VRIJE UNIVERSITEIT AMSTERDAM

MASTER THESIS

Passenger Punctuality Computation using Smart Card and Vehicle Location Data in a Multimodal Public Transport Network

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Abstract

This thesis presents a framework to compute passenger arrival delay in a multimodal public transport network. To compute this delay, we combine Automated Fare Collection (AFC) and Automated Vehicle Location (AVL) data to infer the realized passenger journey and to derive the corresponding planned itinerary. We execute this case study in a public transport system that uses different smart card validation procedures for different modes of transport. We therefore propose a methodology to estimate the passenger's moment of arrival at the origin stop for tram and bus legs at the beginning of a journey. For metro legs, we introduce a vehicle assignment strategy. This approach provides us with suitable planned and realized itineraries for all modes. Additionally, this work proposes a method to process transfers. For this, we estimate the planned minimal transfer time for each transfer relation and we identify passenger journeys that include elective transfer delay. Combining these components eventually allows us to iteratively compute the arrival delay of the individual passenger. By computing the arrival delay of 206,275,821 passenger journeys recorded in the multimodal public transport network of Amsterdam between January 2019 and April 2020, we are able to derive a passenger oriented service reliability indicator.

Keywords: Public Transport, Punctuality, Smart Card Data, Vehicle Location Data, Multimodal Network, Vehicle Assignment

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[1]They always lasted longer than ten minutes.

Contents

List of Abbreviations

Chapter 1

Introduction

The demand for personal mobility in the Netherlands has been rapidly increasing over the past years. The number of commuters as well as the number of tourists visiting especially the metropolitan areas increase every year. However, the public transit share of mobility has not been growing as fast as the total amount of traveled kilometers in the Netherlands (Kennisinstituut voor Mobiliteitsbeleit, 2018). To keep cities accessible, it is important to increase the number of passengers in public transport. Federal government, public transit providers and public transport authorities are planning major investments in public transit infrastructure and service reliability to increase the number of public transport users and the quality of service offered to them (Ministerie van Infrastructuur en Waterstaat, 2019).

Service quality and reliability are important to achieve this increase in the number of public transport passengers. From the passenger perspective, an appropriate reliability indicator should ideally cover all the aspects of the passenger's journey. For this, one could for example think of waiting times at stations, vehicle occupancy rates, access and egress times and service punctuality (Barabino et al., 2015; van Oort, 2011).

Various punctuality measures have become the main instruments to measure the operational performance of many public transport companies nowadays (Trompet et al., 2011). However, many of these punctuality measures are operator-oriented. That is, operational performance is often measured in terms of vehicle punctuality or service regularity (i.e. headway adherence), without focusing on the extend to which these measures represent the punctuality experienced by the (individual) passenger. The rise of new technologies like sophisticated Automated Vehicle Location (AVL) and Automated Fare Collection (AFC) systems, nowadays provides Dutch public transport operators with large-scale detailed information on passenger behaviour in their public transport networks (Pelletier et al., 2011).

This research uses these relatively new data sources to close the gap between traditional operator-oriented punctuality measures on one side, and punctuality as it is experienced by the individual passenger on the other side. To achieve this, we compute passenger punctuality (in terms of delay), which we define as the difference between the realized and planned arrival times at the passenger's final stop in the public transit network. By executing a case study in the Amsterdam public transport network, this study shows that we can implement the passenger punctuality computation algorithm, to obtain a more passenger-oriented performance measure than the traditional punctuality measures used by many local public transport providers.

The present work is inspired by Wolters (2016), who analyses the punctuality measure on passenger level that is developed by Nederlandse Spoorwegen (NS) (Dutch National Rail). We extend this work by focusing on a more complex public transport environment, with various modes of transport, more complex transfer relations and multiple different journey registration procedures. Furthermore, the current research introduces a more accurate procedure by adjusting the most suitable planned journey to the passenger's estimated arrival time at the origin stop or station.

With this work, we do not strive to provide a fully complete, statistically sound approach. This is due to the various system- and time-related limitations we face during the project. Therefore, we advice the reader to consider this work more as a framework. With this framework, we aim to show how a passenger punctuality performance measure can be developed and implemented in a complex multimodal local public transport network, rather than motivating and justifying all the system-specific parameter settings. Using this more general approach, we try to make our methodology flexible and applicable to other (similar) public transport environments as well. It goes without saying that other approaches are also possible and that further work could be devoted to making the present approach more system-specific in order to obtain better results.

This report is organized as follows. First we start with a detailed problem statement and a description of the Amsterdam public transport environment in which we execute this case study (chapter 2). The available literature on the various aspects related to this work is reviewed in chapter 3. In chapter 4, we describe the different data sources that are used during this study. Next, chapter 5 describes the methodology we use to combine different data sources and to compute the passenger punctuality measure. This is followed by chapter 6, where we present the results of the passenger punctuality computation. In chapter 7 we present the main conclusions, whereas in chapter 8, we elaborate on future research perspectives.

Chapter 2

Problem Statement

This internship research is supported by GVB, the local public transport company in Amsterdam. Therefore, this chapter starts with an introduction to the company. Next, we briefly describe the current punctuality measures used at GVB. Then, we formulate our research question and we motivate how this research can contribute to the Amsterdam public transport operation, as it extends the traditional punctuality measures. This chapter is concluded by some general remarks regarding this study.

2.1 GVB

GVB has been providing public transport in the city of Amsterdam for over 150 years. The company used to be a public organization until 2007 (GVB: Gemeentelijk Vervoersbedrijf, English: Municipal Transport Company). Nowadays, GVB is a private company owned by the city of Amsterdam. The company operates 5 metro lines, 15 tram lines and 23 bus lines.[1] Furthermore, a different branch of the the company operates several ferry connections. These are fully financed by the municipality and therefore mostly free of charge for passengers. Hence, no ticket validation takes place for passengers boarding the ferries. Therefore, we exclude them from this research. A separate public transport network provides public transport throughout the night. This night service consists of 11 bus lines. An overview of the different lines and the services provided on these lines is presented in Appendix A.

2.2 Traditional Punctuality Measures

The Amsterdam public transport concession, obtained by GVB in 2012, gives the company the sole rights to provide public transport in the Amsterdam region and comes with a statement of obligations (Dutch: Programma van Eisen (PvE)). This PvE describes all the requirements that come with the concession. Two important aspects regarding the imposed service level of the provided public transport are the agreements regarding cancellation and punctuality rates.

2.2.1 Cancellation

Cancellation is defined in terms of both the number of cancelled vehicle trips, as well as the number of cancelled vehicle trip kilometers. The definition of a cancelled trip is straightforward. It describes a trip that was scheduled, but was not accessible for passengers. The minimal requirements imposed by the local transport authority

[1]We exclude 4 so-called *commercial* bus lines in this work, as these lines are financed by third parties and are free of charge for passengers. Hence, Automated Fare Collection data (see chapter 4) is missing for passengers traveling on these lines.

Vervoerregio Amsterdam (VRA) as it issued the Amsterdam concession in 2012 are as follows:

- At least 99.25% of all bus vehicle trips should not be (partially) cancelled.
- At least 99.00% of all tram vehicle trips should not be (partially) cancelled.
- At least 99.00% of all metro vehicle trips should not be (partially) cancelled.

A bonus-malus arrangement stimulates the operator to minimize the number of cancelled vehicle trips (Stadsregio Amsterdam, 2013, p. 33).

2.2.2 Punctuality

In addition to the cancellation requirements described above, the Amsterdam public transport concession (roughly speaking) covers the following requirements considering punctuality:

- At the first stop/station of the line, as well as some specific larger stations[2], buses, trams and metro vehicles should never (i.e 0.00%) depart earlier than indicated in the schedule.
- At the first stop of the line, at least 88.00% of the vehicle trips of each bus line should depart within 120 seconds after the scheduled departure time.
- At the first stop of the line, at least 86.00% of the vehicle trips of each tram line should depart within 120 seconds after the scheduled departure time.
- At the first station of the line, at least 90.00% of the vehicle trips of each metro line should depart within 120 seconds after the scheduled departure time.
- For bus and tram lines, the aforementioned performance requirements also include the measurements at some specific larger stops[3] (not being the first stop on the line), where vehicles should depart within 180 seconds after the scheduled departure time.

A bonus-malus arrangement stimulates GVB to optimize vehicle punctuality (Stadsregio Amsterdam, 2013, p. 34).

It has to be noticed that punctuality is reported in terms of departure times and not by arrival performance. Since most vehicle trips are planned to arrive (terminate) shortly before the scheduled departure time of the return journey, there is an intuitive interaction between arrival and departure punctuality.[4] Internal Key Performance Indicators (KPIs) on vehicle arrival punctuality exist and follow a definition comparable to the departure KPIs.

2.3 Data Sources

To be able to report on the aforementioned KPIs, data on public transport operations are recorded. GVB operates several Automated Vehicle Location (AVL) systems that for example record the scheduled and realized arrival and departure times of the vehicles at the different stops. These systems are extensively described in **??**.

[2]See Stadsregio Amsterdam (2013, p. 18) for a list of these stops/stations.
[3]See Stadsregio Amsterdam (2013, p. 18) for a list of these stops.
[4]GVB typically schedules two minutes of *buffer time* at termini during peak hours.

Similar to many other public transit agencies (e.g. Bagchi & White, 2005; Pelletier et al., 2011; Seaborn et al., 2009), GVB uses a smart card Automated Fare Collection (AFC) system to collect revenue. The Dutch national public transport smart card OV-Chipkaart (OVC) was first used in 2005 and subsequently got introduced by different transit agencies over different modes of transport. Since 20014, the OV-Chipkaart fully replaces paper tickets for almost all public transport in the Netherlands. We extensively describe various aspects of this smart card system in **??**. For now, we limit ourselves to mentioning some characteristics of the system that are important for the remainder of this chapter.

The OV-Chipkaart can be used in various ways (e.g. using subscriptions for a specific area for frequent passengers, or by loading prepaid credit on the card for occasional use) and appears in various forms (e.g. a personal card with photo, or a transferable card that is not linked to an individual). An OVC is always valid for only one person at the time, meaning that all individual passengers should have their own card. After loading credit (or a subscription) to the card, the card needs to be validated before and after every leg of a journey. These procedures are referred to as Check-In (CI) and Check-Out (CO) respectively. The exact procedures differ for different modes of transport:

- Bus & Tram: CI is required every time a passenger boards a vehicle. This is done by holding the smart card in front of a card reader inside the vehicle. When alighting from the vehicle, CO happens by again holding the card in front of a reader inside the (same) vehicle. This procedure is repeated on transfer. Hence, when traveling with bus or tram, Check-In and Check-Out are recorded for every leg of the passenger journey.

- Metro & Train: CI is only required when the passenger enters his[5] origin station.[6] The Check-Out happens when a passenger leaves the station at his final destination (or before transferring to a different mode or operator). Hence, the CO/CI procedure is not required when transferring within the train or metro system of a single operator.

For more detailed information on the OV-Chipkaart mechanism, we refer to **??** and Trans Link Systems B.V. (2019).

2.4 Research Goal

We observe that the punctuality measures discussed in section 2.2 are operator-oriented On-Time Performance (OTP) indicators, representing the percentage of vehicles that depart from checkpoints (i.e. specific stops/stations) within predefined time windows around scheduled departure times (Barabino et al., 2015). They represent the company's punctuality performance merely in terms of vehicle trips. It goes without saying that these vehicle related KPIs are an indication of the service offered to passengers. However, limited knowledge is available about the exact relation between the two. As the company's goal is to bring her passengers to their destination on time, GVB would like to develop a methodology to monitor a KPI on *passenger punctuality*. The main goal of this research is to calculate an appropriate punctuality measure. To achieve this, we combine the data from the vehicle location information systems (AVL) with the data coming from the passenger-oriented fare

[5]The personal pronoun 'he' ('his') as used in this work should be read as 'he or she' ('his or her').

[6]OVC readers are often implemented as ticket gates at metro and train stations.

collection system (AFC). This connection between the two data sources has hardly ever been made in the company's business operations. This research faces the challenge of combining these data sources to answer the following research question:

How can Automated Vehicle Location data and Automated Fare Collection data be combined to compute passenger punctuality on individual passenger level, in order to derive the empirical passenger journey arrival delay distribution?

As addressed in chapter 1, we will compute passenger punctuality for each passenger journey recorded in the AFC data and express this punctuality in terms of delay at the destination stop (or station) of the passenger journey. Combining the results of all passengers eventually yields an empirical arrival delay distribution. Subsequently, by making a business decision on the definition of *on Time* (i.e. a threshold defining maximum delay tolerance), one obtains the desired KPI value. That is, the percentage of passengers that arrived on time at their final stop/station in the GVB network.

2.5 Potential Business Value

The information related to the delay of each passenger journey, the KPI, and the monitoring tool that will be developed based on the results of this project, will mainly be used by the GVB Transport Development team. This team is responsible for every aspect of optimizing the Amsterdam public transport network. The overall goal of this department is to increase the number of passengers in the GVB transit network, as well as the provided service quality. In order to achieve this, GVB would like to get all areas in Amsterdam optimally connected by aligning her supply with the passenger's demand. The main challenge is to optimize the network under the constraints of limited (financial) resources (e.g. vehicles, infrastructure capacity) and the (minimal) requirements imposed by local government.

Data analytics is of vital importance to master this optimization problem. However, the GVB Transport Development team mainly uses the AFC and AVL data as separate sources of information nowadays. That is to say, one either reports on (vehicle) punctuality (AVL) or on numbers related to passenger journeys (AFC). Combining the data of both sources is assumed to be difficult, due to the fact that systems were developed for different purposes (transit operation management and fare collection respectively) and were never designed to be fully integrated.

Since GVB would like to become a more customer-oriented business, the company has set several strategic targets that need to be achieved in the near future. The fact that achieving 90% passenger punctuality is one of these targets, clearly shows that answering the research question stated above is important to motivate this target and to monitor the performance on the corresponding KPI (GVB Holding N.V., 2019).

In addition to these KPI related results, a proper combination between AVL and AFC over all legs of the passenger journey yields additional insights related to the following topics:

- Waiting and transfer times at stops need to be derived from the data. These data only arise from the combination of AVL and AFC data, and hence, any quantified business information related to transferring and waiting is not yet available to the organization.

- This can be extended by looking at the quality of specific transfer hubs. Currently, there is not much information available about the quality (e.g. walking and waiting times) of major transfer points in the Amsterdam transit system. By connecting the two data sources and looking at the complete passenger journey instead of individual legs, one obtains travel time related information about these transfer points.

- Since the aforementioned information is based on individual passenger journeys, its resulting insights are also available at this level of detail. Hence, this supports the goal of focusing on passenger-oriented performance instead of only abstracting vehicle-based information.

2.6 Research Components

In this section we briefly introduce the different **problem components** we identify in order to be able to eventually compute the arrival delay for each passenger journey. We regularity refer to these different components throughout the rest of this report. The relations between these different aspects are visualized in Figure 2.1.

We start by looking at the structure of a passenger journey in the GVB network. This starts by investigating the first leg of the journey. Based on the difference in AFC procedure (see section 2.3), we distinguish two different scenarios based on the mode of transport.

If the first leg of the journey is made by bus or tram, we know that CI happens inside the vehicle. This forces us to **estimate the arrival time of passengers at their departure stop**.[7] The reason why this is a necessary first step is probably best explained by an example:

Example: Planned vehicle trip not recorded in AFC data

Assume all buses to run perfectly according to schedule with a 10 minute headway, some passenger P_1 to arrive at a bus stop 2 minutes before the departure time of bus B_1 and P_2 to arrive at the same bus stop 3 minutes before the departure time of bus B_2. Here we define B_2 to be the next bus on the same line, directly after B_1 (one 10 minute headway between the two). Now, as both buses run perfectly according to schedule, both passengers will not face any departure delay. But let us now assume that B_1 is cancelled. In that case P_1 faces 10 minutes delay by having to wait for B_2, whereas P_2 is still on time. Since ticket validation happens inside the vehicle, we do not know when P_1 and P_2 arrived at their origin stop and therefore cannot distinguish between P_1 being delayed and P_2 being on time, since both will be recorded on B_2 by the AFC system in exactly the same way.

This example shows that an estimation of the arrival time at the departure stop is needed in order to **derive the vehicle a passenger planned to board**. Once we estimated this arrival time at the passenger's origin stop, we can derive the planned and realized vehicle trips of this passenger. This is extensively discussed in section 3.4 and **??**.

If the first leg of the journey is traveled by metro, we face the advantage that the arrival time at the station is assumed to be known in this case, i.e. the moment of

[7] In what follows, we will refer to metro stops as stations, whereas we will use the term stop for bus and tram.

ticket validation. This is due to the fact that ticket validation happens at the station and not inside the vehicle (see section 2.3). However, this also comes with a disadvantage: It is not trivial to derive what route and vehicle the passenger traveled (and planned to travel) on. This is due to the fact that there can be multiple feasible routes/itineraries that fit between the moments of CI and CO. This **(passenger-) vehicle assignment problem** is discussed in section 3.5 and **??**. After we solved this problem, we are able to **determine the planned and realized vehicle trip(s)**[8] of this journey leg.

Once we determined the planned and realized vehicle trip(s) that belong to a leg of a passenger journey, we can **derive the corresponding planned and realized arrival times at the destination stop/station of that leg**.

Next, we need to identify whether there is a next leg in the journey of the passenger (i.e. whether a transfer is recorded in the AFC data). If there is no next leg, we derive the arrival delay from the aforementioned arrival times, since we assume that the passenger has reached his destination. If there is next leg in the journey, we again distinguish between tram/bus and metro.

If the next leg is traveled by tram or bus, we need to **estimate the (planned) walking time between the arrival location of current leg and the departure stop of the next one**. After adding this value to the planned arrival time of the current leg, we can use this to determine the planned trip of the next leg. Hence, we close the loop to determining the planned and realized vehicle trip as indicated by Figure 2.1. Note that for tram and bus, the only difference between the first and second leg is the way in which we determine the arrival time of the passenger at the departure stop of the journey leg.

If the next leg is traveled by metro, we need to **estimate the walking time between the arrival location of current leg and the ticket readers of the departure station of the next one.** At first sight, there might appear to be no difference between tram/bus and metro here. However, the opposite will be motivated in **??**.

We now introduced all components of the iteration loop over the different legs of the passenger journey (see Figure 2.1). That is, we illustrated the outline of the problem structure independent of the number of legs in the passenger journey.

2.7 General Research Approach

We conclude this chapter with some general remarks regarding the business requirements of this research and the impact these have on how we solve the problem and answer the research question.

From the GVB business perspective, the primary goal of this study is to develop a well-founded, but also explainable methodology to compute passenger punctuality. Therefore, any element of the implementation should be well-motivated and explained in order to convince business management (and later possibly also third parties) about the correctness of the resulting KPI value. This is why this report includes several examples. These are indicated by blue boxes, like the example on the previous page. For the same reason, we stress any major assumption and business choice we make, by presenting them in a green box like the one below.

Business Rule: Example

[8]One journey leg can contain one or more metro transfers, as passengers do not need to Check-Out and Check-In if they transfer within the metro system (see section 2.3).

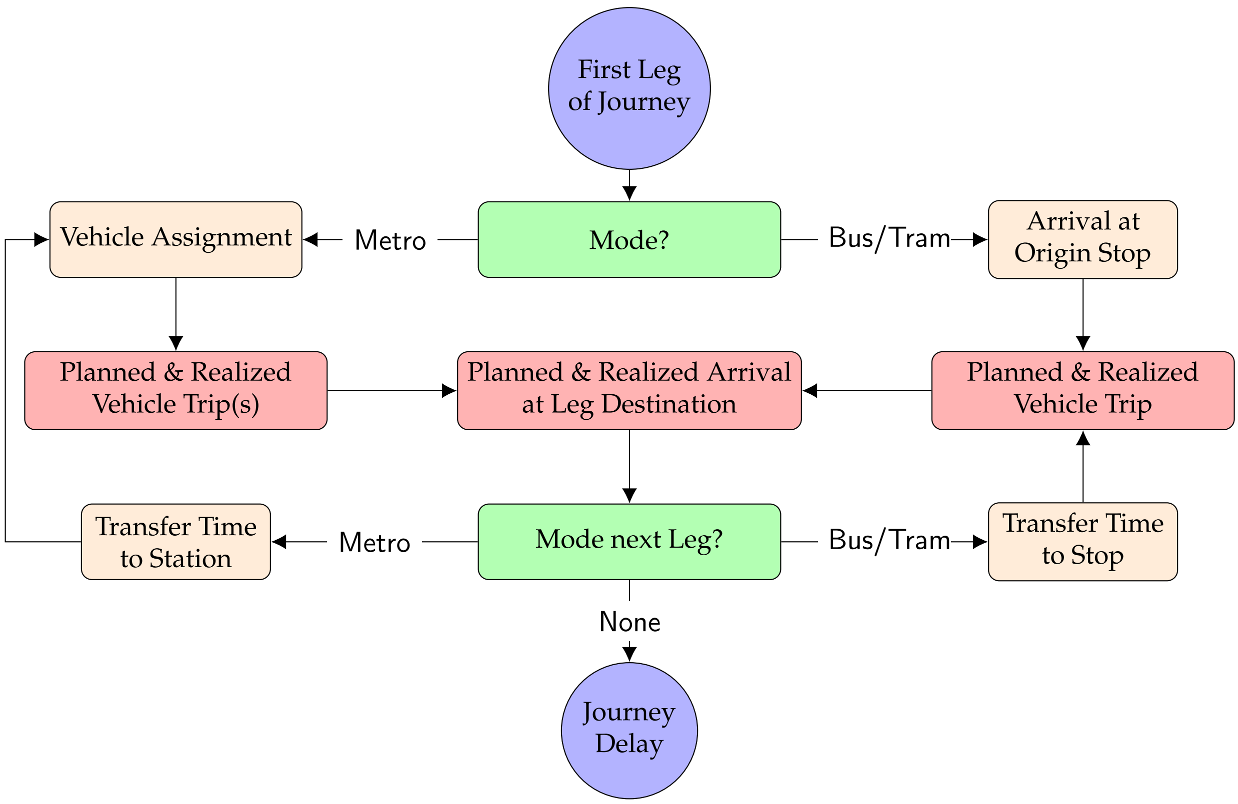

FIGURE 2.1: Overview of the general structure of the problem.

Chapter 3

Literature Review

Public transport has become a popular field of study over the last decades. As already touched upon in chapter 1, the increase in research related to transportation seems to be empowered by various newly introduced data sources.

We begin this section by briefly discussing some major research topics in the field. Thereafter, we will focus on the Automated Fare Collection (AFC) and Automated Vehicle Location (AVL) data-related work. The core of this chapter is devoted to punctuality related research. This part is structured by separately discussing the main research components introduced in section 2.6.

3.1 Public Transport Research

Research has been done on a broad spectrum of public transport-related topics. This for example reaches from public transport applications of vehicle scheduling methods trying to cover the scheduled vehicle trips with a minimal number of vehicles (e.g. Bunte & Kliewer, 2009), to simulation studies regarding transfer synchronization in bus networks (e.g. Ceder et al., 2013). Pelletier et al. (2011) present three different levels of studies related to public transport.[1] One of these branches is the *operational level*. This branch covers research on operational performance. This considers research on how to optimize operations, based on the given public transport network. This for example includes estimation of waiting times and short-term prediction of demand. Furthermore, this category covers research on performance measures relating to characteristics like cancellation, punctuality, frequency and regularity. Since the present work contributes to this branch of study, we will discuss related work in more detail in section 3.3.

The second branch is the *tactical level*. Service adjustment is the main research topic here. For example, work has been done on visualizing transit flows and schedule optimization. An example of research in this branch is provided by Jang (2010), who presents an intuitive method to use fare collection data to gain insight in transfer stations with long transfer times (see section 3.6).

The last branch covers the *strategic level* studies. This concerns research mainly related to long-term transport network development and estimation of long-term future demand. This branch has become well-studied, especially over the last decade. The reason for this research increase is twofold. On one side, Automated Data Collection (ADC) systems have become more frequently used and data quality has significantly increased over the years. On the other side, strategic long term network planning research is important to be able to increase the attractiveness of public

[1] Pelletier et al. (2011) present them in the context of AFC-related studies. We generalize this to public transport planning-related studies in general.

transport and to be able to provide reliable public transport with enough capacity in the future (Hörcher et al., 2017). An important research topic on this strategic level is the development of various route choice models (e.g. Hörcher et al., 2017). Since recent studies in all three branches focus more and more on using AFC and AVL data, we will first discuss literature on these data sources (section 3.2), after which we will get back to related work on punctuality, as this is the major topic of the present work.

3.2 AVL & AFC Data

As already mentioned in the previous section, Pelletier et al. (2011) provide an interesting overview of the the different types of research based on smart card AFC systems. It is not in the scope of the present work to provide another extensive overview of the available literature. We therefore limit ourselves to summarizing the major advantage of the use of smart card and vehicle location data, as well as to some examples relevant to our present research.

Traditional public transport research is often based on so-called Stated Preference (SP) data. Zhao (2004) intuitively explains how these works often lead to restricted results, as sizes of the datasets are often limited. This is due to the fact that these data are typically gathered using (costly) surveys. When using data from (smart card) AFC systems, data are gathered automatically, which allows us to collect larger volumes of data containing Revealed Preference (RP) data. In all branches of public transport study, both types of data have their advantages and disadvantages, but the emerging body of AFC-based literature shows how this still relatively new technology extends the data-based research possibilities in this field (Anderson et al., 2017).

Already in 2005, Bagchi and White identify the potential of smart card data. They especially stress the possibilities of combining this data with other data sources. This work is followed by various case studies, for example to identify commuting patterns (Ma et al., 2017), to predict (long-term) public transport demand (Li et al., 2018; Sun et al., 2016), or to develop extensive route choice models by combining AFC and AVL data (Hörcher et al., 2017).

Combining AFC and AVL data also opens up new possibilities to develop service quality indicators for public transport. As this is the main goal of our present research, we discuss previous research related to this topic in the next section.

3.3 Punctuality

Reliability of service is an important aspect of the public transport quality offered to passengers. In this sense, reliability consists of several components like passenger loads, provided frequencies, service regularity and punctuality (van Oort, 2011). However, as described in chapter 2, these components are frequently translated to operation-oriented performance indicators, which do not always accurately represent the passenger's experience. An example of such a measure is the trip On-Time Performance (OTP), i.e. the number or proportion of on time arrivals or departures at stops or stations. Henderson et al. (1990) identify that this indicator does not represent passenger punctuality, since no connection is made between the number of passengers traveling from, to, or via the corresponding stop. They take a first step in making OTP more passenger-oriented, by weighting it with proportions of passengers traveling on the corresponding vehicles.

Over the past years, more and more work on passenger-oriented quality indicators has become available. We refer to e.g. Diab et al. (2015) for a review on both operator-oriented, as well as passenger-oriented reliability measures. Gittens and Shalaby (2015) identify three components of reliability: punctuality in arriving at the destination, short waiting times at the origin stop and consistent waiting and travel times. They assert twenty different passenger-oriented indicators, for which they define five different categories: travel time indicators, schedule adherence indicators, headway regularity indicators, waiting time indicators and composite indicators. They conclude that non of the twenty indicators in these five categories is well-suited to capture all three elements of reliability. They find that only the passenger journey time delay indicator (i.e. the value resulting from subtracting the planned journey duration from the realized journey duration) reflects the experience of reliability. However, they face difficulties in applying this measure, since they do not succeed in determining actual waiting times at bus stops (Gittens & Shalaby, 2015).

A comparable measure is proposed by Zhao et al. (2013) as Excess Journey Time (EJT) (i.e. the difference between the actual passenger journey time and the journey time implied by the timetable). By means of a London Overground case study, they motivate EJT to provide a useful balance between the passenger's and operator's perspectives of public transport service quality (Zhao et al., 2013).

Uniman et al. (2010) introduce another reliability measure, Reliability Buffer Time (RBT), being the additional buffer time a passenger should allocate to assure his on time arrival to a certain degree of uncertainty (Bagherian et al., 2016; Uniman et al., 2010).

As an additional reliability measure, Gittens and Shalaby (2015) introduce Journey Time Buffer Index (JTBI), where they weight the impact of bus travel time variability by means of an arrival penalty on one side, and the variability in departure times at the origin stop on the other side. This measure can roughly be seen as a combination of e.g. Barabino et al. (2015), where only the departure component is considered, and work related to arrival delay, like Uniman et al. (2010).

Bagherian et al. (2016) identify that a large body of earlier research mainly focuses on AFC systems where ticket validation happens at the station, and not on-vehicle. This leads to various issues like vehicle-assignment problems, which make it hard for transport authorities and operators to assimilate the proposed indicators in their daily operations. This is why they propose two other metrics for regularity and punctuality. Their regularity measure is defined as a passenger-oriented Daily Variation (DV) reliability measure, reflecting the regularity of a service over a defined time period. Their punctuality measure is a Schedule Deviation (SD) measure, indicating the deviation of the individuals' actual travel time from the scheduled time (Bagherian et al., 2016). By a hands-on application of their methodology to the The Hague bus and tram network (using the same smart card system as the Amsterdam network in our study), they show that their metrics can directly contribute to an increase of passenger-oriented monitoring of the quality of public transport operation.

3.3.1 Punctuality Indicators from a Business Perspective

Despite the relatively new work of for example Bagherian et al. (2016), the survey study of van Oort (2014) clearly shows that public transport operators and authorities are typically focusing on operator-oriented performance measures, although more and more exceptions can nowadays be found in practice.

Looking at impressive business examples like Swiss National Rail (Schweizerische Bundesbahnen, 2020; Schweizerische Bundesbahnen & Affeltranger Weisser, 2018), German National Rail (Deutsche Bahn, 2019) and Nederlandse Spoorwegen (NS) (Dutch National Rail) (Nederlandse Spoorwegen, 2019), we observe that many rail transport operators use more or less the same passenger-oriented reliability measure, being the passenger's arrival delay at their destination station. Although exact definitions differ for each business application, we observe that the general approach is the same for each of the aforementioned companies. That is, they combine the data from either their booking systems or the AFC data, with AVL (and other journey planning) data, in order to derive the passenger's arrival delay.

We observe that explainability is an important factor influencing the choice of reliability indicators in business operations (Deutsche Bahn, 2019). From a business perspective, it is often preferred to use a passenger-level service quality indicator. The arrival delay indicator used by many rail operators can be assigned to every individual passenger journey and therefore typically yields an explainable service quality indicator.

As mentioned in chapter 1, Wolters (2016) provides an in-depth analysis of the passenger arrival punctuality KPI of NS. Den Heijer (2018) builds on this work by looking at the impact of disruptions on this KPI. Throughout this report, we will therefore regularly compare the methodology of Wolters (2016) to the approach we use in the present work.

We identify that, to the best of our knowledge, sound passenger arrival punctuality computation methodologies have only been developed for unimodal (rail) network operations (e.g. Nielsen et al., 2009; Wolters, 2016). No complete, explained application seems to have been developed for, and applied to, (local) multimodal public transport networks. The present work aims at closing this gap by developing a methodology to compute the passenger's arrival delay at his final stop/station based on AFC and AVL data from the multimodal Amsterdam public transport network.

In the remainder of this chapter, we will focus on the literature related to the individual research components identified in section 2.6.

3.4 Arrival at Origin Stop

As described by the example in section 2.6, we need to estimate the arrival time of passengers at their origin stop. This information is necessary to be able to derive the planned vehicle trip of the first passenger journey leg.

Already in 1977, Chapman et al. state: *"There is a good deal of consensus on waiting times and no further studies may be needed."* However, it seems that the opposite is true, when we look at related studies published since then (Chapman et al., 1977; Müller, 1981).

Müller (1981) nicely illustrates the main research topics covered by this field of study. He notices that when we investigate passenger arrival[2] behaviour, we can identify two groups of passengers, both discussed in what follows.

A fraction of the passengers does not know the timetable. This leads to the fact that these passengers randomly arrive at the stop and that we cannot predict the

[2]Note that we mean arrival at the origin stop here, i.e. at the beginning of the passenger journey. This is a completely different question than the passenger arrival punctuality (at the destination) question that this work generally tries to answer.

arrival time of these passengers individually. We refer to this group as *schedule independent* and observe that the mean waiting time of these passengers corresponds to halve of the headway, since their arrivals follow a uniform distribution (Lüthi et al., 2007; Müller, 1981). Furthermore, Müller (1981) motivates that, on a relatively small time scale, this leads to the fact that it is appropriate to assume that the expected number of arrivals of this group between two consecutive trips is not different from the number during two other consecutive trips, as long as both scenarios are operated with the same headway.

The rest of the passengers is assumed to know the next (scheduled) departure time (either by looking up the schedule or from experience) and we therefore assume that these passengers try to limit their waiting time by planning their arrival time closely before the departure of the vehicle. While mainly focusing on (expected) mean waiting times, early research on the arrival behaviour of this group focuses on the *realized* intervals between busses. Nowadays, it is generally accepted that the arrival behaviour of this group should be based on the departure times that passengers can consult. That is, the *planned* headways (Bowman & Turnquist, 1981; Lüthi et al., 2007; Müller, 1981). Various distributions were proposed to describe the arrival behaviour of this *schedule dependent* group in relation to the planned headway. Early work mainly expresses this by describing the relation between headway and expected waiting time (Lüthi et al., 2007; Müller, 1981).

Based on a case study in Leeds, O'Flaherty and Mancan (1970) conclude that a linear model can be used to describe the relation between average waiting time and headway. However, it should be noticed that this work mainly focuses on short headways during peak hours.

Jolliffe and Hutchinson (1975) present a different approach, as they assume that three different groups of passengers exist: a fraction q, of which the arrival time is causally coincidental with the departure time of the bus, a group of size $p(1-q)$ that arrives at the optimal time (the time at which the expected waiting time is smallest), and a proportion $(1-p)(1-q)$ who arrive at random. They conclude that p increases with the headway (i.e. less randomness if intervals increase), and that p is also larger during peak hours. However, they did not find relationships for q, which made them assume a constant value $q = 0.16$ being appropriate based on their measurements. They presents a linear relation between mean waiting time and headway (Jolliffe & Hutchinson, 1975; Lüthi et al., 2007).

A (piece-wise) linear relation is also identified by the extensive Zürich case study of Müller (1981). However, this work clearly stresses that there are many different factors that influence the passenger arrival distribution. Besides headway, e.g. the location of the stop (in the surrounding area, as well as within the public transport network itself), the time of the day and reliability of service are important factors as well. This limits the transferability of results.

3.4.1 Johnson S_B Distribution

Lüthi et al. (2007) perform a case study in which they investigate passenger arrival behaviour at 28 stops in Zürich. they focus on short, as well as on long headways. They identify that the relation between the median passenger arrival time before planned departure and the planned headway is not linear, but can much better be approximated by a logarithmic function. This observation indicates that the aforementioned works may overstate passenger wait time, especially for longer headways. They therefore propose a different model for the passenger arrival distribution. Like many of the aforementioned work, they assume that there is a proportion

c_{sd} of *schedule dependent* passengers, whereas the other group ($c_{si} = 1 - c_{sd}$) arrives randomly, according to the a uniform distribution (Equation (3.1)). The fraction c_{sd} is assumed to arrive according to a Johnson S_B distribution: $JSB(a, b, \alpha_1, \alpha_2)$ (Equation (3.2)). Both distributions have some predefined domain $[a, b]$ and the latter has two parameters $\alpha_1 \in \mathbb{R}$ and $\alpha_2 > 0$. These parameters describe the shape of the distribution. The JSB is related to the normal distribution and is skewed left for $\alpha_1 < 0$. This skewness intuitively suits the observation that passengers plan their arrival closely to the scheduled departure time of the vehicle (Lüthi et al., 2007; Zhang et al., 2014). We visualize this in Figure 3.1.

$$f_{U(a,b)}(x) = \begin{cases} \frac{1}{b-a} & \text{if } a < x < b \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

$$f_{JSB(a,b,\alpha_1,\alpha_2)}(x) = \begin{cases} \frac{\alpha_2(b-a)}{(x-a)(b-x)\sqrt{2\pi}} e^{-0.5\left(\alpha_1 + \alpha_2 \ln\left(\frac{x-a}{b-x}\right)\right)^2} & \text{if } a < x < b \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

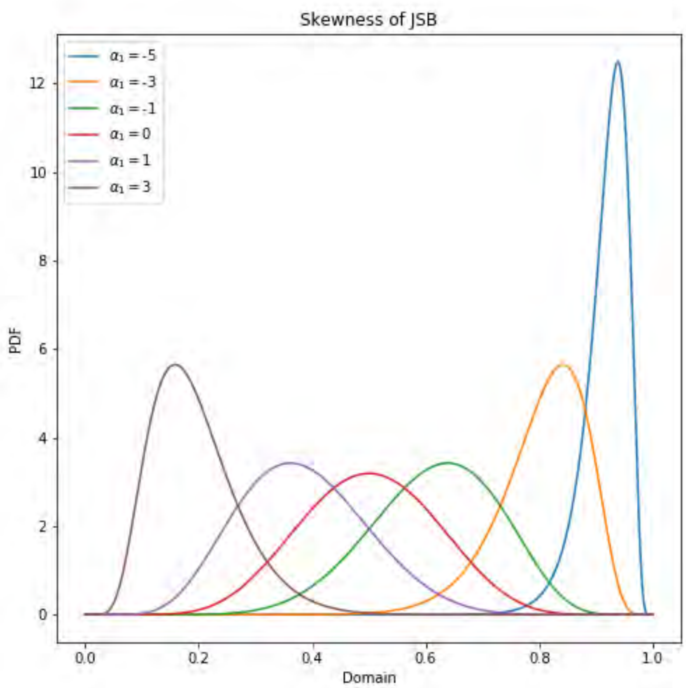

FIGURE 3.1: PDF of $JSB(0, 1, \alpha_1, 2)$ for different values of α_1.

Lüthi et al. (2007) also introduce an additional shifting parameter $\delta_{ts} \in [0, b)$, which is a reliability and headway dependent parameter. This parameter describes the fact that people may know that vehicles regularly depart later than indicated in the schedule. If passengers know this, they might plan their arrival after the scheduled departure time, which leads to a shifted $JSB_{sh}(a, b, \alpha_1, \alpha_2)$, as described in Equation (3.3).

$$f_{JSB_{sh}(a,b,\alpha_1,\alpha_2,\delta_{ts})}(x) = \begin{cases} \frac{\alpha_2(b-a)}{(x+b-\delta_{ts}-a)(\delta_{ts}-x)\sqrt{2\pi}} e^{-0.5\left(\alpha_1+\alpha_2 \ln\left(\frac{x+b-\delta_{ts}-a}{\delta_{ts}-x}\right)\right)^2} & \text{if } a < x < \delta_{ts} \\ \frac{\alpha_2(b-a)}{(x-\delta_{ts}-a)(b+\delta_{ts}-x)\sqrt{2\pi}} e^{-0.5\left(\alpha_1+\alpha_2 \ln\left(\frac{x-\delta_{ts}-a}{b+\delta_{ts}-x}\right)\right)^2} & \text{if } \delta_{ts} < x < b \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

Since the (unshifted) passenger arrival domain is defined as $(0, h)$, with h the scheduled headway, 0 and h are appropriate values for a and b respectively. Finally, we superimpose the arrival distributions of the schedule sensitive and insensitive passengers, which yields the final arrival density $f_{pa}(x, \alpha_1, \alpha_2) = c_{si} \cdot f_{U(0,h)} + c_{sd} \cdot f_{JSB_{sh}(0,h,\alpha_1,\alpha_2,\delta_{ts})}$ as presented by Equation (3.4) (Lüthi et al., 2007).

$$f_{pa}(x, \alpha_1, \alpha_2, \delta_{ts}) = \begin{cases} \frac{c_{si}}{h} + \frac{c_{sd}\alpha_2 h}{(x+h-\delta_{ts})(\delta_{ts}-x)\sqrt{2\pi}} e^{-0.5\left(\alpha_1+\alpha_2 \ln\left(\frac{x+h-\delta_{ts}}{\delta_{ts}-x}\right)\right)^2} & \text{if } 0 < x < \delta_{ts} \\ \frac{c_{si}}{h} + \frac{c_{sd}\alpha_2 h}{(x-\delta_{ts})(h+\delta_{ts}-x)\sqrt{2\pi}} e^{-0.5\left(\alpha_1+\alpha_2 \ln\left(\frac{x-\delta_{ts}}{h+\delta_{ts}-x}\right)\right)^2} & \text{if } \delta_{ts} < x < h \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

What remains is finding a method to estimate the parameters. α_1 and α_2 can be estimated by fitting the distribution to data, using various statistical methods like the Chi-Square test (Lüthi et al., 2007), Kolmogorov-Smirnov test (Zhang et al., 2014) or combination of different procedures like Maximum Likelihood Estimation (MLE) and least square errors (George & Ramachandran, 2011).

One also needs to estimate the value of c_{sd} (or c_{si}). Literature shows that this is a very challenging task, as there are many factors that influence the proportions c_{sd} and c_{si}. There seems to be some consensus regarding the idea that there is some threshold headway, below which arrivals all seem to happen randomly (i.e. $c_{sd} = 0$, $c_{si} = 1$). However, the value of this boundary is controversial. O'Flaherty and Mancan (1970) identify this boundary at a headway of 5 minutes during peak periods and 12 minutes off-peak in their Leeds case study. Jolliffe and Hutchinson (1975) (London) agree on this 12 minute boundary. Müller (1981) (Zürich) identifies $c_{sd} = 0$ for headway $h \leq 5$ minutes and $c_{sd} > 0$ for headway $h \geq 7$ during rush hour, where he notices that c_{sd} is significantly larger in the morning rush hour than in the evening. Results are inconsistent for $h = 6$. Furthermore, he identifies $c_{sd} \leq 0.20$ for $h < 10$, $c_{sd} \leq 0.50$ for $h \in (10, 14]$ and $c_{sd} \approx 0.90$ for $h = 15$ minutes.

Lüthi et al. (2007) conclude that c_{sd} is larger during peak hours for all headways, and that, for almost every headway, the fraction of schedule aware passengers is larger during the morning peak than in the evening. They present a graph showing the proportion c_{sd} for $h \in [4, 15]$ for the different moments of the day (i.e. morning peak, evening peak and off-peak) in Zürich. Müller (1981) and Lüthi et al. (2007) identify that headways that yield departure times that are typically considered to be *easy to remember* (e.g. 5 minute headway), lead to an increase of c_{sd}, whereas the latter also presents that service irregularities lead to an increase of c_{si}. From a case study in The Hague, Van Oort (2011) concludes that c_{si} is approximately between 40% and 50% for both peak and off-peak hours.

We should conclude that there are no generally accepted values of c_{si} and c_{sd} for different headways, since many location-, network- and operator-specific characteristics influence the passenger arrival behaviour (Bowman & Turnquist, 1981; Furth & Muller, 2006; Lüthi et al., 2007; Müller, 1981; van Oort, 2011). The rise of new technologies like AFC and AVL systems provide us with new possibilities to easily collect large datasets to further investigate the factors that influence arrival and waiting times (e.g. Berggren et al., 2019; Tavassoli et al., 2018). One should be aware of the fact that new research will never be completely transferable to other public transport environments (due to location-specific factors) and that the fraction of passengers planning their arrival time based on real-time departure information will increase when new sources of real-time information become available (Lüthi et al., 2007).

3.5 Passenger-Vehicle Assignment Problem

Depending on the characteristics of the AFC system at hand, solving the (passenger-) vehicle assignment problem might be a necessary step to derive the route and vehicle a passenger traveled on. As described in section 2.6, this is typically the case for systems where ticket validation happens at the station instead of on the vehicle, such as the Amsterdam metro system. In this section, we discuss the related literature considering this vehicle assignment problem.

As identified by Hörcher et al. (2017), the quality of an assignment method generally depends on the corresponding quality of the available data regarding passenger and train movements. In 1989, Spiess and Florian take a first step in solving the vehicle assignment problem. They use the (average) planned frequency of trains to determine the average occupancy of these trains in a corresponding time interval. Due to the limited level of detail in their schedule data, more detailed results cannot be obtained. Later, assignment methods are published using more detailed schedule data. One of these studies is Kusakabe et al. (2010), where the scheduled arrival and departure times at every station are used, which leads to a more fine-grained assignment. However, Kusakabe et al. (2010) notice that they are not able to assign all passengers in their case study, where they use data from a Japanese railway company. They identify that this group of passengers might become assignable when one would use the realized arrival and departure times, instead of the schedule data. This statement seems to be even more relevant when looking at case studies where train punctuality rates are lower, which also holds for our present work.

One of these studies using vehicle realization data (i.e. AVL data) is Paul (2010). In her case study, she uses London Underground AFC and AVL (realization) data to infer the passenger's route choice and to derive train loads. She first investigates passengers for which only one feasibly itinerary exists. That is, she looks at passengers for which there is only one feasible train (or set of trains in case of transfers) of which the departure and arrival times fit within the time span between the passenger's ticket validation at the origin and destination stations. Since train assignment is trivial in this case, she uses the train assignment information of this group of passengers to derive the distribution of egress times for each (destination) station. She then derives the corresponding access time distribution by assuming that the ratio between access and egress times can be preserved from passenger movement survey data. Next, she uses these access and egress distributions to assign passengers with multiple possible itineraries. In this procedure she assumes that the access time (at the boarding station) is the same percentile of the corresponding distribution, as the egress time (at the destination) is of the egress time distribution. That is, she assumes that walking speed is a (relative) characteristic of the individual passenger and that this characteristic is the same for access and egress behaviour. Although this behavioural characteristic being constant is definitely a strong assumption, it does result in a consistent train assignment method for (almost) every passenger in the London underground metro system she investigated (Hörcher et al., 2017; Paul, 2010).

In her Hong Kong Mass Transit Railway case study, Zhu (2014) focuses on journeys without transfers. By only looking at off-peak periods, she avoids problems related to crowding and failed boardings. She initially uses walking speed distributions as input for her model, which, under the assumption of walking distances, allows her not to make strong assumptions related to consistent walking speed of individuals (contrary to Paul (2010)). In her work, she also introduces a method to estimate the parameters of these walking time distributions.

Hong et al. (2016) introduce an alternative method focussing on the grouping of CI and CO timestamps of passengers traveling on the same trains. They assume that the CI timestamps of passengers traveling on only a limited number of subsequent trains may overlap[3] and that the CO timestamps of passengers coming from subsequent trains may never overlap. These assumptions allow them to assign passengers to itineraries based on so-called *arrival waves* in the AFC CO data, while using *reference passengers* with only one feasible itinerary to reliably identify the connection between these waves and the corresponding trains.

In the context of developing a discrete route choice model, Hörcher et al. (2017) extend the work of Zhu (2014), as they include transfers in their methodology. They again use passengers with only one feasible itinerary to derive station specific access and egress time distributions. They then introduce the concept of *delayed access time* distributions, derived from the access times of passengers with multiple possible itineraries (e.g. due to failed boardings). For the group of journeys including a transfer, the assignment is based on the delayed access time distribution (at the origin station) and the egress time distribution at the destination station. This then yields a *delayed transfer time distribution* for transfer stations, which allows them to assign the last remaining group of passengers; the group with more than one transfer. Contrary to Zhu (2014), who uses additional walking time distributions as input, Hörcher et al. (2017) use only the AFC and AVL data as input to derive the distributions and apply their likelihood-based method. As a consequence, Hörcher et al. (2017) do not make a distinction between walking and waiting times, which was done by Zhu (2014).

In a recent publication, Zhu et al. (2017) motivate the limitation of needing a large sample size to derive a significant *delayed access time* distribution as proposed by Hörcher et al. (2017). Furthermore, Zhu et al. (2017) reflect on the fact that Hörcher et al. (2017) do not explicitly include the impact of failed boardings at transfer stations, which might limit the accuracy of the assignments in the latter study.

Zhu et al. (2017) extend the approach of Zhu (2014). They are able to capture and quantify the impact of failed boardings at individual passenger level, but only for journeys that do not include a transfer.

The aforementioned publications mainly focus on large-scale, high frequency (suburban) rail networks. The central goal of these works is to retrospectively infer the actual passenger behaviour. Now, let us get back to the context of the present research. We notice that we merely need the vehicle assignment method to derive the scheduled and realized arrival time of the passenger. That is to say, the vehicle assignment method itself is not the main goal of our research. Hence, we should ask ourselves whether an approach like the ones discussed before yields the desired

[3]Hence, this implies the assumption that the effect of failed boardings at the origin and transfer stations is rather limited.

result we need to compute passenger arrival punctuality. Since they face a similar challenge, we conclude this section by briefly discussing the approach of NS.

The Dutch National Railway company uses its own journey planner application to derive the planned itinerary. That is to say, based on CI and CO locations, they retrospectively *request* the first possible itinerary from the moment the passenger checks-in at the station. Note that this yields the planned itinerary based on a snapshot of the schedule data from two days prior to the moment of travel. This is done under the assumption that passengers expect their journey to be as it shows up when they plan their trip two days in advance. This prevents the planned itinerary from being changed based on the current situation (e.g. disruptions) which leads to adapted travel advice in the journey planner application (Wolters, 2016).

Roughly speaking (see Wolters (2016) for an exact description), six relevant realization scenarios exist:

- If a train has a delay of at least 15 minutes before departure, the CO timestamp minus the predefined walking time between the platform and card reader at the destination station is used as realised arrival time.
- If the planned train does not depart, the CO timestamp minus the predefined walking time between the platform and card reader at the destination station is used as realised arrival time.
- If a train does not arrive at the destination or planned transfer station, the CO timestamp minus the predefined walking time between the platform and card reader at the destination station is used as realised arrival time.
- If the realized transfer time (e.g. due to delayed arrival of the previous leg) is less than the planned transfer time, the CO timestamp minus the predefined walking time between the platform and card reader at the destination station is used as realised arrival time.
- If the first train is missed because it departed too early (i.e. when the time between CI and the realized departure time is less than the predefined walking time at the origin station), the CO timestamp minus the predefined walking time between the platform and card reader at the destination station is used as realised arrival time.
- In all other cases, the realized itinerary is assumed to consist of the same train(s) as the planned journey. In this case, the realized arrival time of the passenger is assumed to be equal to the arrival time of the last train in the journey at the passenger's CO station (Wolters, 2016).

Although Wolters (2016) proposes several alternatives to *reschedule* in order to infer the most likely realized itinerary, this rescheduling is not part of the current passenger punctuality implementation of NS. The set of business rules to replace the realized arrival time by the passenger's CO timestamp clearly shows that it is not necessary to infer a realized itinerary in a passenger punctuality framework.

In **??** we discuss how our vehicle assignment approach balances between inferring the realized itinerary and finding a sound basis for passenger punctuality computation in the Amsterdam metro network.

3.6 Walking & Transfer Times

In the last section of this chapter, we discuss earlier research on transfers and transfer planning in public transport. Earlier work like Van Hagen (2011) motivates that especially transfer time between modes is least appreciated by passengers. In the context of our present work, we therefore consider it to be useful to have a closer look at literature considering transfers.

With the rise of AFC systems, large volumes of data have become available to analyse transfer behaviour. As with all other topics discussed in this chapter, the exact implementation details depend on the AFC system at hand. However, some more general research approaches were published over the last two decades.

To start with, Jang (2010) provides an intuitive approach to identify transfer stations that might need quality improvement. By identifying stops with more than 5,000 transfers per day, more than 50% transfer rate and an average transfer time of at least 10 minutes, this work intuitively identifies frequently used transfer stations in the Seoul transit system that might need transfer quality improvement. However, this work also faces the drawback we introduced in section 2.6. That is, due to ticket validation taking place inside the vehicle, no distinction can be made between walking and waiting times at transfer stations. Hence, the headways of the various services at these transfer points are expected to largely influence the results of Jang (2010).

As described in section 3.5, Zhu (2014) and Zhu et al. (2017) were able to derive a distinction between walking and waiting times inside stations. However, this requires walking time distributions at the different stations to be available and was not applied to transfers in their studies.

Schakenbos et al. (2016) use SP data to investigate the disutility of transfers between train and bus/tram/metro in the Netherlands. They motivate that transfer disutility differs significantly between different trip purposes and therefore does not only depend on trip characteristics (e.g. travel time, mode, station characteristics), but also on personal characteristics of the passenger. They conclude that transfer optimization could lead to a significant decrease in passenger disutility.

In their London case study, Seaborn et al. (2009) investigate the impact of transfers in a multimodal network. However, due to limited AVL data, they have to make strong assumptions regarding the transfer locations.

This impact of transfers has also been investigated in the context of route choice modelling. For example Anderson et al. (2017) and Hörcher et al. (2017) motivate how disutility of transfers may influence the passengers route choice. This conclusion gives rise to mathematical optimization models like Jansen et al. (2002), who try to minimize the transfer times by optimizing the timetable.

When looking at the available literature we discussed, we notice that it all focuses on proposing a methodology to gain insight in current transfer behaviour and many of them yield an approach or motivation to improve transfer quality in future schedules. However, as we discussed in section 2.6, the main transfer-related challenge we face in the present work is not to identify optimization opportunities, but to estimate appropriate minimal transfer times at, and walking time between, transfer location. That is, we are not looking for an approach to optimize the schedule itself, but are trying to find a suitable methodology to infer minimal planned and realized passenger transfer times for the current schedule and its realization.

To conclude this section, we therefore again look at how Wolters (2016) deals with this problem in the NS passenger punctuality computation. Here, NS uses three different scenarios, that are all based on predefined values. First of all, one checks whether a predefined transfer time for the specific combination of arrival and departure platforms at the transfer station exists. If this is the case, this value is used as minimal transfer time. If no such value exists, a second rule applies. That is, one uses a station specific minimal transfer time (where no distinction between different pairs of platforms is made). Intuitively, this is not desirable for larger stations where walking times do differ between different pairs of platforms due to physical distances. In the rare event of both values being undefined, one uses a default value of 5 minutes as minimal transfer time. Although small differences between realization and planning exists, one could roughly state that this minimal value is used to check the feasibility of both planned and realized transfers (Wolters, 2016).

Wolters also discusses some alternative methods to estimate transfer feasibility, as well as minimal transfer times. We refer to Wolters (2016) for the corresponding details.

In long-distance train networks like NS, it is completely justified to only include transfers where the arrival and departure of the transfer happen at the same station. Due to the typically larger distance between stations, it is no problem to assume that passengers do not walk from one train station to the other within a predefined maximum transfer time implied by the AFC system (see **??**). This assumption allows to manually define minimal transfer times in a platform-platform-matrix of maintainable size. However, this assumption does typically not hold in a multimodal local public transport network like the one we investigate in our present study. In our case, distances between different stops/stations are typically walkable and transfers between different stops are sometimes proposed by journey planning applications. Hence, contrary to long-distance rail, in local public transport we sometimes even expect passengers to walk from one stop to the other while transferring. Hence, applying the approach of NS would force use to manually define a very large set of possible transfers between all different stops/stations that are within a 35 minute walking distance (see **??**). This would lead to a manually maintained (sparse) stop-stop-matrix of at least size $\mathcal{O}(10^3) \times \mathcal{O}(10^3)$, which is not a desirable approach.

Hence, one of the challenges we face in the present work is to develop a method, which allows us to define or infer a minimal transfer time that is both maintainable and accurate, in order to make it applicable to the multimodal GVB public transport network.

Chapter 4

Data

<Confidential.>

Chapter 5

Methodology

<Confidential.>

Chapter 6

Results

<Confidential.>

Chapter 7

Conclusion

<Confidential.>

Chapter 8

Discussion

<Confidential.>

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Appendix A

Network Information & Headways

Tables A.1, A.2, A.3 and A.4 give an overview of the timetable headways in the GVB network 2020. This considers the default so-called *winter* schedule. Deviations from this schedule exist e.g. during holidays, events and traffic diversions. More information about the 2020 route network and the corresponding schedule can be found in GVB Exploitatie B.V. (2019). For real-time information we refer to https://reisinfo.gvb.nl/ (GVB Exploitatie B.V., 2020). The GVB Rail network (metro and tram) is shown in Figure A.1.

TABLE A.1: Metro headways in minutes. **EM**= Early Morning, **MR**= Morning Rush Hour, **M**= Morning, **A**= Afternoon, **AR**= Afternoon Rush Hour, **E**= Evening.

Mode	**Line**	**Workday**						**Saturday**				**Sunday**			
		EM	**MR**	**M**	**A**	**AR**	**E**	**EM**	**M**	**A**	**E**	**EM**	**M**	**A**	**E**
Metro	**50**	10	8	10	10	8	12	12	12	10	12	12	12	10	12
Metro	**51**	10	8	10	10	8	12	12	12	10	12	12	12	10	12
Metro	**52**	6	6	6	6	6	7.5	7.5	6	6	7.5	7.5	6	6	7.5
Metro	**53**	10	8	10	10	8	12	12	12	10	12	12	12	10	12
Metro	**54**	10	8	10	10	8	12	12	12	10	12	12	12	10	12

TABLE A.2: Tram and bus workday headways in minutes. **EM**= Early Morning, **MR**= Morning Rush Hour, **M**= Morning, **A**= Afternoon, **AR**= Afternoon Rush Hour, **E**= Evening. *Monday-Wednesday/Thursday-Friday

Mode	Line	Workday						Remarks
		EM	MR	M	A	AR	E*	
Tram	**1**	15	5	7.5	6.7	6	10	
Tram	**2**	15	6	6	7.5	7.5	10/8	
Tram	**3**	15	7.5	10	10	7.5	15	
Tram	**4**	15	12	12	12	10	15	
Tram	**5**	15	7.5	7.5	7.5	6	10	
Tram	**6**		7.5			7.5		Peak hour service
Tram	**7**	15	7.5	7.5	7.5	7.5	12	
Tram	**11**				7.5	7.5		Limited service
Tram	**12**	15	6	6	7.5	7.5	10/8	
Tram	**13**	15	6.7	7.5	6	5,5	10	
Tram	**14**	15	7.5	7.5	6.7	6	15	
Tram	**17**	15	5	7.5	6	5,5	10	
Tram	**19**	15	7.5	7.5	7.5	7.5	15	
Tram	**24**	15	10	10	10	10	15	
Tram	**26**	15	6.7	10	10	6.7	12/10	
Bus	**15**	15	7.5	10	10	7.5	15	
Bus	**18**	15	10	10	10	10	15	
Bus	**21**	10	5,5	6	6	6	10	
Bus	**22**	15	7.5	10	10	7.5	12	
Bus	**34**	15	10	10	10	10	15	
Bus	**35**	10	6	10	10	6	10	
Bus	**36**	15	15	15	15	15	30	
Bus	**37**	10	7.5	10	10	7.5	12	
Bus	**38**	15	15	15	15	15	30	
Bus	**40**	15	15	15	15	15	20	
Bus	**41**	15	10	10	10	10	30	
Bus	**44**	10	10	12	12	10	20	
Bus	**47**	10	10	12	12	10	20	
Bus	**48**	15	15	15	15	15	15	
Bus	**49**	30	30	30	30	30		
Bus	**55**	10	5	10	10	6	15	
Bus	**61**	15	15	15	15	15		
Bus	**62**	15	15	15	15	15	30	
Bus	**63**	15	15	15	15	15	20	
Bus	**65**	15	7.5	10	10	7.5	15	
Bus	**66**	10	6.7	10	10	7.5	20	
Bus	**69**	15	10	12	12	10	30	
Bus	**222**		15			15		Peak hour service
Bus	**231**		30			30		Peak hour service
Bus	**240**		15			15		Peak hour service
Bus	**245**	3x						Early morning buses
Bus	**246**	3x						Early morning buses
Bus	**247**	3x						Early morning buses
Bus	**248**		7.5			7.5		Peak hour service
Bus	**265**		15			15		Peak hour service

TABLE A.3: Tram and bus weekend headways in minutes. **EM**= Early Morning, **M**= Morning, **EA**= Early Afternoon, **A**= Afternoon, **E**= Evening.

Mode	Line	Saturday					Sunday					Remarks
		EM	**M**	**EA**	**A**	**E**	**EM**	**M**	**EA**	**A**	**E**	
Tram	**1**	15	12	7.5	7.5	10	15	12	10	10	10	
Tram	**2**	15	10	6	6	6.7	15	10	6.7	6.7	10	
Tram	**3**	15	12	10	10	15	15	15	12	12	15	
Tram	**4**	15	10	10	10	15	15	12	12	12	15	
Tram	**5**	15	10	7.5	7.5	10	15	15	7.5	7.5	10	
Tram	**6**											Peak hour service
Tram	**7**	15	12	7.5	7.5	12	15	15	10	10	12	
Tram	**11**			6	6				6.7	6.7		Limited service
Tram	**12**	15	10	6	6	6.7	15	10	6.7	6.7	10	
Tram	**13**	15	10	6.7	6.7	10	15	10	7.5	7.5	10	
Tram	**14**	15	10	6	6	10	15	10	6	6	15	
Tram	**17**	15	10	6.7	6.7	10	15	10	7.5	7.5	10	
Tram	**19**	15	12	7.5	7.5	15	15	15	10	10	15	
Tram	**24**	15	10	7.5	7.5	15	15	15	10	10	15	
Tram	**26**	10	10	7.5	7.5	10	15	10	7.5	7.5	12	
Bus	**15**	15	15	15	15	15	15	15	15	15	15	
Bus	**18**	15	15	12	12	15	15	15	15	15	15	
Bus	**21**	15	10	6	6	10	15	10	7.5	7.5	10	
Bus	**22**	15	10	10	10	12	15	15	10	10	15	
Bus	**34**	15	10	10	10	15	15	15	15	15	15	
Bus	**35**	15	10	10	10	15	15	15	10	10	15	
Bus	**36**	30	30	15	15	30	30	30	30	30	30	
Bus	**37**	15	10	10	10	15	15	15	15	15	15	
Bus	**38**	30	30	15	15	30	30	30	30	30	30	
Bus	**40**	20	20	20	20	20	20	20	20	20	20	
Bus	**41**	30	15	10	10	30	30	30	15	15	30	
Bus	**44**	30	15	15	15	30	30	30	30	30	30	
Bus	**47**	30	15	15	15	30	30	30	30	30	30	
Bus	**48**	15	15	15	15	15	15	15	15	15	15	
Bus	**49**											
Bus	**55**	15	15	10	10	15	15	15	10	10	15	
Bus	**61**	30	30	30	30							
Bus	**62**	30	30	15	15	30	30	30	30	30	30	
Bus	**63**	30	30	30	30	30	30	30	30	30	30	
Bus	**65**	30	15	15	15	15	30	30	15	15	15	
Bus	**66**	30	15	15	15	20	30	30	30	30	30	
Bus	**69**	30	30	15	15	30	30	30	15	15	30	
Bus	**222**											Peak hour service
Bus	**231**											Peak hour service
Bus	**240**											Peak hour service
Bus	**245**	3x					3x					Early morning buses
Bus	**246**	3x					3x					Early morning buses
Bus	**247**	3x					3x					Early morning buses
Bus	**248**											Peak hour service
Bus	**265**											Peak hour service

TABLE A.4: Night bus headways in minutes. **Mo**= Monday, **Tu**= Tuesday, **We**= Wednesday, **Th**= Thursday, **Fr**= Friday, **Sa**= Saturday, **Su**= Sunday. Friday night is the night between Friday and Saturday.

Mode	**Line**	**Mo**	**Tu**	**We**	**Th**	**Fr**	**Sa**	**Su**
Bus - Night service	**N81**	60	60	60	60	60	60	60
Bus - Night service	**N82**	60	60	60	60	30	30	60
Bus - Night service	**N83**	60	60	60	60	30	30	60
Bus - Night service	**N84**	60	60	60	60	30	30	60
Bus - Night service	**N85**	60	60	60	60	30	30	60
Bus - Night service	**N86**					30	30	
Bus - Night service	**N87**	60	60	60	60	30	30	60
Bus - Night service	**N88**	60	60	60	60	30	30	60
Bus - Night service	**N89**	60	60	60	60	30	30	60
Bus - Night service	**N91**	60	60	60	60	60	60	60
Bus - Night service	**N93**	60	60	60	60	60	60	60

FIGURE A.1: GVB rail network (tram & metro). Valid from March 3rd, 2019 (GVB Exploitatie B.V., Carto Studio B.V., 2020).

Appendix B

Data Structure AVL

<Confidential.>

Appendix C

Data Structure AFC

<Confidential.>

Appendix D

Data Structure Minimal Transfer Time Journey Planner

<Confidential.>

Appendix E

Questionnaire Arrival at Origin Stop

<Confidential.>

Appendix F

Data Structure Output

<Confidential.>

Appendix G

Management Summary

<Confidential.>