13.308
R_i	627.9	4020.2	14.9	1.5	4020.217	4091.140
R_w	501.5	4392.0	24.2	2.5	501.523	671.348
$R_{w,i,a}$	548.5	4045.9	13.3	1.5	3223.185	3375.892
$R_{w,a,i}$	536.3	4072.4	13.1	1.6	1888.836	2030.207
$R_{w,i,t}$	553.2	4038.2	17.0	1.6	3218.392	3371.506
$R_{w,a,t}$	502.6	4380.8	21.7	2.4	516.915	680.137
$R_{w,i}$	553.2	4038.2	17.0	1.6	3218.383	3371.500
$R_{i,w,a}$	565.3	4026.2	12.4	1.5	4403.449	4538.621
$R_{i,a,w}$	576.6	4021.2	11.3	1.4	4218.903	4321.468
$R_{i,t,w}$	575.7	4021.1	13.2	1.4	4211.129	4312.697
$R_{a,w,i}$	543.6	4057.2	12.1	1.6	1709.715	1806.474
$R_{a,i,w}$	575.1	4021.7	11.3	1.5	2855.449	2935.005
$R_{a,w,t}$	505.7	4328.5	19.0	2.3	352.782	456.404
$R_{a,i,t}$	664.4	4020.3	4.3	1.4	2657.697	2713.467
$R_{t,w,i}$	543.6	4053.2	15.8	1.6	1696.377	1793.184
$R_{t,a,w}$	507.7	4312.5	17.9	2.2	179.365	230.347
$R_{t,i,w}$	573.0	4022.3	12.6	1.4	2843.851	2921.715
$R_{t,a,i}$	664.4	4020.3	4.3	1.4	1329.551	1358.878

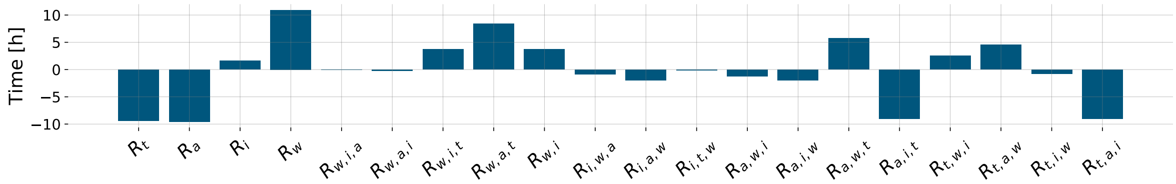
The difference in the indicators with the benchmark case is visualized in figure 4.21. There is a significant difference in the time axis scales between these graphs. The graphs related to passenger travel time have a much larger scale than the graphs indicating train delays. This is because the number of passengers waiting and on board of trains already act as weights for the waiting and in-vehicle time. As a consequence, if β_w or β_i have any value above 0, the objective of the rescheduling becomes heavily inclined towards the passenger side. For this reason, all objectives, except R_w, $R_{w,a,t}$, $R_{a,w,t}$ and $R_{t,a,w}$ (in which β_i is 0), yield less in-vehicle time than the benchmark.



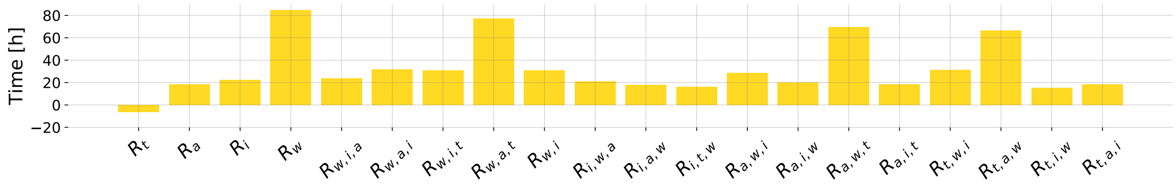
(a) Waiting time



(b) In vehicle time



(c) Delays at all stations



(d) Delays at terminal stations

Figure 4.21: Difference with the benchmark for each objective

A common strategy observed when β_w is predominant in the objective, is to steer the timetable towards more even intra-lines headway in the stretch between Slinge and Rotterdam Centraal, and between inter-line headway before and after the stretch. This is achieved by alternatively postponing and advancing the first departure of line D, and then slowing down the advanced trains between Rhoon and Slinge. A similar approach is employed with line E, advancing the train schedule for the stretch between Slinge and Rotterdam Centraal and then delaying some of the trains. However, the latter is adopted with less frequency. As an example, some of these strategies can be seen in figure 4.22, which presents the time-distance diagram for the benchmark case and the resulting schedule of $R_{w,a,t}$. A milder version of this approach is used when β_a is the highest. The time required for passenger exchange in the benchmark scenario act as a lower bound for the dwell time at stations. Therefore, advancing the first departure of trains that will be delayed due to this excessive dwell time, is a valid approach. This explains why the waiting time is lower than the benchmark for all objectives. Conversely, the only case in which the delays at terminal stations decrease is in R_t, where β_t is the sole weight in the objective. Due to the small scale handled in the delays at the terminal station, this objective gets easily overridden by any other weight in the objective function. Overall, the TRM fulfils the purpose it is designed for: it can be calibrated to reschedule a timetable from a passenger perspective, having the operators perspective as a secondary objective. If the order of priorities is reverted, β_a or β_t has to be adjusted to a significantly higher order of magnitude than β_w and β_i.

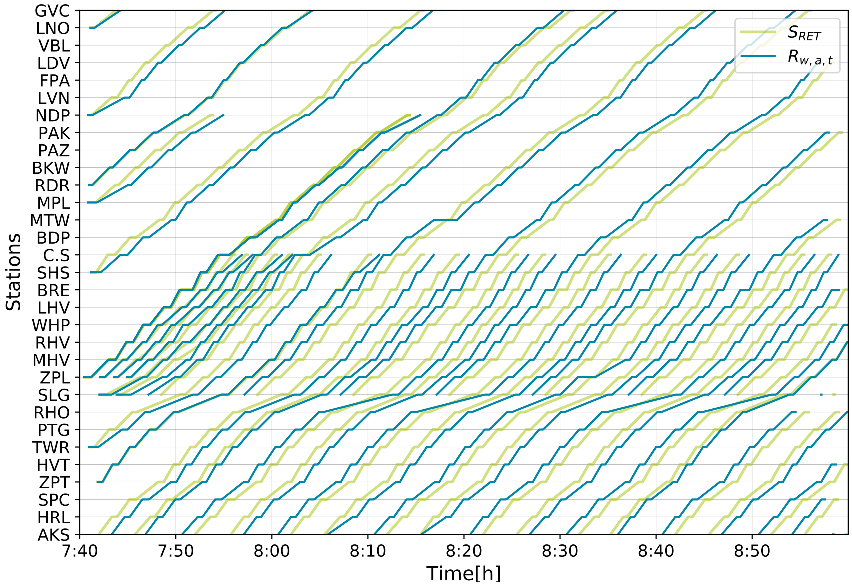


Figure 4.22: Overlapped Time-distance diagrams of R_RET and the $R_{w,a,t}$

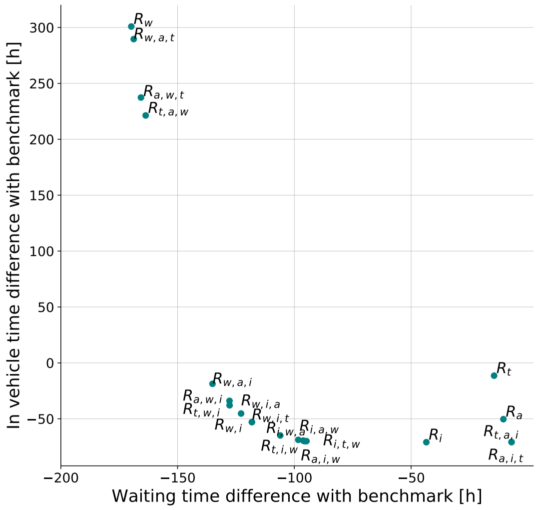
In the case of the in-vehicle time, R_{RET} already has a high performance. Technically, the minimum in-vehicle time achievable if the passenger allocation is fixed consists of running the stretches at the highest possible speed, which is the strategy performed in the benchmark scenario. However, this strategy leads to conflicts in some stretches. When the headway with the predecessor is too small, trains have to stop or slow down, which leads to a longer running time that translates into a higher in-vehicle time. The approach adopted by TRM is to slow trains with a short headway with their predecessor on the first stations of the trip, where the train load is smaller. These create a longer headway that enables the train to speed up in subsequent stretches, where the train load is higher. As a result, in-vehicle time of the more crowded segments is lowered in detriment of the travel time in segments with less trainload.

The results obtained suggest that rescheduling a timetable based on schedule adherence is not necessarily more beneficial to the passenger. Figure 4.23 presents a scatterplot of the performance of the schedules according to the different objectives for both passenger and operator perspective. Figure 4.23b presents some correlation between the two objectives related to the operator. This is because the delays at the terminal station are included in the objective that seeks to minimize all station delays.

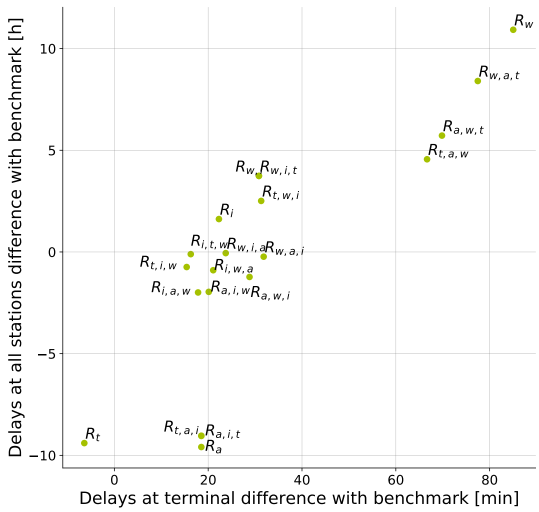
Conversely, figure 4.23a does not present a correlation between both passenger related objectives, but it rather shows the trade-off between waiting and in-vehicle time, resembling the Pareto frontier. This is a conventional outcome of a multi-objective optimization, in which improving the performance under one criterion worsens the performance on another.

Schedules that minimize the waiting time often increase the in-vehicle time. Objectives $R_{w,i,t}$ and $R_{w,i}$ yield the highest combined waiting and in-vehicle time reduction as compared with the benchmark. These two objectives, in fact, yield the same rescheduling solution, since the magnitude of the passenger related terms in the objective function override the β_t included in $R_{w,i,t}$. As can be seen, the rescheduled timetable based on these objectives, lead to an increase in train delays.

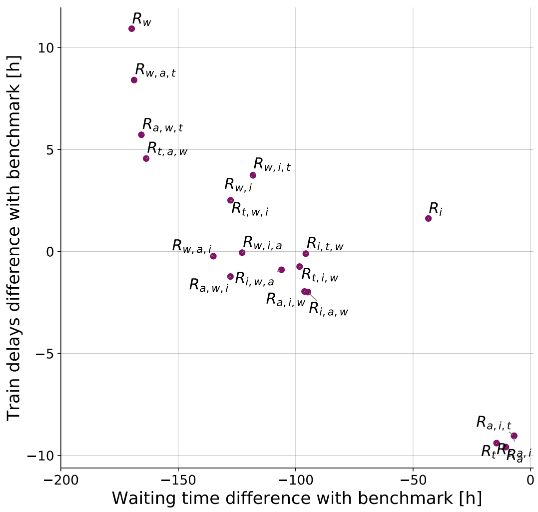
With regards to the trade-off between operator and passenger, figure 4.23e presents a scatter plot of the reduction in total travel time of passengers versus the reduction in train delays at all stations as compared to R_{RET}. For a more disaggregated view, figures 4.23c and 4.23c present scatter plots of the train delay reduction versus the in-vehicle time reduction and the waiting time reduction respectively. Perhaps the most visible feature is that the distribution of datapoints in figure 4.23e resembles that of 4.23d, with a shift of around 130 hours decrease in the x-axis. This is because the scale handled in the in-vehicle time is approximately twice the scale of the waiting time. The difference in scales relates to the crowding factor that multiplies the in-vehicle time and the fact that passengers spend most of their travel time inside the vehicle rather than waiting for it. Figure 4.23c shows the Pareto frontier for train delays and waiting time reduction. The rescheduling strategies that yield the highest waiting time reduction are those that include β_w but exclude β_i from the objective function. This is explained by the difference in scales between both passenger-oriented objectives, that leads to a dominance of in-vehicle time over the waiting time unless the weights of the objective function are tweaked accordingly. The rescheduling strategies that yield the smallest waiting time reduction are those in which β_w is 0. It is remarkable that some of the rescheduling strategies that have β_t larger than 0 still yield a deterioration in schedule adherence. This is once again due to the difference in scales. The waiting time factor has a much larger scale than the train delays. Therefore, if β_w is larger than 0, the train delay factor is easily overridden. An example of this case is $R_{t,a,w}$. In spite of β_t being the largest parameter, this rescheduling strategy results in a higher train delay in favour of a decrease in the waiting time. Despite the dominance of passenger-oriented objectives over schedule adherence objectives, it seems that the train delay reduction is less conflicting with the in-vehicle time reduction than with waiting time. This means that improving the schedule adherence does not have much impact on the in-vehicle time reduction. As a matter of fact, R_a yields 50 hours reduction of the in-vehicle time compared to R_{RET}. This is because lowering the in-vehicle time is done by speeding up trains, particularly when they are crowded, regardless of their departure time. When β_a is included, the departure times of trains are changed, as long as their trip time is not modified. This means that the entire journey of a train is shifted to better suit the original schedule.



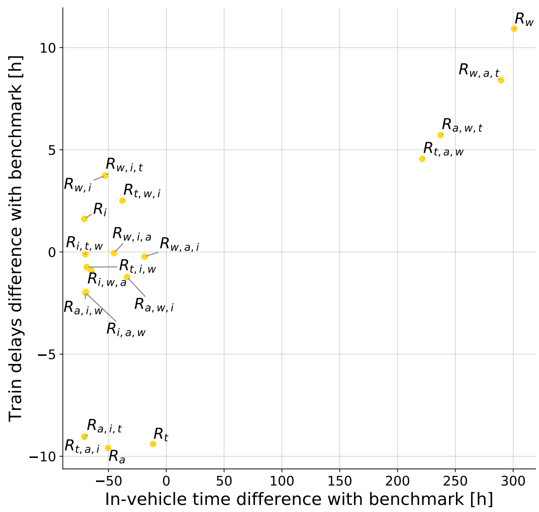
(a) In vehicle time reduction vs. waiting time reduction



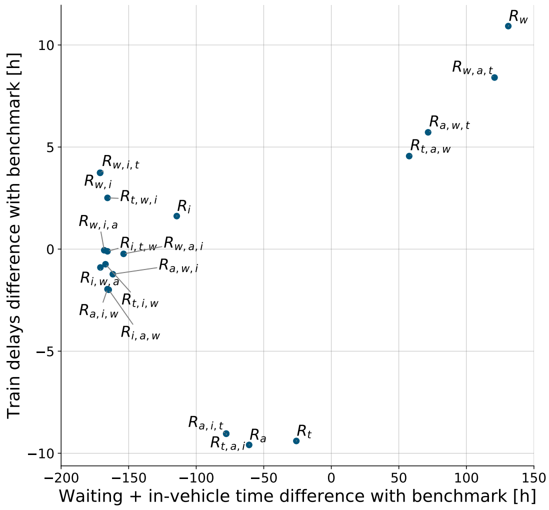
(b) Delays at stations vs. delays at terminal reduction



(c) Waiting time reduction vs. delays at stations reduction



(d) In-vehicle time reduction vs. delays at stations reduction



(e) Passenger travel time reduction vs. delays at stations reduction

Figure 4.23: Passenger and operator perspective for each objective

The best set of parameters to run the SBTM-MN depends on the particular objective of the user. If the objective is to lower the impact on passengers without worsening the train delays, an overview of the rescheduling strategies tested suggests that $R_{w,i,a}$ is preferred. This set of parameters successfully lower the in-vehicle and waiting time, and even have a minimal positive impact on schedule adherence. If a strictly passenger-oriented approach is taken, $R_{w,i}$ is recommended. For this set, the gain on the passenger side is higher than for R_5. However, the total delays of train at stations increases. If the passenger perspective is completely disregarded, and schedule adherence is aimed for, R_a is suggested.

4.3.3. Simulation Based Traffic Management for Metro Network (SBTM-MN) experiments

This section explains the practical application of the SBTM-MN model and how to implement it for a real-world case study. Furthermore, it presents preliminary results for two scenarios in which 9 iterations are performed. Since it was not possible to set the first departure time of each train online before the train is created the rescheduled timetable had to be imported manually before the start of the simulation in each iteration. Therefore, the number of iterations is limited due to the low speed required to run the simulation, the manual work involved, and time constraints. It is expected that, throughout the iterative process, the rescheduled timetable reduces the in-vehicle and waiting times for the considered horizon, since it is a passenger-oriented rescheduling objective.

For this experiment, the TSM-RW is run from the start of daily operations until 7:40:00 with the demand pattern mentioned in section 4.2.1 for Tuesday the 5th March 2019. Two disturbance scenarios are tested, $S^p_{(0,0)}$ and $S^p_{(10,0)}$. At 7:40:00, the SBTM-MN is triggered. The train and station occupation, as well as the realised events, are reported from the TSM-RW to the SBTM-MN. The prediction horizon is set for an hour, until 8:40:00. The first simulation of the TSM consists of running the trains at 100% and top speed and trying to stick to the original RET schedule. This run is denominated I_{RET}. The values of total waiting time and total perceived in-vehicle time are used as a benchmark for further iterations. The parameters of the TRM are the explained in section 4.2.2, with weights $\{\beta_w, \beta_i, \beta_a, \beta_t\} = \{1, 2/3, 1/3, 0\}$. These values correspond to $R_{w,i,a}$, which is the set of parameters recommended for a passenger-oriented rescheduling that has operator's preferences as a secondary objective. The stepsize allowed from iteration to iteration, u, is of one minute.

The results of each iteration in terms of passenger travel time, in-vehicle time. deviation from arrival to the terminal station and departure deviation at all stations are shown in Table 4.8. Table 4.8a shows the results when SBTM-MN is applied in disturbance scenario $S^p_{(0,0)}$, whereas table 4.8b presents the results for disturbance scenario $S^p_{(10,0)}$. These tables are divided in two sections, one corresponding to the values estimated by the TRM and one with the realised values when the derived timetable is run in the TSM. The difference between the estimated and the realised values for each iteration is due to the passenger reallocation. Within the TRM, passenger allocation is static because passenger movements are not modelled in this environment. The TRM computes an optimal timetable for a given passenger allocation, assuming that passengers do not board different trains. Therefore, the TRM can only estimate the value of the rescheduled timetable, under the assumption of static passenger allocation. However, when the timetable is run in the TSM, passengers are re-distributed in the trains according to their new arrival and departure times. Within the TRM, for example, it might seem a suitable strategy to delay a train that is crowded to run it faster. However, when passengers are reallocated, the train has a higher load. This means that, although the trip time of the train might be lower, the perceived travel time of passengers is higher due to an increase in the crowding levels. Passenger-train interaction might also have an impact on the realisation of the timetable. For instance, if the number of passengers boarding a train increases significantly from one iteration to the other, the rescheduled dwell time might not suffice, which would lead to a delay in the departure time of the train.

Table 4.8: Values of each iteration performed

(a) Values obtained for a scenario without disturbance $S^p_{(0,0)}$

	Estimated by the TRM					**Realised in though the TSM**				
	Waiting time [h]	**In-vehicle time [h]**	**Deviation at terminal [h]**	**Deviation from all departures [h]**	**Total cost [h]**	**Waiting time [h]**	**In-vehicle time [h]**	**Deviation at terminal [h]**	**Deviation from all departures [h]**	**Total cost [h]**
I_{RET}						484.33	2620.16	0.25	3.26	2232.19
I_1	447.07	2606.18	0.38	4.56	2186.04	480.63	2646.59	0.43	4.96	2246.67
I_2	458.08	2653.73	0.48	5.12	2228.94	475.25	2632.82	0.53	5.59	2232.32
I_3	457.15	2609.29	0.64	6.26	2198.76	478.23	2642.70	0.58	6.17	2242.08
I_4	464.28	2620.57	0.66	6.29	2213.43	473.38	2616.64	0.64	6.34	2219.92
I_5	458.88	2596.91	0.78	6.68	2192.38	465.75	2597.23	0.74	6.54	2199.42
I_6	448.54	2577.62	0.92	7.60	2169.49	464.83	2600.38	0.78	6.78	2200.67
I_7	450.85	2579.36	0.89	7.05	2172.77	455.00	2569.61	0.86	7.00	2170.40
I_8	437.54	2543.15	0.98	7.57	2135.50	451.43	2557.62	1.01	7.72	2159.09
I_9	**436.62**	**2531.33**	**1.04**	**7.80**	**2126.77**	**447.05**	**2537.31**	**0.99**	**7.67**	**2141.14**

(b) Values obtained for a scenario with a 10 minute disturbance in Zuidplein $S^p_{(10,0)}$

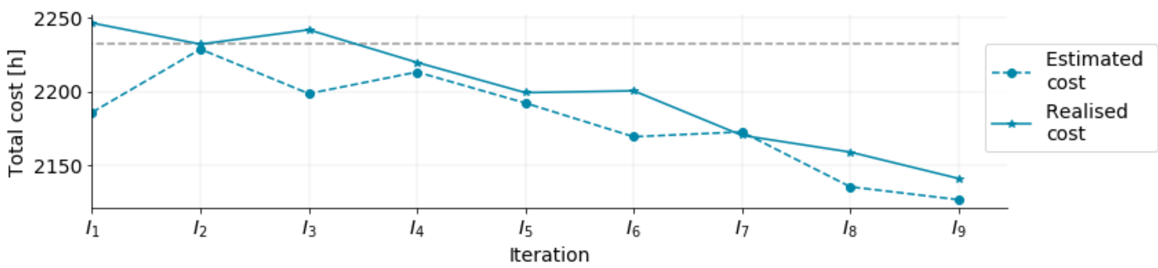
	Estimated by the TRM					**Realised in though the TSM**				
	Waiting time [h]	**In-vehicle time [h]**	**Deviation at terminal [h]**	**Deviation from all departures [h]**	**Total cost [h]**	**Waiting time [h]**	**In-vehicle time [h]**	**Deviation at terminal [h]**	**Deviation from all departures [h]**	**Total cost [h]**
I_{RET}						509.43	2798.51	1.04	12.22	2379.18
I_1	478.62	2744.82	0.97	12.23	2312.58	504.29	2781.44	1.08	13.05	2362.94
I_2	483.77	2748.27	1.08	12.39	2320.08	499.28	2769.29	1.17	13.20	2349.87
I_3	483.13	2735.09	1.19	12.71	2310.76	506.80	2822.20	1.28	13.52	2392.77
I_4	**485.12**	**2781.67**	**1.30**	**13.49**	**2344.07**	**492.10**	**2765.59**	**1.37**	**14.23**	**2340.57**
I_5	477.34	2716.41	1.43	13.99	2292.94	501.39	2811.41	1.50	14.80	2380.60
I_6	482.33	2766.50	1.52	14.93	2331.64	490.90	2772.26	1.58	15.96	2344.39
I_7	476.84	2721.28	1.56	15.27	2296.11	497.75	2785.26	1.64	16.10	2359.96
I_8	477.79	2740.05	1.58	15.77	2309.75	490.63	2763.62	1.70	16.95	2338.70
I_9	476.50	2712.83	1.58	15.58	2290.25	504.19	2813.93	1.69	16.65	2385.69

The estimated and realised total cost presented in table 4.8 was calculated by replacing the waiting time (W), the in-vehicle time(I), the deviation from the time of arrival at terminals (T) and the deviation from departures at all stations(A) in the following equation:

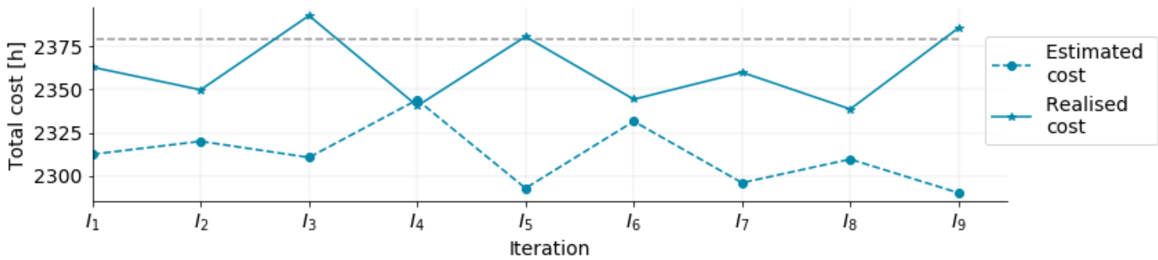
$$Cost = \beta_w * W + \beta_i * I + \beta_a * A + \beta_t * T \tag{4.1}$$

Figure 4.24 presents a visualization of the total costs throughout iterations, where the mismatch between realised and estimated costs due to passenger re-allocation is visible. The cost for the benchmark case, I_{RET} is depicted as a grey horizontal dashed line. For scenario $S^p_{(0,0)}$, I_9 yielded the best results, whereas for scenario $S^p_{(10,0)}$, the best timetable is considered to be the one obtained in I_4. This is because, although I_8 provides a lower cost than I_4, the difference is minimal, and I_8 requires more iterations and higher deviation from schedule, which may affect future events outside of the considered time frame.

In all cases, the estimated cost of a schedule is higher than the realised once passengers have been distributed accordingly. Moreover, there is a fluctuation in the cost of the timetable throughout the iterations. There are many reasons why this fluctuation occurs. Firstly, the mentioned passenger re-allocation that causes a mismatch between expected and realised results. Secondly, the SBTM-MN does not 'learn' from iteration to iteration. Instead, each realised timetable is a starting point for the TRM to compute a new one, without contemplating how previous timetables performed in the TSM. Another aspect that adds to this fluctuation is that, although the same variables are considered from iteration to iteration, this does not ensure that the number of passengers remains the same. Indeed, if the last arrival at a station in the framework is delayed in an iteration, more passengers are captured at this station in the next iteration. The opposite occurs if the last arrival at a station is advanced. Figure 4.24 shows that, in the case of $S^p_{(0,0)}$ the decrease in costs is higher than for $S^p_{(10,0)}$, whereas the latter presents more fluctuation between iterations. This is because in the case of $S^p_{(0,10)}$, after the disturbance ends, trains are stacked one after the other, which leaves less room to modify their arrival and departure times.



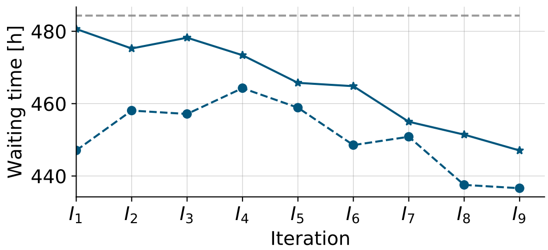
(a) Total cost for iterations for scenario $S^p_{(0,0)}$, dashed grey line represents the cost of I_{RET}



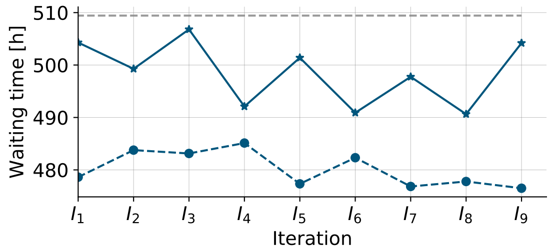
(b) Total cost for iterations for scenario $S^p_{(10,0)}$, dashed grey line represents the cost of I_{RET}

Figure 4.24: Visualization of estimated and realised total cost per iteration

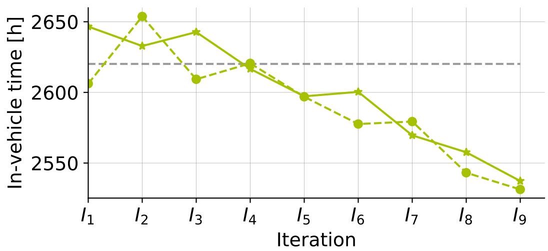
Figure 4.25 shows the evolution of the components in the objective function throughout the iterative process for both disturbance scenarios under study. Figures 4.25a and 4.25b show that all iterations, for both cases, yield less waiting time than I_{RET}. Once again, the fluctuating behaviour is evident in the case of $S^{p}_{(10,0)}$. In the case of in-vehicle time, figures 4.25c and 4.25d show that, in some cases, the in-vehicle time was higher than that of I_{RET}. Figure 4.25d shows that, in I_4, the realised in-vehicle time is lower than the expected. This suggests that passenger re-allocation can be favorable for the crowding levels, although not by design. This, in turn, decreases the perceived in-vehicle time. In general, given a static passenger allocation, the only strategy to lower in-vehicle time is to run trains as fast as possible, since the train loads cannot be modified. In order to decrease the waiting time, the TRM changes the departure and arrival time of trains, and might even shift a whole train trip. This has consequences in the crowding levels, which can be either detrimental or beneficial to the in-vehicle time. However, this is not foreseen within the TRM environment. Figures 4.25e and 4.25f show a steady increase in the deviation of from departures at all stations. This is reasonable, as the rescheduling strategy is heavily oriented towards passenger perspective.



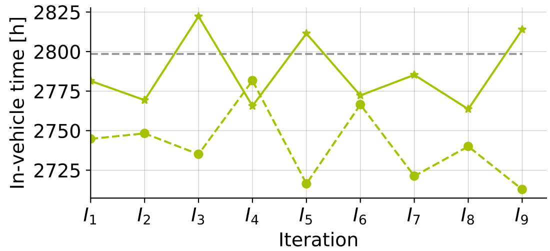
(a) Waiting time for iterations in scenario $S^{p}_{(0,0)}$



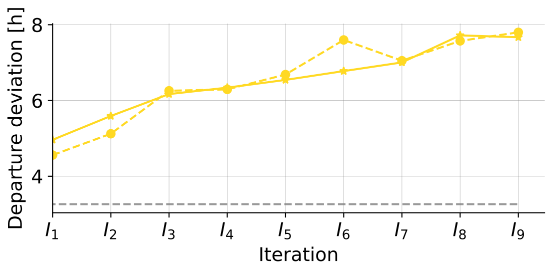
(b) Waiting time for iterations in scenario $S^{p}_{(10,0)}$



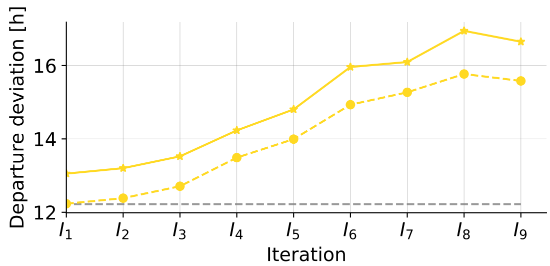
(c) In-vehicle time for iterations in scenario $S^{p}_{(0,0)}$



(d) In-vehicle time for iterations in scenario $S^{p}_{(10,0)}$



(e) Deviations from departure for iterations in scenario $S^{p}_{(0,0)}$



(f) Deviations from departure for iterations in scenario $S^{p}_{(10,0)}$

Figure 4.25: Evolution of the components of the objective function through the iterations

Figure 4.26 shows the time-distance diagrams corresponding to the benchmark and the ninth iteration performed on $S^{p}_{0,0}$, overlapped for comparison. Figure 4.27 presents the overlapped time-distance diagram for the benchmark and the fourth iteration. As expected, the trajectories are shifted towards more even headways. This causes for trains in line D to be often delayed for the sake of the inter-headway in the stretch Slinge-Rotterdam Centraal. The perceived in-vehicle time for line E usually lessens throughout iterations, except for trains that end at Nootdorp. These trains are delayed to lower the crowding in trains in line E that end at The Hague Central and are more crowded. Closer to the end of the prediction horizon, however, all trains are made to depart ahead of the original scheduled time. The reason behind this is the myopic view of the TRM. Certainly, advancing the departure of these trains will negatively affect events later in time, but this effect is not observed. For instance, some passengers that were taking the last but one train in I_{RET} will have to board the last train in the considered timespan instead. This means that in the following iteration, a shorter part of these passenger's trips is considered. As a result, the in-vehicle time may seem to be lower, but in reality, the rest of these passenger's trip is now out of the considered events.

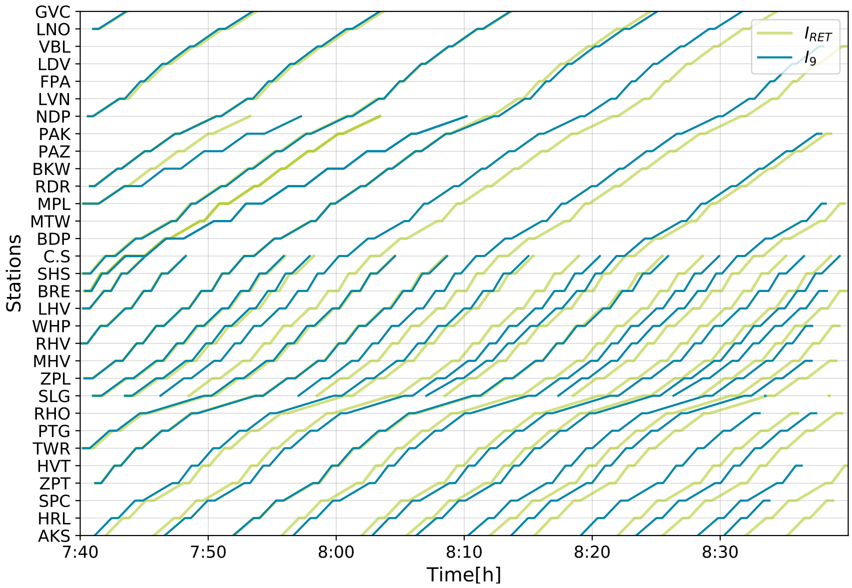


Figure 4.26: Time-distance train diagrams for $S^p_{0,0)}$ for benchmark and iteration 9

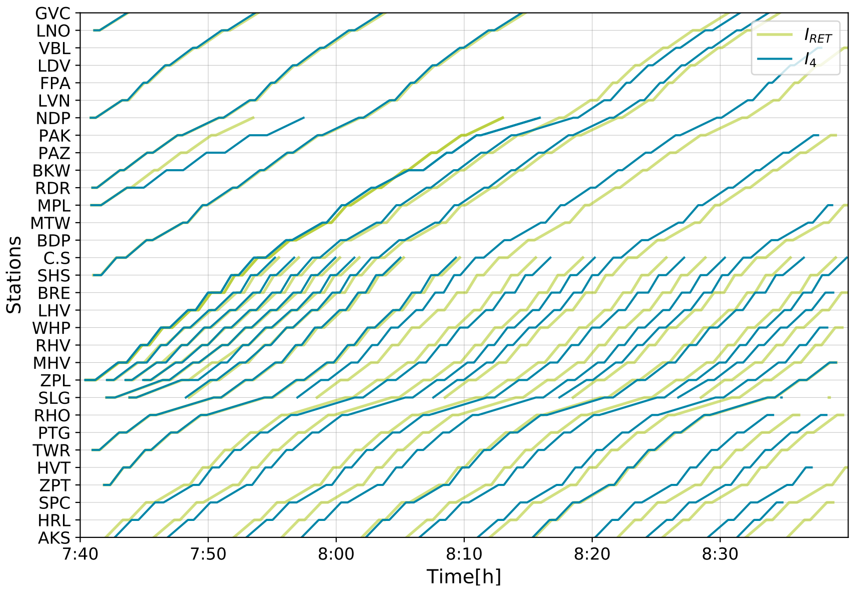


Figure 4.27: Time-distance train diagrams for $S^p_{10,0)}$ for benchmark and iteration 4

5

Conclusions and Recommendations

The objective of this research is to help mitigate the impact of delays when disturbances take place in densely utilized metro networks, whilst including passenger flows and perspective. Currently, the rescheduling of the timetable in these situations still relies on contingency plans or human judgement. In general, these strategies aim at regaining schedule adherence, with a clear perspective on the side of the operator. Furthermore, the impact of the demand in the feasibility of the train schedule is ignored. Additionally, scientific research into metro rescheduling also tends to disregard the repercussion of passenger demand in the train schedule, and in turn, how this affects passengers themselves. Furthermore, most of the research done involves exclusively mathematical models, with a restricted level of detail, which confines the approach to a rather theoretical domain. These mathematical models often require a large set of simplifying assumptions that hinder the representativity of the system in real life. Conversely, a microscopic simulation tool is able to represent infrastructure and train processes with a higher level of detail. As a result, higher accuracy in the evaluation of a timetable is obtained. This research intends to be a step in bridging the gap between scientific research and practical rescheduling, whilst considering passenger movements in the network and planning for them.

To reach this objective, a conceptual framework for rescheduling metro lines, the Simulation-Based Traffic Management for Metro Network (SBTM-MN), is developed. This comprises two models that interact iteratively, the Transport Simulation Model (TSM), and the Train Rescheduling Model (TRM). The TSM integrates a train simulation in OpenTrack, with a passenger module, in order to model passenger-train interactions. The TRM modifies arrival and departure times of trains according to a base schedule and the corresponding passenger allocation. A set of experiments is performed to evaluate the applicability of these models and the framework itself.

The remainder of this chapter is structured as follows: Section 5.1 summarizes the findings of the executed experiments and the answers to the research questions, and section 5.2 introduces the main contributions of this research. Afterwards, the limitations of the modelling approach and the software used are discussed in section 5.3. Finally, section 5.4 proposes lines of future research.

5.1. Answers to research questions

This section presents the answers to the research questions. Since the research sub-questions were crucial to gain supportive knowledge to answer the main research question, they are discussed first.

1. *What is the effect of incorporating passengers in traffic modelling of metro lines on the development of delays?*

   This sub-question is answered by the design of a Transport Simulation Model (TSM), that integrates passenger movements with a train simulation environment. Firstly, a literature study is performed to evaluate how demand affects vehicle processes. This reveals that the dwell time of a vehicle grows with the number of passengers boarding and alighting. Furthermore, the crowding levels of platform and trains influence passenger exchange rates. Higher demand implies additional trips, which translates in more passengers boarding and alighting and increasingly crowded stations and platforms. This leads to a longer dwell time of trains at stations because more time is needed for passengers to alight and board.

Secondly, based on these findings, the TSM is designed. This model integrates the microscopic simulation tool OpenTrack and a passenger module, which is designed and developed to account for passenger movements. These modules interact with one another every time a train arrives or departs at a station. The passenger module modifies the dwell time of trains according to the passenger exchange and levels of crowding whilst keeping track of passenger allocation.

Thirdly, the TSM is run for different disturbance intensities and locations. These scenarios are also run excluding the influence of passengers in the dwell time of trains. By comparing the performance of both types of simulations, it is proven that there is a significant difference in the development of delays when considering passenger-train interactions. Particularly when passenger demand is high, a disturbance can easily trigger bunching effects along a metro line. In this way, delays increase along the trip instead of diminishing by using the buffer time, as expected when passenger movements are neglected. Furthermore, it is shown that the location and time of the triggered disturbance influences the spread of delays. Delays provoked at a stretch where demand is low, may recover if buffer time exceeds the time required for passenger exchange. Moreover, in stretches where headways between trains are sufficiently long, knock-on delays may be avoided. Conversely, when disturbances occur in stretches of high demand and short headways, delays easily spread and affect other trains. This difference in the growth of delays when considering passenger-train interactions directly influences the level of crowding. Excluding the impact of passengers in the dwell time during the simulation of a timetable is likely to underestimate levels of crowding and perceived in-vehicle travel time as a result.

2. *How does the trade-off between passenger and operator perspective influence the recommended rescheduling strategy?*
To answer this sub-question, a Train Rescheduling Model (TRM) that accounts for passenger and operator's perspective is designed. This model optimizes the arrival and departure time of trains for a given passenger allocation and realised timetable. This implies that the re-timing of trains is done by speeding up or slowing down trains and increasing their dwell time. Constraints such as minimum running time, dwell time, and headways between trains are included. Since the objective of the proposed framework relates to the passenger travel experience and the schedule adherence preference from the side of the operator, the objective function minimizes the weighted sum of the following terms:

    - Passenger waiting time: measured as the total waiting time at each station summed up across them. The waiting time at each station is calculated as the average between the passengers waiting when a train arrives and the passengers left behind by the previous train, multiplied by the elapsed time.

    - Passenger in-vehicle time: calculated by multiplying the number of passengers by the time a train takes to run a segment and summed up across trains. This component includes multipliers to account for the level of crowding in vehicles as an aggravating factor in the passenger's perception of the travel time.

    - Deviation from departures at all stations: calculated by adding all the deviations from scheduled departures of all trains at stations. This component represents the inclination of the operator towards schedule adherence.

    - Deviations from arrival at the terminal station. This term might be important to avoid the impact of the rescheduled timetable in the rolling stock schedule. It is calculated by adding the difference in arrival time at the terminal station for all trains that reach the end of their trip within the considered time frame.

Finally, the TRM is run for different weights in the objective function, to observe how the trade-off between perspectives influence the resulting timetable. The model has a strong inclination towards passenger benefit unless explicitly calibrated to cater for the operator's preference. These experiments verify that, when a disturbance occurs, regaining schedule adherence does not necessarily imply the highest benefits for passengers. Furthermore, solely running all trains at 100%performance and top speed may not be the best strategy to minimize the sum of all train delays in the network. If possible, it may be useful to dispatch some trains earlier, when it is known that the high demand will delay the train further on. In cases in which the original timetable runs trains at 100% performance and top speed, there is no conflict between in-vehicle time objective and schedule adherence objectives, as long as passenger allocation remains the same. This is because, given a static load in the train, the smallest in-vehicle time is obtained by running trains as fast as possible, which is done in the original timetable. Objectives related to the waiting time, on the other hand, steer the timetable towards a more evenly distributed headways. This is because the model prioritizes lowering the waiting time (i.e. the headway with the previous train) of trains that have a significant number of passengers boarding. A significant number of passengers boarding coincides with a high headway for a given location and time frame, if an arrival rate of passengers is considered. In this way, the model intends to reduce large headways between trains. If the original timetable has uneven headways, a trade-off between waiting time and operator's perspective arises, in which a timetable that lowers waiting time of passenger might hinder schedule adherence, and vice-versa.

3. *How does dynamic passenger allocation impact the effectiveness of a rescheduling strategy?* In order to answer this sub-question, a framework is designed, in which, in every iteration,a schedule derived by the TRM is run in the TSM. The TRM calculates the optimal timetable for a given passenger allocation. However, once the arrival and departure of trains are modified, the passenger allocation changes accordingly. This means that once the resulting timetable is applied, the cost might be different than the estimated by the TRM.

   The preliminary results obtained from running nine iterations of the SBTM-MN in two disturbance scenarios in the case study showed the importance of considering passenger allocation when rescheduling a timetable. The reallocation of passengers in each iteration heavily influences the performance of the rescheduled timetable. In particular, reallocation of passengers might create a different level of loads in trains. Since crowding is heavily penalized, the effect of this reallocation is amplified. For instance, the TRM shifts a whole train trip later in time in order to lower the waiting time of the following train. When considering static passenger allocation, delaying the whole trip would yield the same in-vehicle time. However, when the new timetable is in the TSM, the load in the delayed train increases. If the train was already busy, the crowding multipliers severely penalize the increase in load. This effect is not foreseen by the TRM because passenger flows are not modelled within its environment. The results of these experiments suggest that a more integrated approach is required if the development of an optimal scheduled is pursued.

These conclusions served as the basis to answer the main research question: ***Considering a disturbance in a metro network, what is the effect of passenger demand on the performance of the timetable and what is the recommended rescheduling strategy for passengers and operator?***

The framework developed and the experiments performed suggest that passenger demand has a significant effect on the performance of a timetable. Neglecting the passenger-train interactions (i.e. the influence of passenger exchange in the dwell time of a vehicle) severely underestimates the vehicle delays. As a consequence, the crowding levels and perceived in-vehicle time are also undervalued. With regards to the recommended rescheduling strategy, all scenarios of the numerical experiments in which the priority was to cater for passenger travel experiences, steering the timetable towards more even headways, rather than towards schedule adherence, seemed beneficial to passengers. However, the rescheduling strategy depends on the location of the initial disturbance and the demand pattern. Overall, rescheduling strategies that attempt to reduce perceived travel time should include the modelling of passenger-train interaction and take into account on-board crowding. Neglecting these factors would lead to a significantly different rescheduling decision, suitable only for a scenario where the dwell time is completely independent of the passenger exchange, for instance, where the scheduled dwell time surpasses the time required for passenger exchange. These cases could arise, for instance, when the demand is significantly low. Although this research represents a significant step in the inclusion of passenger-train interaction and passenger perspective, further integration is recommended to achieve more suitable rescheduling strategies.

5.2. Main contribution

In the field of real-time rescheduling for metro systems, there is an on-going shift towards passenger perspective. Authorities and operators consider passenger travel experience as one of the cornerstones of public transport service. However, passenger-based rescheduling in metro systems is still a recent research area. Some studies have taken passenger benefit as the main rescheduling objective. Nonetheless, this is rarely combined with a detailed modelling of dwell time as a function of passenger demand. Furthermore, most studies take an exclusively mathematical approach, often based on the macroscopic modelling of the network. This tends to be a rather theoretical approach because of all the assumptions necessary to solve the problem with a reasonable computation time. To the best of the author's knowledge, this is the first study that combines passenger-oriented metro rescheduling with a microscopic simulation tool that considers passenger influence on disturbances and keeps track of passenger allocation.
There main scientific contributions of this study are:

- A conceptual simulation-based rescheduling framework for metro lines (SBTM-MN). Although this framework needs further development to be suited for real-time rescheduling purposes, it could already be used to adjust the base timetable at a planning stage by including a passenger-oriented perspective.
- The development of a transport simulation model (TSM) that combines a commercial microscopic simulation tool with a passenger module, being able to track passenger allocation and represent the impact of demand on dwell times of trains.
- The development of a passenger-oriented rescheduling model (TRM) that includes passenger level of comfort in the generalized cost function according to the level of crowding in trains.
- Experiments performed on lines E and D of the Rotterdam metro network using real APC and AVL data from days between the 4th and the 17th of March, 2019. These experiments provide insights into the performance of the model. Additionally, they allow visualizing how neglecting passenger perspective and their influence in the feasibility of the timetable can potentially lead to radically different results.

5.3. Limitations

The time limitations to perform this research have narrowed its scope and compelled the modeller to make several assumptions that constrain the utilization of the model. These were mentioned in the description of the derivation and implementation of the model, and are summarized in this section.

- The model assumes the availability of in-vehicle and station occupation in real-time. Although APCs currently provide the tap in and out of passengers, this is done per station and does not indicate, in real-time, which vehicle the passenger will board. The destination of passengers and the boarded vehicle would have to be estimated based on historical data. Moreover, as indicated by Morriea-Matias and Cats (2016), APC is seldom transmitted real-time. For the application of the SBTM-MN, the system in place needs to be adjusted to provide measures in real-time. The estimation of station occupation could be improved with the help of cameras, and the vehicle occupation could be determined by sensors. Moreover, an accurate and thorough collection of historic data on passenger movements and the corresponding dwell time of trains is essential for the calibration of the TSM.
- The model only includes a rather narrow set of interactions between lines that might share rails or rolling stock. Crew scheduling and rolling stock scheduling are neglected, apart from the turnaround at stations. Besides, interactions with other lines on a network are not taken into account. It would be necessary to adjust the model to use it for a network or two lines that have a further interaction besides turnaround at final stations.
- Passengers are assigned at the arrival time of a train, which is a debatable choice that has been done to simplify the model. Generated passengers between arrival and departure are not accounted for, since these would in turn influence the departure time itself. This modelling choice tends to underestimate the number of passengers boarding, and the consequent dwell time and train load.
- Denied boarding is neglected, as capacity constraints are not modelled. If the demand is sufficiently high, this might lead to unrealistically high loads in trains that are considerably delayed and a lower load on following trains.

- A short prediction horizon in the TSM might lead to a myopic view of the performance of the rescheduled timetable. However, using a long prediction horizon would deteriorate the prediction quality. This is a trade-off that the user of the model has to carefully consider.
- The model is deterministic, whereas there are stochastics to be found in real life, particularly considering the influence of passengers. For instance, the dwell time and running time of a vehicle could be better represented if stochastics were included.
- One particular problem is that the communication between the simulation in OpenTrack and the passenger module tends to lag, causing unfounded disturbances in the train simulation. For example, if the communication is too slow, the departure command from the passenger module might get to the train module after the assigned departure time. The train cannot depart until this command is received. If this occurs after the assigned departure time, the train departs later than it should, thus inducing a disturbance. This forces the TSM to be run at a speed of ten times real-time, to minimize the chances of inadvertently including a delay in the departure of trains. Furthermore, it was not possible to set the first departure of trains online from the start of the TSM, although the feature is supported by the API of OpenTrack. This means that each time a rescheduled timetable needs to be implemented, it has to be done manually by importing the data file to OpenTrack. The amount of manual work done makes the iterative process prone to mistakes and limits the number of iterations attainable with reasonable time and effort.

5.4. Future research

The present study has fulfilled its objective by developing a conceptual framework and models that include the dynamic interaction of passengers and vehicles, their impact in metro disturbances, and timetable rescheduling for the passenger benefit. Furthermore, it paves the way towards passenger-oriented simulation-based real-time optimal rescheduling through an iterative approach.

Notwithstanding, there are crucial aspects in which the model should be further developed to be useful in real-time operations. This section discusses possible improvements, based on the limitations presented in section 5.3. Furthermore, it proposes ideas for the enhancement of the model, which would expand its functionalities.

Firstly, the computational efficiency of the model has a severe impact on the practical applicability of the model. Not only the coding of the different models could be refined, but the communication of the passenger and train modules through the API has to be upgraded. If a practical usage of the SBTM-MN is intended, it is crucial to minimize the manual work required for each iteration. Reducing human labour and computational time would allow for more iterations and the performance of the model itself could be better assessed.

Secondly, there are many areas in which the model could be expanded. For instance, it could be adapted to be used in networks with the same flexibility as it can currently be used in lines. The SBTM-MN can technically be used for networks as long as no transfer is performed and the operation of lines are independent, except for the turnaround at the end station. However, this might not be the case in real-life. For instance,cases in which a third rail track is present, or a train is scheduled to switch tracks with the opposite direction for a stretch. This would require to model any interaction between lines in the TRM as well as in the TSM. Currently, interactions between trains are modelled in detail in the TSM, but not in the TRM. This is because the TSM is a microscopic model, whereas the infrastructure is modelled at a macroscopic level in the TRM. If potential points for conflicts between different lines and directions are not modelled in the TRM, this will provide timetables that are not feasible or stable at the microscopic level of the TSM. Moreover, including transfers between lines would make possible to have trips instead of rides as inputs. Furthermore, capacity constraints in the vehicles could be included to achieve more realistic results. Stochasticity could be included in SBTM-MN to better represent real-world processes. Other passenger-oriented terms, related to unreliability, such as the standard deviation of the waiting time, could be included in the objective function of the TRM.

Thirdly, the model could be applied at a tactical level to improve a base scheduled with a more demand-responsive approach. This would imply using a representative demand pattern for a weekday, and the base timetable as input and extending the rescheduling horizon to a day. As a consequence, the events in the base timetable would be adjusted to better cater for the expected passenger demand.

Finally, given the recent attention that researchers have put on automated vehicles, it is interesting to evaluate how the developed framework could aid in the design of automated metro services. Since crew schedule would no longer be a restriction, trains could be dispatched and run based on the demand. If the SBTM-MN framework is accordingly adapted, its capabilities might be useful to reschedule the timetable in real-time according to the expected passenger demand for a time horizon.

Regarding the application, with further development, the SBTM-MN could eventually be used as a real-time rescheduling tool. However, at present, the TSM could already be used to asses the performance of timetables with alternative levels of demand, or under different disturbances. This model provides a more realistic approach than the commonly used, which disregards passenger-train interactions. Overall, it is suggested that metro operators should include passengers in the modelling of their operations, for instance, by using the developed TSM. This would provide a better idea of the reliability of their timetable. Furthermore, applying an integrated train-passenger model is a necessary step for the operator to evaluate the passenger perceived travel time in an anticipatory manner.

With some care in the adaptation, the SBTM-MN could also be used for rail networks. The accuracy of the framework depends on, for instance, the availability of alternative routes for passengers, and the influence of transfer points. Given that the SBTM-MN only accounts for rides and route assignment does not vary, the accuracy of the passenger movement modelling might be compromised. If passengers tend to choose alternative routes when disturbances occur, this is not represented in the SBTM-MN, which may yield unrealistic results.

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A

Passenger module pseudo-code

Algorithm 1 Passenger module algorithm

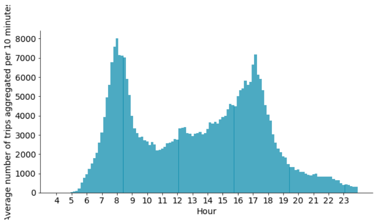
Input: OT_message, message_type, list_of_stations, TM, SM

```
if message_type == simulation_started then
    MessageToSend: "StopSimulation"
else if message_type == train_departure then
    train= OT_message[TrainID]
    station= OT_message[StationID]
    time= OT_message[TimeID]
    stations_to_serve= list_of_stations[station:terminal]
    if station == start_station_of_train then
        TM = empty matrix, (columns = stations_to_serve)
        if number of rows in SM == 0 then
            Time interval= 4:30:00 to time
            Preliminary_station_load = series of arrival counts at platform in time interval
        else
            Time interval== time of previous event at station (SM['Timestamp'][-1]) to time
            Passengers_at_station_after_previous_event = SM[-1]
            Preliminary_station_load = series of arrival counts at platform in time interval + Passengers_at_station_after_previous_event
        end if
        Boarding_passengers: subset of Preliminary_station_load with indices in stations_to_serve
        TM.append(Boarding_passengers)
        SM.append(Preliminary_station_load − Boarding_passengers)
    end if
    MessageToSend: "WaitForDepartureCommand"
```

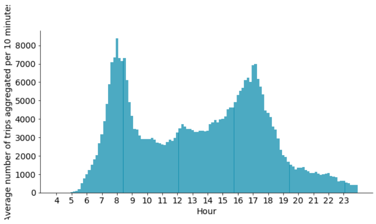
```
else if message_type == train_arrival then
    train= OT_message[TrainID]
    station= OT_message[StationID]
    time= OT_message[TimeID]
    stations_to_serve= list_of_stations[station:terminal]
    if number of rows in SM == 0 then
        Time interval= 4:30:00 to time
        Preliminary_station_load = series of arrival counts at platform in time interval
    else
        Time interval== time of previous event at station (SM['Timestamp'][-1]) to time
        Passengers_at_station_after_previous_event = SM[-1]
        Preliminary_station_load = series of (arrival counts at platform in time interval + Passengers_at_station_after_previous_event)
    end if
    Boarding_passengers: subset of Preliminary_station_load with indices in stations_to_serve
    Train_pre_load = TM[-1])
    TM.append(Boarding_passengers + Train_pre_load)
    SM.append(Preliminary_station_load − Boarding_passengers)
    Total_boarding= sum(Boarding_passengers)
    Total_alighting = TM[row=station][column=station]
    Train_load= sum(TM[row=station])-TM[row=station][column=station]
    Dwell_time= dwellFunction(Total_boarding, Total_alighting, Train_load)
    Departure_time= time+dwell_time
    MessageToSend : "DepartureCommandtrainID = trainstationID = stationtime = DepartureTime"
end if
Return:MessageToSend
```

B

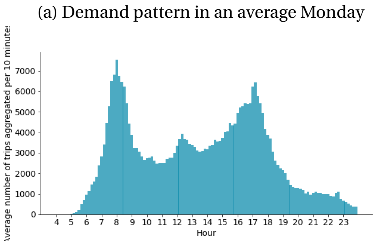
Daily demand patterns



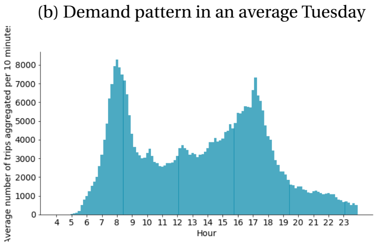
(a) Demand pattern in an average Monday



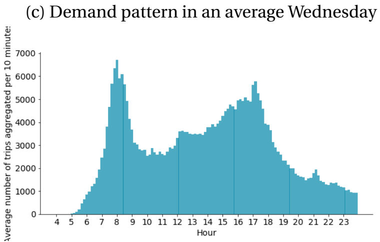
(b) Demand pattern in an average Tuesday



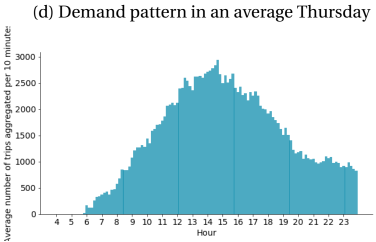
(c) Demand pattern in an average Wednesday



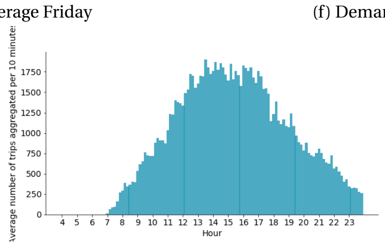
(d) Demand pattern in an average Thursday



(e) Demand pattern in an average Friday



(f) Demand pattern in an average Saturday



(g) Demand pattern in an average Sunday

Figure B.1: Histogram of the demand pattern for each day

C

OD pairs per hour in morning peak

This section presents the Origin-Destination pairs of the 62 stations in the network, as an average per morning peak hour. To preserve the readability of the table, acronyms are used to refer to the stations, some of which have rather long names.

Acronym	Full station name
ALD	Alexander
ABL	Ambachtsland
BKW	Berkel Westpolder
BRE	Beurs
BNH	Binnenhof
BLK	Blaak
BDP	Blijdorp
CCT	Capelle Centrum
CPB	Capelsebrug
CHV	Coolhaven
AKS	De Akkers
TRP	De Terp
TTN	De Tochten
DHV	Delfshaven
GVC	Den Haag Centraal
DZT	Dijkzigt
EDP	Eendrachtsplein
FPA	Forepark
GDW	Gerdesiaweg
GKD	Graskruid
HRL	Heemraadlaan
HSP	Hesseplaats
HVT	Hoogvliet
KLZ	Kralingse Zoom
LNO	Laan Van NOI
LDV	Leidschendam-Voorburg
LVN	Leidschenveen
LHV	Leuvehaven
MHV	Maashaven
MCP	Marconiplein
MPL	Meijersplein

Acronym	Full station name
MTW	Melanchthonweg
NSL	Nesselande
NVT	Nieuw Verlaat
NDP	Nootdorp
OTF	Oosterflank
OPL	Oostplein
PWG	Parkweg
PNS	Pernis
PAK	Pijnacker Centrum
PAZ	Pijnacker Zuid
PTG	Poortugaal
PSL	Prinsenlaan
RHO	Rhoon
RHV	Rijnhaven
RDR	Rodenrijs
RMH	Romeynshof
C.S	Rotterdam Centraal
SKL	Schenkel
SDM	Schiedam Centrum
SLG	Slinge
SLN	Slotlaan
SPC	Spijkenisse Centrum
SHS	Stadhuis
TSL	Troelstralaan
TWR	Tussenwater
VSZ	Vijfsluizen
VBL	Voorburg 't Loo
VSL	Voorschoterlaan
WHP	Wilhelminaplein
ZPT	Zalmplaat
ZPL	Zuidplein

	Destination																						
Origin	ALD	ABL	BKW	BRE	BNH	BLK	BDP	CCT	CPB	CHV	AKS	TRP	TTN	DHV	GVC	DZT	EDP	FPA	GDW	GKD	HRL	HSP	HVT
ALD		6		32	6	22			31	33			7	3		67	7		6	4		8	
ABL	41			41	2	12			10	5			1	1		9	8		2	2		8	
BKW	1			72		6	8	1	1	1					104	4		2	1				
BRE	28	4	6		1	24	25	5	12	199	2	4	12	34	57	548	74	7	8	2	2	4	2
BNH	48	2		45		16		1	7	5			6	2		18	8		1	1		2	
BLK	50	4		171	2			20	32	115		9	6	14		272	45		13	4		7	2
BDP	1		3	39		9		1	2						51	1		2	1				
CCT				86		38			22	8		6		1		20	11		2				
CPB	192	4		584	5	248	1	51		64	1	20	10	6	3	189	61		10	4		6	2
CHV	32	4		57	1	55	1	2	5		1	2	4	4	2	13	23		7			1	2
AKS	9			36	1	12	1	1	2	9			1	2	2	21	4		3		5		6
TRP				150		59		7	35	11				4		48	21		3				
TTN	49			52	1	17			10	8				1		24	7		3	3		10	
DHV	32	2	1	55	1	50	1	4	6	7	1	1	7		1	39	32		7	1	1	2	4
GVC			5	37		1	7	1	2									20					
DZT	15	2		23	1	30		3	11	6		2	4	6			9		4	1	1	1	1
EDP	27	3		16	1	34		6	9	19	1	2	14	7		35			9	3		2	1
FPA				5											9								
GDW	44	1		130		87		5	6	10		2	3	5		34	16			1		3	1
GKD	13	2		44	2	16			8	7			2	1		14	6		4			1	
HRL	9			65		23		1	3	19	4			1	3	51	10	1	1			1	6
HSP	39	4		42	1	14		1	10	4			5	2		14	7		1	1			
HVT	11	1		36		21	1		1	16	4		2	2	2	39	11		1		3	1	
KLZ	113	7		371	2	178		13	19	58		3	12	8		269	54		8	3		6	1
LNO			2	13			1								43			14					
LDV			1	22		2	2			1					32	2		1					
LVN	1		2	75		6	6		1	1				1	87	3							
LHV	1		1	14		2	1								13						1		
MHV	25	1	2	151		16	5	3	7	1	2	1	5	1	22	3	2	1	3	1	1	1	4
MCP	28	3		66	1	47	1	4	9	21	1	3	9	10	1	57	28		6		1	1	4
MPL			2	82		7	5	1	1		1				74	4		1	1				
MTW	1		1	42		4	8	1		1					67	2		1	1				1
NSL	74	4		85	1	30	2		15	15			4	1	1	39	12		4	4		11	
NVT	46	1		47	1	17			15	4			5	1		11	7		1	3		5	
NDP	1		3	36		4	3								73	1		1					
OTF	27	3		129	4	47			23	17			7	5	1	39	18		4	5		11	1
OPL	54	3		151	1	76		4	9	21		3	4	6		53	15		3	1	1	2	1
PWG	11			31		22	1	1	1	14		1		6		32	23		3		1		2
PNS	4			14		6	1	1		7			1	1		20	8						5
PAK	1		2	38		5	2								124	2		3					
PAZ			1	49		5	3		1	1					129	4		1					
PTG	3			46		5	1		1		1				3	2							2
PSL	40	2		87	2	27			7	8			5	3		22	12		2	5		4	
RHO	3			49		5	2				1				3	2			1		1		2
RHV	9		2	68		9	4		2	1	1	1	2		17	2		1	3		1		2
RDR	1		2	104		9	18	1	1	4				1	80	4		1	1				1
RMH	26	1		31	1	11		1	5	4			3	1		9	4		1			1	
C.S	3	1	8	327		9	19	3	7	3	2	1	3		29	5		10	4		2		7
SKL	55	2		105	1	37			15	9			3	3		32	15		4	1		3	
SDM	51	3		152	2	69	8	6	13	210	4	2	2	38	1	392	90	1	6	1	3	3	11
SLG	21	2	2	310	2	30	10	3	6	2	3	2	4	1	37	10	2	1	3	2	2	2	7
SLN				67		27		2	21	8		3		1		17	8		2				
SPC	30	1		113	1	28	5	3	4	58	16	2	1	4	7	87	13		5	1	3	1	19
SHS	1			31		2	1	1	1						10			1				1	2
TSL	13			40		20	1	1	4	10	1	1		5		36	29		1			1	3
TWR	3			20		8		1	1	10	2			2		22	4		1		1		2
VSZ	33	1		82		32	2	1	5	28	2	1		5	1	62	47		1	1	1	1	9
VBL			1	14		1									34			1					
VSL	66	2		106	1	103		5	7	10		2	7	3		48	12		1	1		2	1
WHP	11	1	2	140		11	7	2	2				3	1	46	2		3	4	1	1		3
ZPT	4			19		6				5	3	1		1	1	8	2				2		5
ZPL	39	4	4	409	2	37	16	4	9	6	6	3	11	2	52	4	2	4	5	1	5	4	16

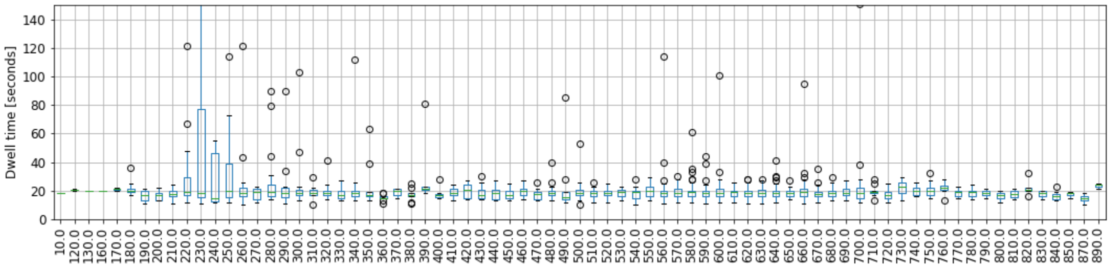
	Destination																		
Origin	KLZ	LNO	LDV	LVN	LHV	MHV	MCP	MPL	MTW	NSL	NVT	NDP	OTF	OPL	PWG	PNS	PAK	PAZ	PTG
ALD	202						7			5	3		6	23	1				
ABL	12					1	3		1	8	1		6	3					
BKW	12	60	4	22	11	2		2	8			1	3	4			3		
BRE	58	23	6	31	88	64	125	23	49	2	2	2	8	28	13	8	7	3	9
BNH	12				1	1	2						6	4		1			
BLK	395				2	1	45			4	2		15	55	2	3			
BDP	18	23	4	14	10	4		3	10		1	2	1	3			4	2	
CCT	20						7							7	1				
CPB	103			2	1	1	23		1	6	12		44	33	2	1			
CHV	52			2	4	2	14	2	3	1	1		5	14	4	2			
AKS	10	1		2	13	8	11	2	2				2	3	3	3			2
TRP	37				1	1	8		1					12	1				
TTN	12						4			8	2		12	4					
DHV	41	1		2	4	6	30	2	6	2			3	28	19	2	2		1
GVC	12	21	14	60	14	4		12	19			20	2	4			23	5	
DZT	33	1		2	1	1	14			2	1		5	10	2	1			
EDP	57				2	2	26			2	1		9	24	3	2			
FPA	1	3			1														
GDW	23				1	1	15			1	2		7	6	1				
GKD	12				1		2			5	1		7	5					
HRL	22			2	23	6	13	1	6				2	9	5	2	1		3
HSP	12						2			6	2		7	6	1				
HVT	15	1		2	15	11	14	2	4				2	6	3	3			6
KLZ					1	1	23		2	2	2		30	43	1	1			
LNO	5		8	24	7	1		6	8			8		1			6	2	
LDV	4	15		4	6	1		3	4			4		2			4	1	
LVN	27	43	3		17	3		4	19			9	1	7			7	5	
LHV	5	4	1	2		6		2	3					2			1		1
MHV	28	8	2	11	36		4	10	17	1	1	1	4	14			7	1	4
MCP	51			1	6	7		1	1	2	2		5	20	15	5			
MPL	6	30	3	11	18	5			5			1		5			4	2	
MTW	7	26	3	16	10	4		6				1	1	2			5	3	
NSL	24						3		1		3		26	7					
NVT	12				1		3			7			10	5					
NDP	8	43	4	21	7				4					3			3	1	
OTF	44				1	1	9			4	2			10	1	1			
OPL	41				1	1	21			1	2		6		2	1			
PWG	13			1	2	2	13		2					5		5			
PNS	5						3		1				1	2	1				
PAK	9	60	8	42	8	4	1	2	9			5	3	3				3	
PAZ	8	72	4	54	11	2		2	5			2	3	5			5		
PTG	8	1		1	14	5			2				3	2					
PSL	21					1	6		1	3	1		3	9					
RHO	9	2			16	4		1	1			1	5	3			1		1
RHV	11	7		4	14	18	1	4	6				2	5			2		3
RDR	24	35	3	15	13	4		3	14			1	6	4			3	3	
RMH	9						3			1			5	3					
C.S	47	14	10	54	146	62		40	124		1	8	2	10			11	5	11
SKL	19				1		6			3	1		6	7					
SDM	123		1	1	15	8	85	2	2	2	5		16	27	15	23	1		1
SLG	22	16		8	80	28	2	6	12	1			7	16	1		3	1	6
SLN	16						5							2	1	1			
SPC	64	2	1	3	43	14	28	2	12			1	3	16	8	6			12
SHS	5	4	1	5	16	13		2	2		1	1	1	3			1		2
TSL	13			1	3	1	15		3				2	8	6	4	1		
TWR	8			1	8	3	10		3				2	4	4	8			9
VSZ	33			1	2	3	26	1	4		3		8	10	9	16			
VBL	3	13	1	8	5			1	3			1		1			3	1	
VSL	26						9			2	1		7	5					
WHP	20	17	3	14	23	9	2	10	15		1	1	2	11			3		4
ZPT	7			2	6	6	6	2	2				2	2	2	2			2
ZPL	49	16	4	19	125	30	7	20	55	2	1	1	6	18			4	2	14

	Destination																			
Origin	PSL	RHO	RHV	RDR	RMH	C.S	SKL	SDM	SLG	SLN	SPC	SHS	TSL	TWR	VSZ	VBL	VSL	WHP	ZPT	ZPL
ALD	28				5	1	9	3					1		3		10			
ABL	13				1	2	1	3		1					1		3	2		
BKW	3	1	3	4		117			4		1	22				3	1	41	1	12
BRE	10	18	38	43	1	510	5	111	92	3	28	208	10	8	66	4	8	527	6	271
BNH	10				1	2	2	2		1	1	1			1		4	2		1
BLK	30				3	1	10	24		8	3	1	3	1	20		22	5	1	3
BDP	2		2	12		57	1		6	1	2	8				3	2	37		18
CCT			1			2		7		2	2			2	2		3	1	1	1
CPB	38	1	1	1	3	13	12	33	2	67	6	3	2	2	16		28	10	3	13
CHV	8	1	2	4		31	4	92	4	3	7	7	3	4	11		9	17	1	11
AKS	4	4	6	2		59	1	35	23		62	23	2	8	12		2	34	10	41
TRP						5		11	1	10	3	2	2	1	4		11	2	1	3
TTN	15					1	2	3		1		1			1		4	4		1
DHV	11		5	6	1	26	4	120	9	3	5	8	24	3	13		10	23	3	27
GVC	1	1	6	12		22			4		1	16				2		52		16
DZT	8		1	1	1	10	2	43	1	1	5	2	2	1	9		6	7	1	5
EDP	15		2		2	1	4	34	1	2	2		6	2	31		9	6		5
FPA						5						1						3		1
GDW	10	1	1			4	4	13		5	1	1	2	1	6		1	3		2
GKD	7				1	3	1	2	1			1			1		3	1		2
HRL	1	6	7	2		79	2	62	22	1	23	40	4	10	14		2	50	9	47
HSP	11					1	2	5				1					4	2		1
HVT	2	6	11	1		53	1	66	36	1	73	33	5	4	16		1	36	4	60
KLZ	31		1	1	1	8	7	22	1	10	2	3	1	1	9		28	8	1	1
LNO			2	10		7			2			6						24		5
LDV			1	2		27			2			8						19		4
LVN	1	1	2	5		94	1		4		1	34				2	1	45	1	15
LHV		2	6	4		59			8		4	10		1			1	26		22
MHV	6	3	25	15	1	249	2	4	24	1	18	61		9	1	1	5	42	3	66
MCP	4	1	8	3	2	4	5	114	10	2	12	5	21	7	26		10	31	3	30
MPL	1		3	3		122			6		2	25		1	1	1	1	64		16
MTW	2	2	8	8		71			8		2	8				2	1	32	1	20
NSL	22					3	2	6		1	1	1			1		9	4		1
NVT	12					2	1	4				1			1		4	1		2
NDP			2	2		30			1		1	11				1		28		5
OTF	10				2	3	6	11	1	1	1	1	1		6		10	5		2
OPL	12		1	1	1	2	4	22	1	8	4	1	3	1	7		6	4	1	4
PWG	2		1	1		5		63	2	1	10	8	6	8	34		1	17	1	9
PNS	1					5		26			7	3	4	13	12			3	19	1
PAK			4	8		53			3		2	10				5		18	1	8
PAZ	1		1	10		75	1		1		1	15				4	1	26	1	7
PTG	3	2	8	1		67	1		13		60	18		30			1	26	16	32
PSL						2	1	8			1	1		1	1		5	2		1
RHO	2		9			74	1		12		28	20		20			2	28	8	27
RHV	4	4		4		118	1		17	1	7	26		1			2	9	1	96
RDR	1		5			165			9	1	1	22		1		3	1	55	2	20
RMH	6						2	2			1				1		3	1		
C.S	4	13	42	70			2		85	1	35	73		7		4	3	733	12	263
SKL	3				1	4		6	1			1	1		2		8	3		2
SDM	15		7	5	2	8	4		13	2	43	15	31	33	123		8	102	15	50
SLG	8	9	35	8		283	1	3		2	30	105	1	19		2	4	119	15	104
SLN						3		2			1				1		4	1		1
SPC	8	13	22	4	1	187	3	152	88	1		92	6	22	47		6	101	40	149
SHS	1	2	5	6		27	1	1	16		10			2				71	2	53
TSL	2		1	1		6	1	94	1	1	8	10		8	27		1	18	2	10
TWR	2	11	4	2		30		59	24		41	12	40		26		1	16	10	34
VSZ	4		6	2		14	2	153	1		25	17	24	26			2	39	5	13
VBL			1	1		18			1			6						16		2
VSL	13				1	3	3	8		4	2	1	2		3			2	1	
WHP	3	4	6	17		223	1	3	13	1	8	70		3	1	1	3		3	44
ZPT	2	2	2	2		27		22	18	1	51	15	2	2	5			12		34
ZPL	13	21	108	21	1	536	3	4	33	3	61	197		32	2	2	6	214	35	

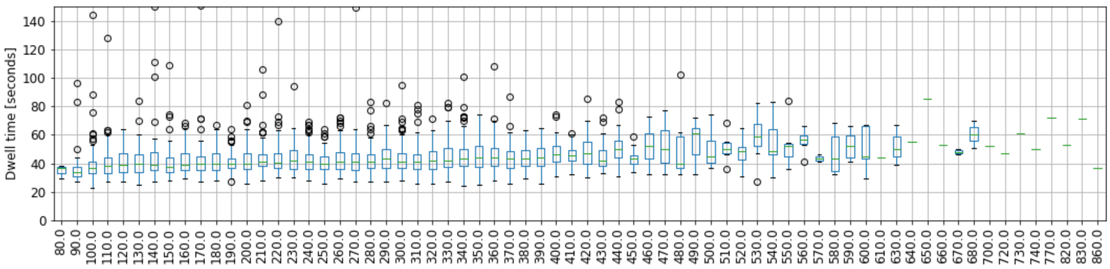
Table C.1: Average Origin-Destination pairs per hour for the whole network during the morning peak

D

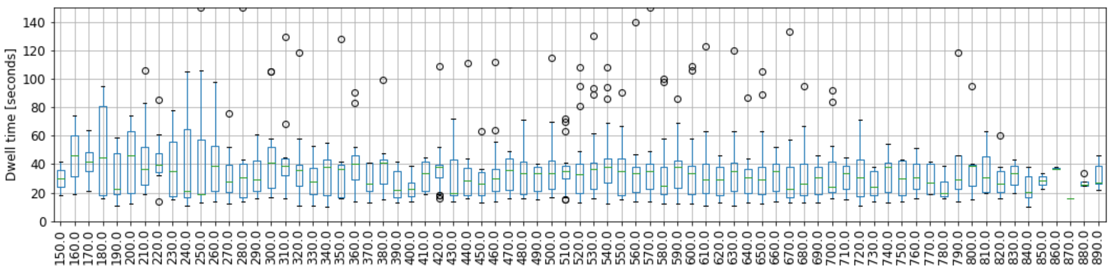
Dwell time vs. headways



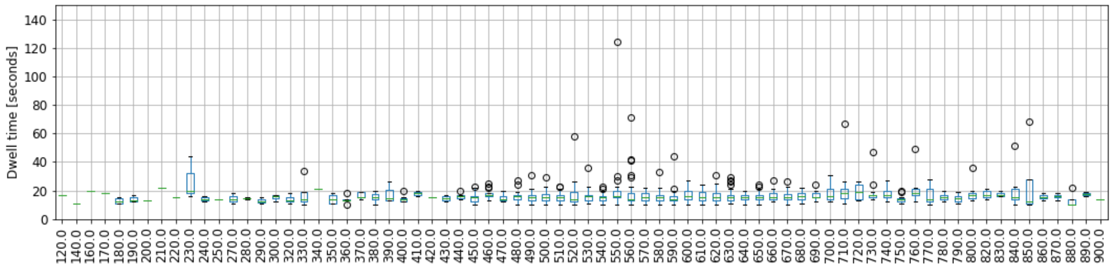
(a) Dwell time [s] versus headway for Berkel Wespolder grouped in 10 seconds



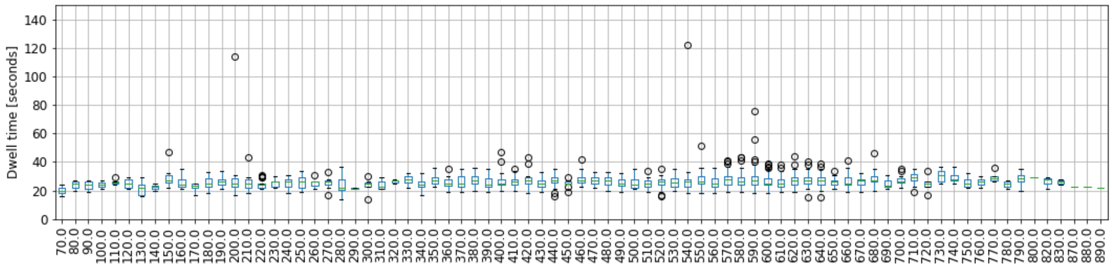
(b) Dwell time[s] versus headway for Beurs grouped in 10 seconds



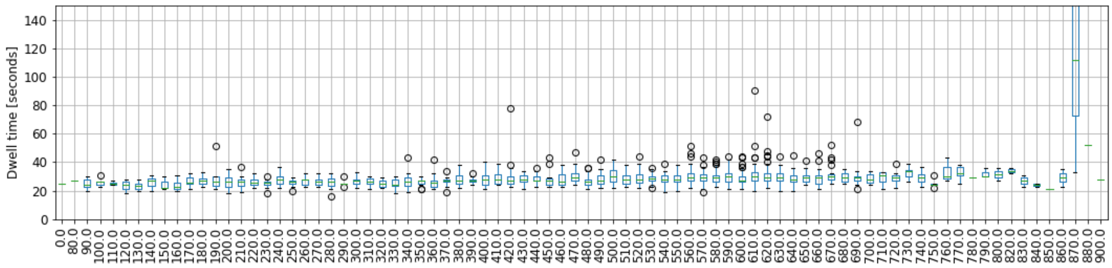
(c) Dwell time[s] versus headway for Blijdorp grouped in 10 seconds



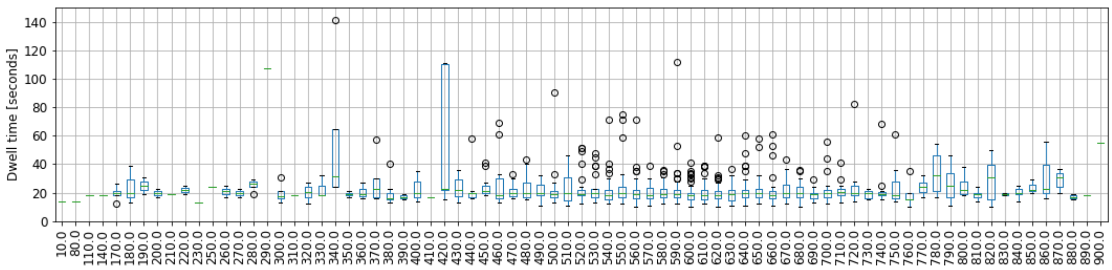
(d) Dwell time [s] versus headway for Forepark grouped in 10 seconds



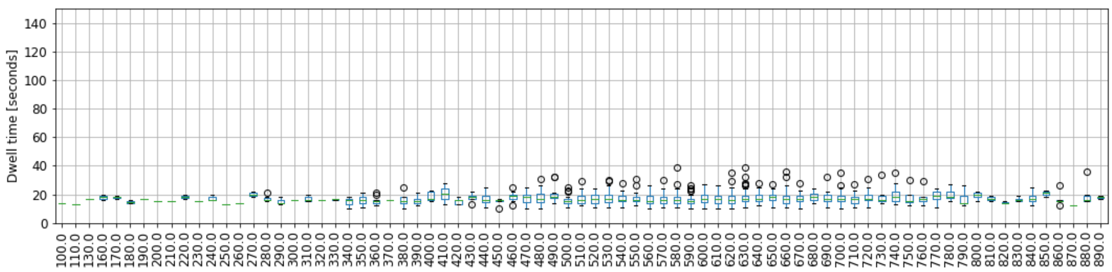
(e) Dwell time[s] versus headway for Heemraadlaan grouped in 10 seconds



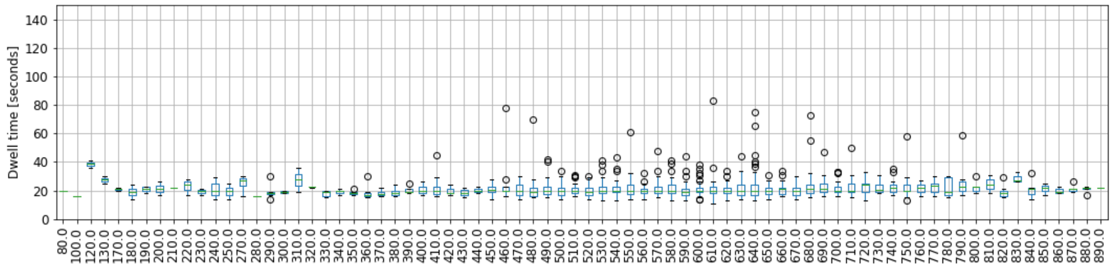
(f) Dwell time [s] versus headway for Hoogvliet grouped in 10 seconds



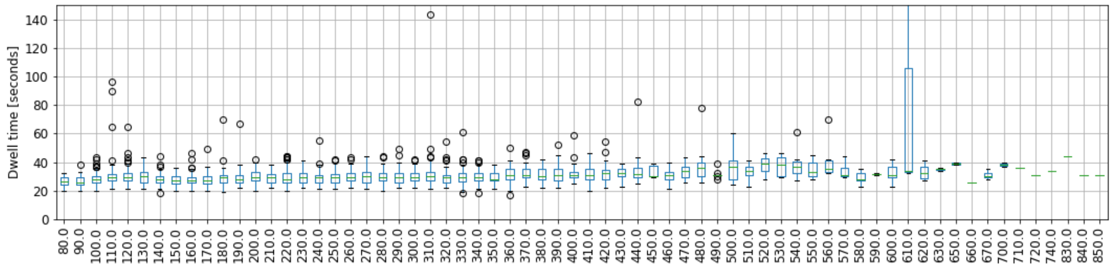
(g) Dwell time [s] versus headway for Laan van NOI grouped in 10 seconds



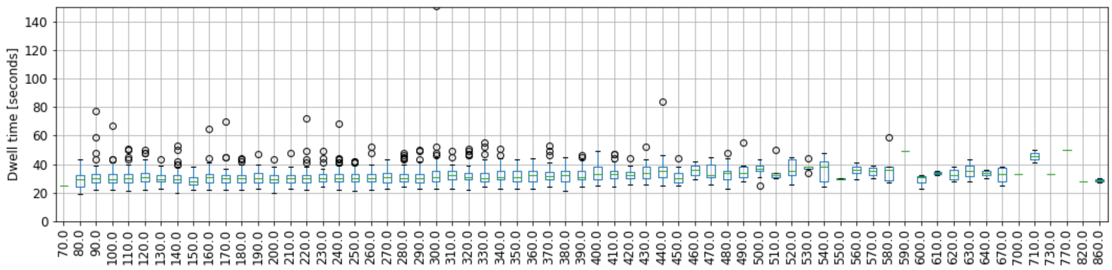
(h) Dwell time [s] versus headway for Leidschendam grouped in 10 seconds



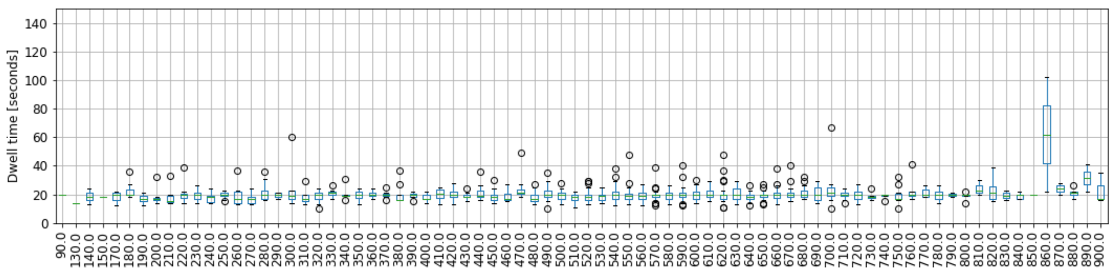
(i) Dwell time[s] versus headway for Leidschenveen grouped in 10 seconds



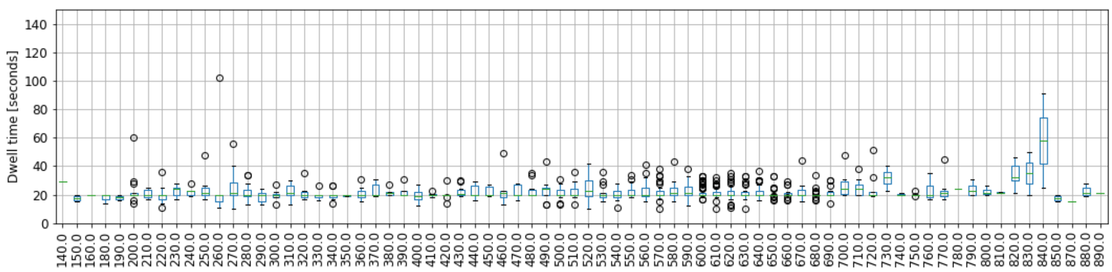
(j) Dwell time[s] versus headway for Leuvenhaven grouped in 10 seconds



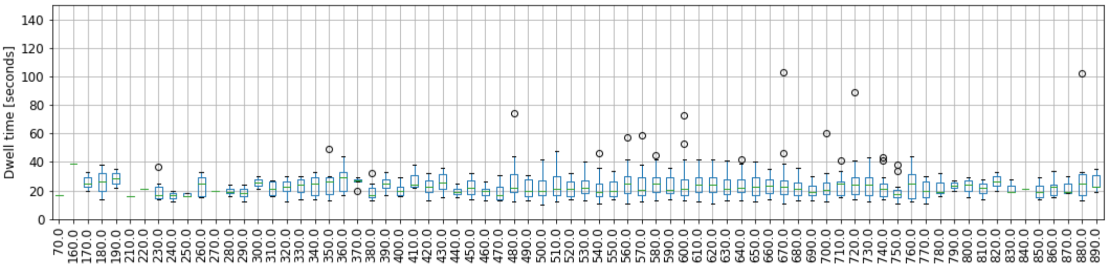
(k) Dwell times[s] versus headway for Maashaven grouped in 10 seconds



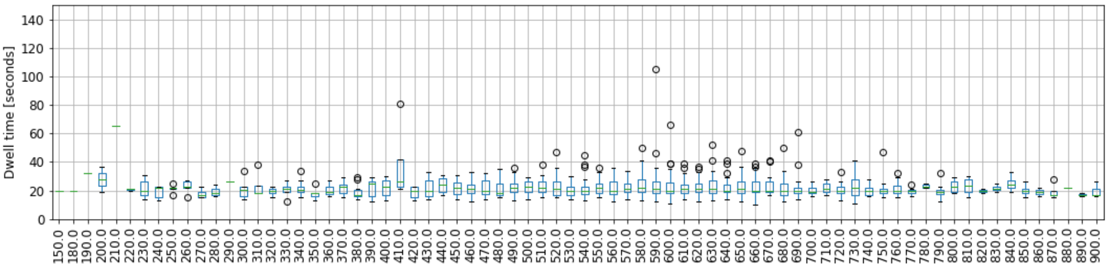
(l) Dwell time[s] versus headway for Meijersplein grouped in 10 seconds



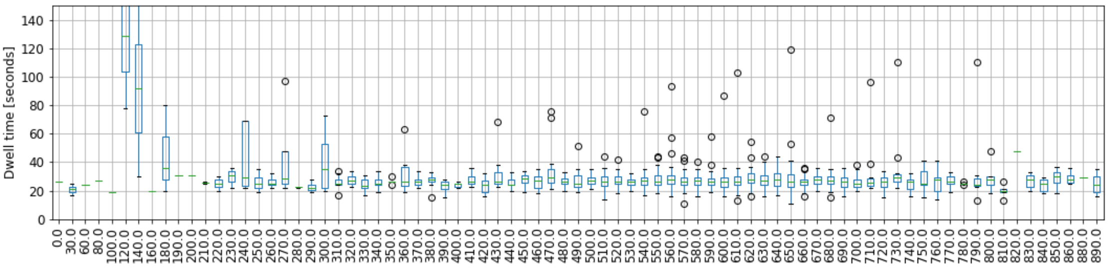
(m) Dwell time[s] versus headway for Melanchtonweg grouped in 10 seconds



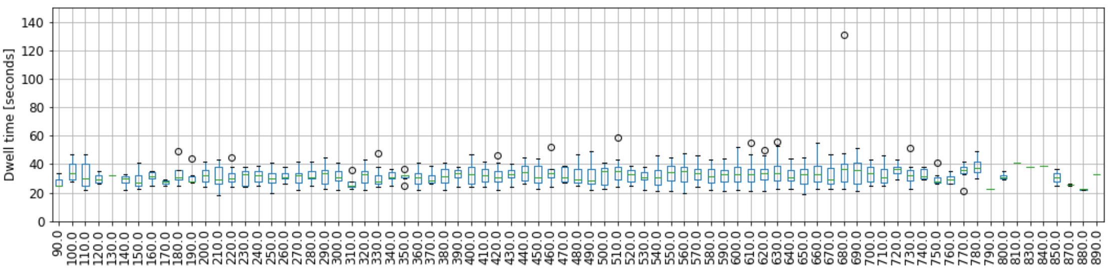
(n) Dwell time[s] versus headway for Nootdorp grouped in 10 seconds



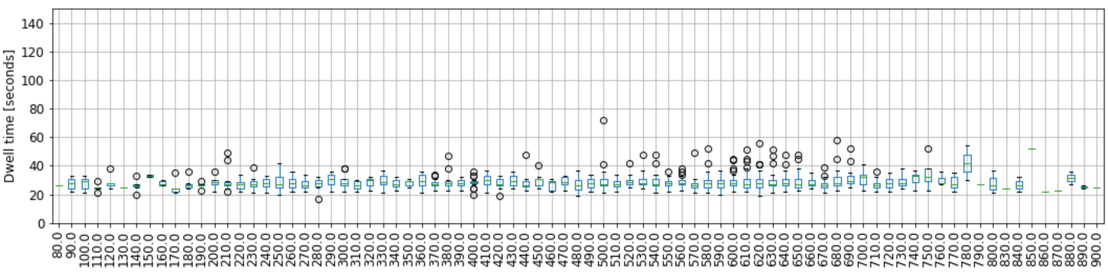
(o) Dwell time[s] versus headway for Pijnacker Centrum grouped in 10 seconds



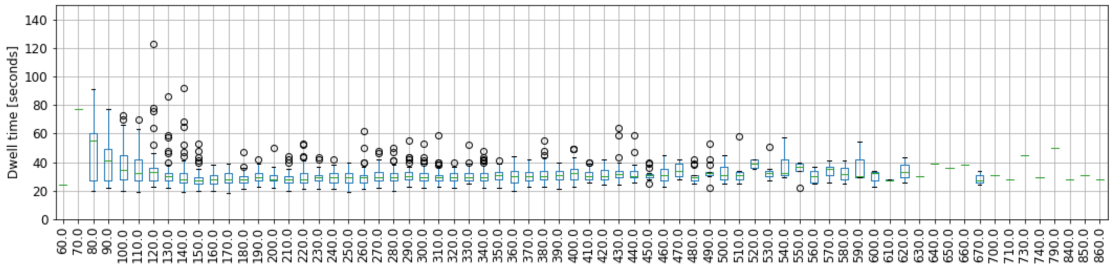
(p) Dwell time[s] versus headway for Pijnacker Zuid grouped in 10 seconds



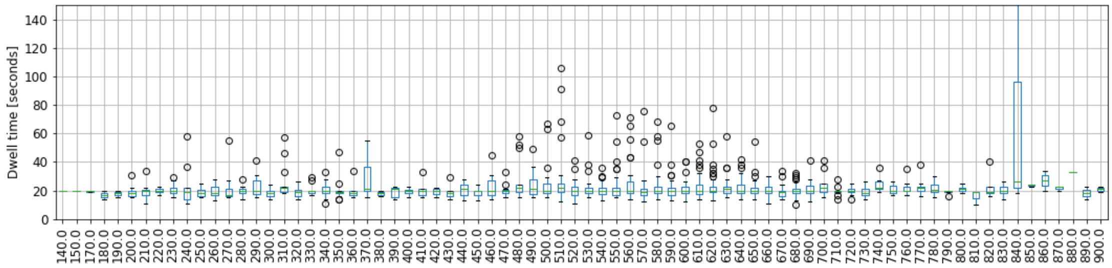
(q) Dwell time[s] versus headway for Poortugaal grouped in 10 seconds



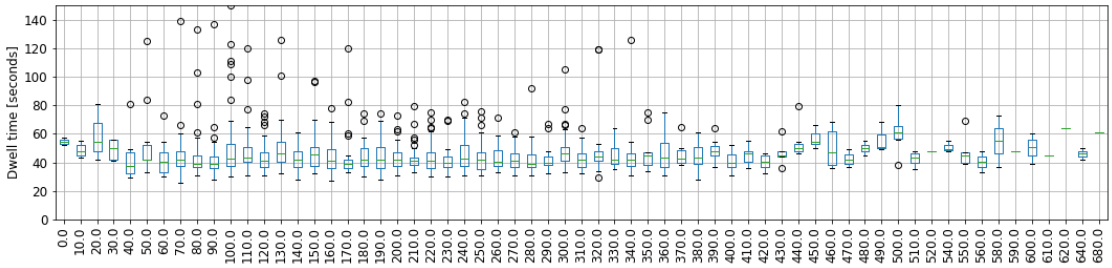
(r) Dwell time[s] versus headway for Rhoon grouped in 10 seconds



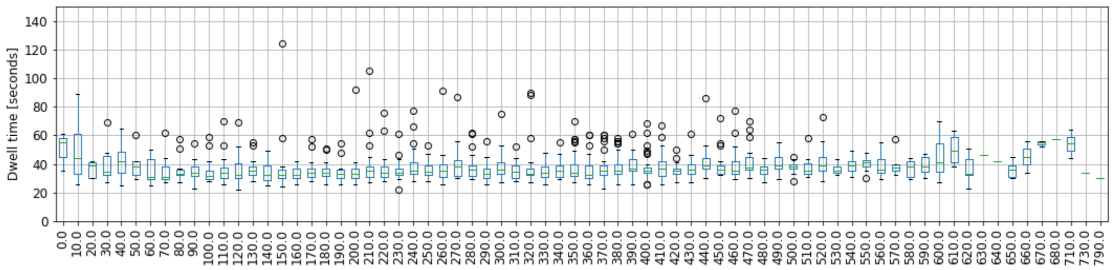
(s) Dwell time[s] versus headway for Rijnhaven grouped in 10 seconds



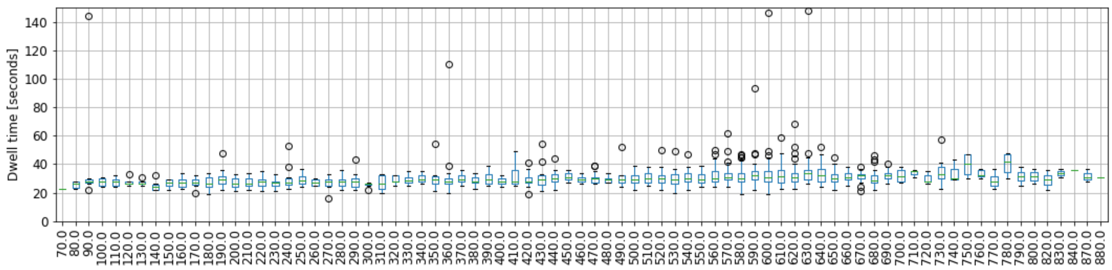
(t) Dwell time[s] versus headway for Rodenrijs grouped in 10 seconds



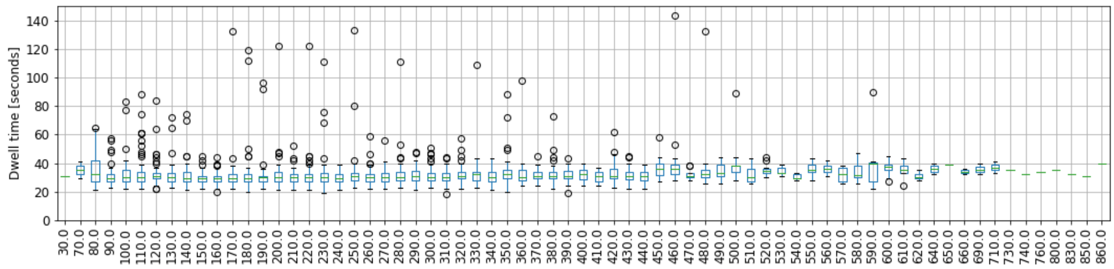
(u) Dwell time[s] versus headway for Rotterdam Centraal grouped in 10 seconds



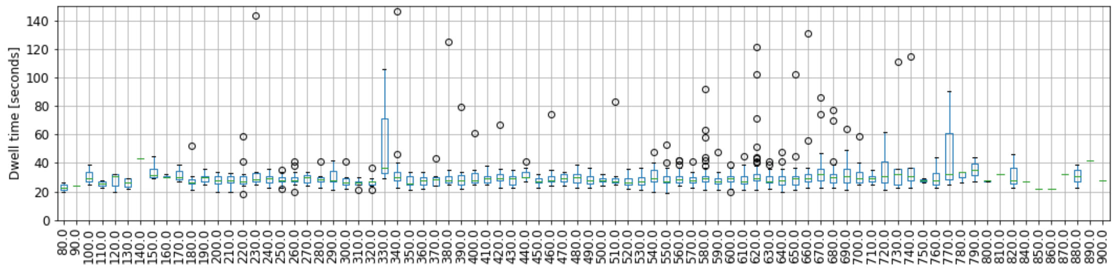
(v) Dwell time[s] versus headway for Slinge grouped in 10 seconds



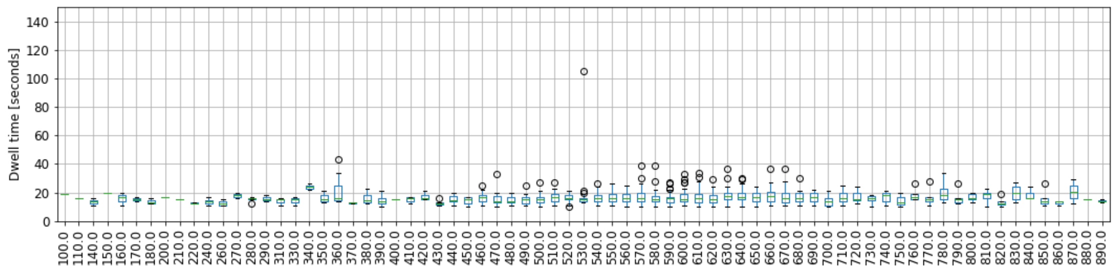
(w) Dwell time[s] versus headway for Spijkenisse Centrum grouped in 10 seconds



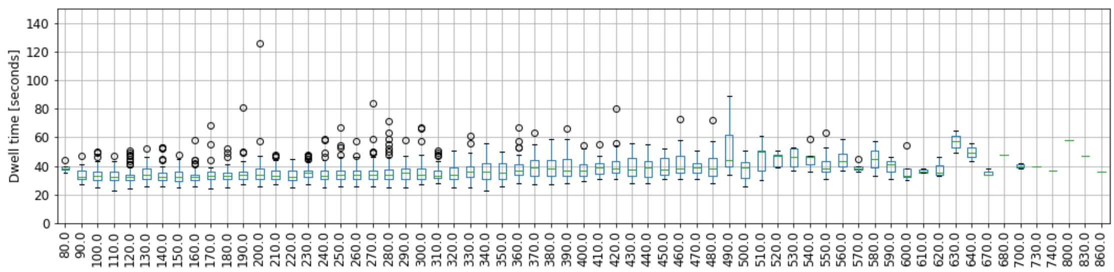
(x) Dwell time[s] versus headway for Stadhuis grouped in 10 seconds



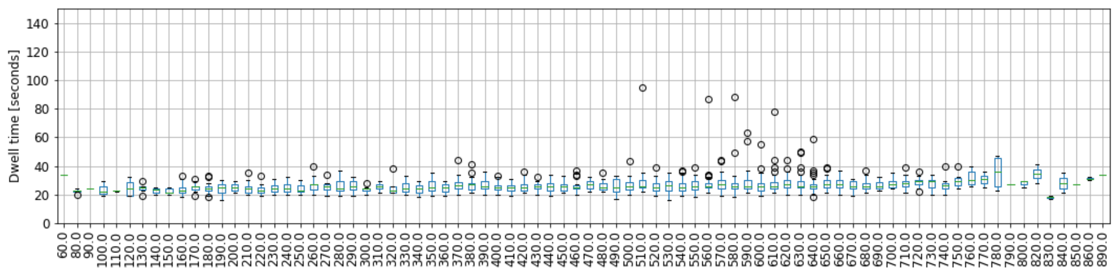
(y) Dwell time[s] versus headway for Tussenwater grouped in 10 seconds



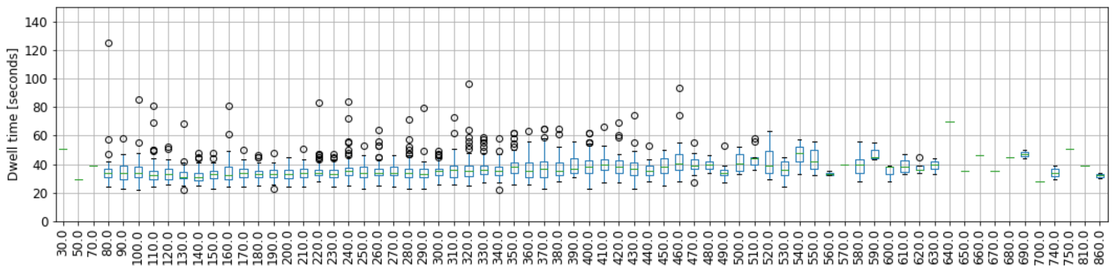
(z) Dwell time[s] versus headway for Voorbrug ́ Loo grouped in 10 seconds



(aa) Dwell time[s] versus headway for Wilhelminaplein grouped in 10 seconds



(ab) Dwell time[s] versus headway for Zalmplaat grouped in 10 seconds



(ac) Dwell time[s] versus headway for Zuidplein grouped in 10 seconds

E

Overlapped time-distance diagrams

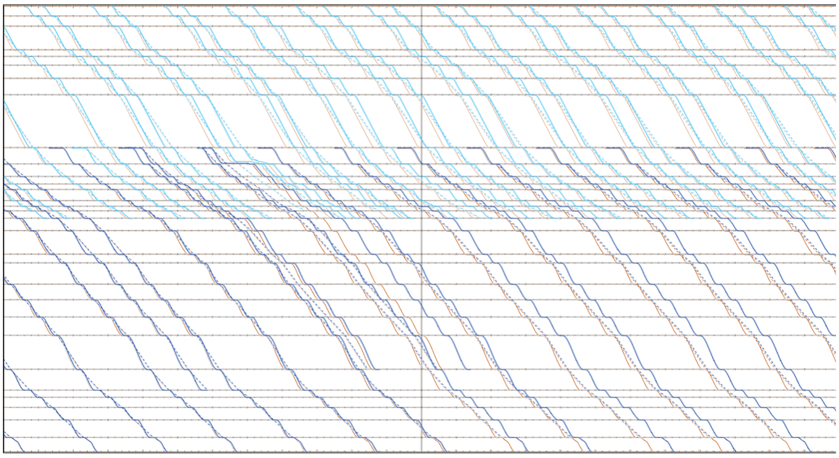


Figure E.1: Overlapped time-distance diagram for scenarios $S^c_{5,0}$ and $S^p_{5,0}$ (x-axis = time[10min], y-axis=stations)

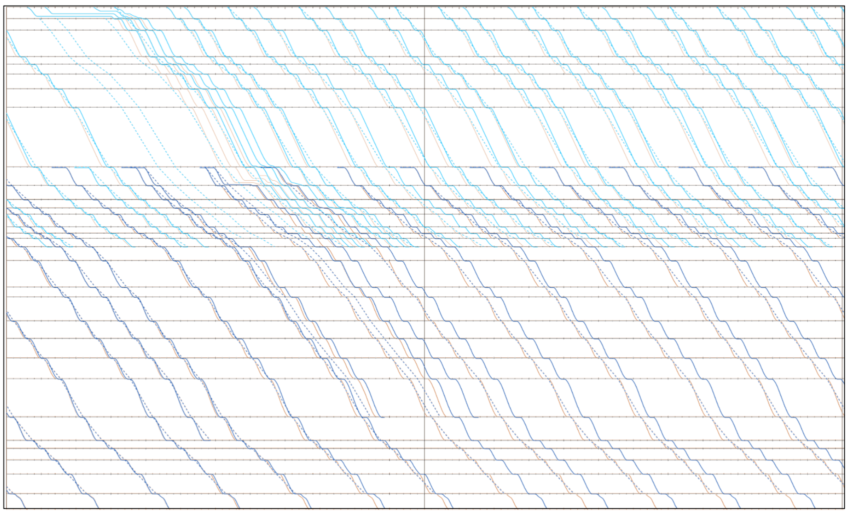


Figure E.2: Overlapped time-distance diagram for scenarios $S^c_{5,15}$ and $S^p_{5,15}$ (x-axis = time[10min], y-axis=stations)

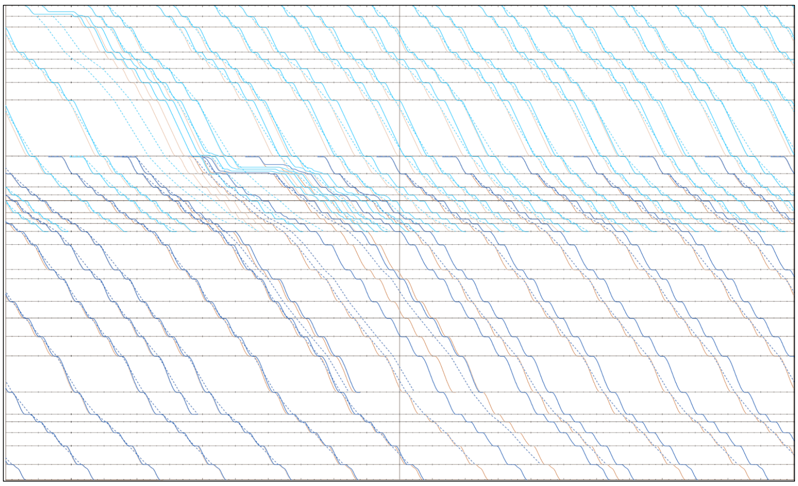


Figure E.3: Overlapped time-distance diagram for scenarios $S^c_{10,10}$ and $S^p_{10,10}$ (x-axis = time[10min], y-axis=stations)

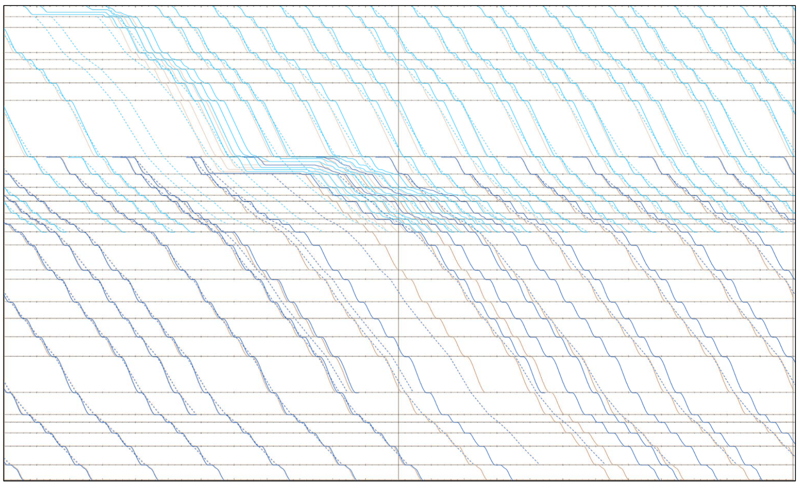


Figure E.4: Overlapped time-distance diagram for scenarios $S^c_{15,15}$ and $S^p_{15,15}$ (x-axis = time[10min], y-axis=stations)