Development of Prediction Schemes for Real-time Bus Arrival Information

by

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Abstract

Intelligent Transport Systems (ITS) are increasingly used in public transport systems in order to provide real-time information (RTI) to passengers and operators. In particular, the RTI related to the prediction of remaining time until the arrival of the next vehicle is the most commonly provisioned information and the main focus of research. A number of predictions methods have been proposed without clear evidence of their real-world applicability, mainly because of their highly computational complexity. Moreover new sources of information, which could be used in RTI generators, become available but they have not been utilized yet.

This thesis formulates a widely used real-world RTI generation method, which is based on the scheduled travel time. Then, the potential contribution of real-time public transport data to RTI generation is investigated. Furthermore, a method that considers both the recent downstream running time information as well as anticipated headways and their impact on downstream dwell times is proposed.

The generated predictions have to be compared against empirical bus arrival data in order to analyse the performance of the different schemes. Automatic Vehicle Location (AVL) data of the trunk bus network in Stockholm, were used for the evaluation of the proposed prediction schemes.

The results illustrate the successful introduction of a robust methodology for bus arrival predictions, which outperforms the currently applied RTI generator. This methodology by integrating real-time public transport data is expected to reduce significantly passengers waiting time. In addition, the second proposed method provides a milestone for the incorporation of the dwell time component in the computation process of RTI.
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Chapter 1

Introduction

1.1 Background and Motivation

In recent years, Intelligent Transportation Systems (ITS) has been extensively deployed in planning, control and management of modern transportation systems. ITS based systems are increasingly funded and implemented by traffic and public transportation agencies. The latter agencies have either successfully implemented or, are in the process of transforming their systems by adapting ITS applications in public transport planning while also infrastructure maintenance and operation. These applications could be categorized as follows (Ezell, 2010):

- Advanced Traveller Information Systems (ATIS) which provide with real-time travel and network information regarding public transport routes and schedules, public transport route and mode planning, information about delays, accidents;
- Advanced Transportation Management Systems (ATMS) which consist of applications that focus on traffic control devices, such as traffic signals, ramp metering and variable message signs (VMS). In the case of public transport networks they are responsible of signalling priority for buses;
- ITS-Enabled Transportation Pricing Systems which mainly focus in road tolling and congestion changing applications, but they are embedded also in public transportation fare systems (e.g. price per kilometre, price per hour);
- Advanced Public Transportation Systems (APTS) which includes applications such as the real-time tracking of public transportation vehicles, provide real-time information to passengers, management of new generation pay fares systems (e.g. smart cards, mobile phone tickets); and
- Vehicle-to-infrastructure (VII) and Vehicle-to-vehicle (V2V) Integration

Public transportation systems are increasingly equipped with information and communication technologies in order to improve passenger level of service and fa-
cilitate fleet management (Casey et al., 1991). The dissemination of accurate and reliable information to passengers is of great importance for the agencies. Advanced Traveller Information Systems (ATIS), and Advanced Public Transportation Systems (APTS), such as Automatic Vehicle Location (AVL) and Automatic Passengers Counts (APC) were first used in order to improve operations and management. Later on, they were also utilized to provide real-time information (RTI) to passengers (FHA and FTA, 2000; TCRP, 2008). With the development of such systems, public transport agencies obtain details regarding bus travel time, bus location, speed, passengers on board and dwell time. As a next step RTI can refer to information on service disruptions, crowding conditions, prescriptive journey planners or the remaining time until the arrival of the next vehicle. The latter one is the most commonly provisioned information and the main focus of research.

1.2 Information Provision

Nowadays, the two most commonly provisioned sources of information, regarding bus arrival time at a stop, are: the timetable; and the real-time information system (RTI). The static source of information (e.g. timetables) is constructed based on fleet scheduling, aggregated passengers’ demand profiles and aggregated traffic conditions. Thus, timetables, as a source of information, have a limited value as they relate to historical states of the system at a given time period. This period refers to the stage in which the timetables are created (e.g. data collection and timetable design periods). The provisioned static information corresponds to the average performance of the network and hence does not reflect variations in service performance. Caulfield and O’Mahony (2009) investigated the opinion of passengers concerning public transport information provision. Bus passengers ranked with the lowest score the provision of timetables at stops. On the other hand, the high preference of passengers towards RTI is supported by numerous of empirical studies which reported that 70-100% of passengers uses RTI as a source of information whenever available (TCRP, 2003). The advantage of RTI is the ability to adjust to the current conditions of the network, and thus could achieve more accurate predictions of bus arrivals. Watkins et al. (2011) delved into the importance of providing accurate information and its implications on passengers’ perception of waiting time. In their study passengers perceived the waiting time as 0.83 minutes longer than the actual waiting time they have experienced. On the other hand, for passengers who used real-time information, their perceived wait time equals to the actual. Moreover, the average wait time of the latter group was 30% shorter compared with those using traditional arrival time information. However, the benefits of RTI for passengers are not limited to effects at the single trip level. Labell et al. (1992) reported the assets of RTI in: 1) improving the chosen terminal and the time of arrival from it, based on pre-trip information (e.g. initial connections); 2) improving the usage of time in/near the terminal; and 3) informing passengers of public transport operating characteristics and reducing passengers anxiety associated with the uncertainty
1.3. OBJECTIVE

of travel time. From the operators’ perspective the existence of real-time tracking systems providing RTI is of great importance for the regularity of their service. As Ingemarson (2010) highlighted, the punctuality of the public transport system is measured and rewarded accordingly. The operator is obliged to pay penalties for a poorer performance and receives bonuses for better performance. RTI could be used in order to keep record of service’s progress in comparison to the scheduled constrains. By monitoring the on-time performance of the system, the operator is able to act dynamically and take a proactive approach and control of the service in order to prevent inevitable irregularities.

1.3 Objective

Public transport operations and especially bus services function in a dynamically changing environment. Thus, they are influenced by significant stochastic variations related to factors such as traffic conditions, demand fluctuations, supply constrains, architecture of public transport network and intersections delays. These variations could potentially enforce buses to deviate from their predetermined schedule. The latter leads to longer passengers’ waiting times for buses and hence to a devaluation of bus services and decrease of passengers’ trustiness and comfort. The provision of accurate bus arrival information though ATIS can help passengers’ decision-making process (e.g. route/mode/stop-choice, departure time from origin) and reduce average waiting time at stops.

On this track, the objective of this thesis is to formulate and evaluate a robust, accurate and timely methodology for generating RTI regarding the remaining time until the arrival of the next vehicle. This methodology will try to overcome the main drawbacks, which have been observed for the existing RTI prediction systems.

1.4 Thesis Outline

The remainder of the thesis is organized as follows. Chapter 2 presents the literature review with a detailed description of sources of variability in public transport services. Moreover, input sources for the generation of RTI and an extended review upon the suggested in literature RTI generation schemes are outlined. Chapter 3 introduces the methodological approach for the construction of a RTI generator with the formulation of three different prediction algorithms and related evaluation metrics. Chapter 4 presents the case study network and the case specific implementation details. Chapter 5 provides the results of the application of the RTI generators for the case study network. The last chapter summarizes the performance of the RTI methods and identifies directions for further research.

Appendix A presents the methodological part in a compact block diagram representation. Appendix B demonstrates the spatial performance of the three RTI methods across the network. Appendix C includes a scientific paper that was written based on the current thesis and peer-reviewed.
Chapter 2

Literature Review

The sources of variability in public transport services, and specifically travel and dwell time are first discussed. Then sources of inputs for the RTI for passengers and existing RTI generation schemes are reviewed.

2.1 Sources of Variability in Public Transport Services

2.1.1 Travel time

Travel time variability investigation is one of the most important and complex field in modern transport systems. As it was indicated (Van Lint et al., 2005; Tu et al., 2008), travel times are subject of traffic flow operations. Sequentially, such operations could describe the interactions between traffic demand and traffic supply. Tu et al. (2008) illustrated the aforementioned characteristics on Fig. 2.1. It should be clarified that the presented factors strongly overlap and depend (non-linearly and dynamically) upon each other. The fluctuations in traffic demand and supply, which are strongly dependent to each other, result in a travel time distribution. The existence of such fluctuations in demand and supply could in turn cause variability in link travel times. Consecutively, this variability could potentially influence the quality of travel time predictions and thereafter the accuracy of the provided real-time information.

Travel time variability in public transport operations is affected by both internal and external factors. Internal factors consist of features such as the vehicle type and capacity, fare collection process and the number of bus stops on the route (Strathman and Hopper, 1993; Hensher, 2007). The external factors are highly associated with traffic conditions, passenger demand and general characteristics of the service area. The traffic conditions confederate to the level of congestion during certain times (e.g. peak hours) or traffic incidents (e.g. traffic accidents, road maintenance) (Noland and Polak, 2002). In focus of that, Strathman and Hopper (1993) indicate that travel time variability increases during afternoon peak, leading to longer headways and high passenger demand.
CHAPTER 2. LITERATURE REVIEW

Figure 2.1: Schematic overview (note: not exhaustive) of factors influencing the distribution of travel times (Tu et al., 2008)

From passenger’s perspective, inaccuracy in real-time information increases the uncertainty in decision-making regarding departure time and route choice, while also the anxiety and stress caused by such provided information. From operator’s perspective, inaccurate RTI could influence in short run the scheduling of trips, strategies of fleet management, identification of incidents, while also in the long run potential widespread irregularities and consecutive penalties by the authorities. Hence, the knowledge of travel time variability is critical for improving the reliability of traffic information services and the accuracy of travel time predictions. The knowledge upon travel time variability could be achieved by investigating the impacts of each of the factors mentioned in Fig. 2.1. For that reason, the contribution of real time data such AVL and APC could be critical.

2.1.2 Dwell time

Dwell time describes the time spent in public transport operations in order to discharge and take on passengers at a stop, including opening and closing the doors,
2.1. SOURCES OF VARIABILITY IN PUBLIC TRANSPORT SERVICES

while also the time spent standing (Officials, 2009). For public transport operations, dwell time constitutes one of the most important components of the overall travel time. Bertini and El-Geneidy (2004) analysed disaggregate AVL and APC data from the metropolitan area of Portland. They found that almost one third of the total bus travel time is lost in order to serve stops. More specifically, 16% of the total bus travel time is spent with open doors at stops. Moreover as TCRP (2003) indicates, dwell time could be considered as a significant source of unreliability as it is associated with high variability (coefficient of variation in a range of 0.6 to 0.8).

Delving into determinants of dwell time variation, (TCRP, 2003, 2013), five main factors are indicated:

1. Passengers’ demand and loading. Specifically, this factor is related to the number of people who board or alight from the highest volume door. Moreover, the level of crowdedness in the vehicle, while also at the stop, greatly affects the overall dwell time;

2. Bus stop spacing. Lines with few stops along their route are expected to meet high demand per stop, as population is distributed over fewer points. On the other hand, very frequent stops reduce the average speed of the vehicle and therefore the overall travel time of the trip (acceleration-deceleration, waiting time at signals) is increased;

3. Fare payment procedures. The time spent in order to collect or evaluate boarding passengers’ tickets is one of the most important factors affecting public transport services. On this track, modern public transport services are equipped with automatic fare systems (e.g. smart cards) in order to reduce this time;

4. Vehicle types. Low floor buses could significantly reduce the service time, especially in cases where the line is used by elderly, people with disabilities, or people with strollers or bulky carry-on items; and

5. On-board circulation. Encouraging people to alight only from the rear doors helps in the de-congestion of the front door, which constitutes in most systems the exclusive boarding point.

Ryan (2012) illustrates the core components of dwell time in the following Fig. 2.2. It should be noticed that in reality the proportion of time spend in different stages of the dwell time is not constant. These time stages consist of high variability which is related to numerous of factors such as vehicle type (e.g. capacity, low/high floor, type of doors), accessibility at the stop for vehicle and passengers, the availability of a dedicated public transport line, demand levels of the stop and bunching phenomena. The latter refers to cases where passengers’ demand is high and dwell times at stops are longer than scheduled. Thus the headways, between consecutive vehicles, become shorter than scheduled, and platoons of buses develop. When bunching overgrows it could produce significant increase of delay for passengers and capacity problems for vehicles (e.g. overcrowded or empty) (Aashto, 2009).
2.2 Automatically Collected Data Sources

In order to generate RTI a variety of data sources is needed as input. One of the most important of these inputs pertains to the real-time location of the approaching vehicle. However, other data could potentially provide important information, which could impact the accuracy of the predictions. These data could be (TCRP, 2003): current traffic conditions (e.g. real-time traffic speeds); the real-time progress data from the last several buses on a particular route that passed a specific stop (e.g. running time between stops); historical traffic conditions (e.g. traffic speeds by day of the week, and time of the day, in the past); historical bus operations data (e.g. running time between specific time-points by time of the day). Furthermore, input data related to dwell time, passengers demand profiles, bus stop type information (e.g. a time-check point stop versus a regular stop) may also be given as an input to RTI generators.

2.3 RTI Generation Schemes

2.3.1 Historical data based models

This type of prediction models is based on the assumption that the traffic conditions remain stationary over time. Thus the generated RTI relies on the historical travel time of previous vehicle trips on the same time period. Williams and Hoel (2003) observed that traffic conditions follow nominally consistent daily and weekly
patterns. These patterns provide a strong indication that historical averages of the conditions at a particular time and day of the week could potentially provide reasonable forecast of conditions for the corresponding time period, day and week. Such models could provide accurate forecasts in places where the traffic conditions remain stable e.g. rural areas. As an example, Lin and Zeng (1999) developed four simple GPS data-based arrival time estimation algorithms based on historical data gathered from the area of Blacksburg-USA. This area could be characterized as rural with relatively stable traffic patterns. The four algorithms were developed based on different sets of inputs. Bus location data, schedule information, the difference between schedule and arrival time (schedule adherence), and waiting time at time-check stops constituted the inputs of the models. The performance of the algorithms was evaluated in the terms of: overall precision, robustness, and stability, while the evaluation was held by using real-data from Blacksburg. The algorithm which utilized the total of aforementioned inputs gave the most accurate arrival time predictions.

Considering the characteristics of the network (rural area), the authors of the above research did not consider the effects of traffic congestion and the dwell time at stops. However, a common approach suggests the combination of historical data based models with other sources of inputs, such as traffic data, in order to provide real-time travel information.

On the latter approach Sun et al. (2007) proposed a two parts methodology, where the real-time location data from GPS data were combined with average speeds of individual route segments, by taking into account historical travel speeds. Specifically, the first algorithmic part tracked the approaching bus in order to obtain the remaining distance for approaching a bus stop, while also the direction of the trip. The second component was to predict the bus arrival time using average travel speed in different temporal and spatial segmentations. In order to evaluate the performance of this algorithm, which was the prediction accuracy, a case study on a real bus route was conducted. The proposed system was found to be relatively accurate in predicting bus arrival times. However, it was noted that the model was found less accurate during peak hour than off-peak hour. This was explained by the fact that as the level of congestion increases, the variation in traffic conditions and thus the speeds increase, respectively. This results in less predictable travel times at downstream stations.

In general, historical based models require a significant set of historical records, which is not always available in practice. This issue is most crucial in cases where the traffic patterns vary significantly. Moreover, the computation of average conditions, such as average travel time and average speed, could be exhaustive for an entire network. Furthermore, their accuracy largely relies on the percentage similarity between real time and historical traffic conditions.
2.3.2 Regression and non-parametric regression models

Regression models

Patnaik et al. (2004) introduced a set of multiple linear regression models for the estimation of bus arrival times using as input automatic passenger counts (APC). In their models they incorporated distance, number of stops, dwell times, number of boarding and alighting passengers as well as weather descriptions as independent variables. Specifically, the number of boarding and alighting passengers refers to the passengers observed when buses visited the stops. This research reveals the high correlation between dwell time and number of boarding and alighting passengers which led authors to incorporate only dwell time in their final model. Even so, they observed that dwell times at upstream stops directly impact vehicle arrival times in further downstream stops. They characterized their final results as reasonable and promising for providing RTI to passengers. However, they indicated that the pure quality of input data, despite the proper treatment, could not eliminate the possibility that some erroneous figures were included in the modelling. Jeong and Rilett (2004) proposed an approach with multiple linear regression models, which used a different set of inputs. In this research the developed regression models were outperformed by other approaches (e.g. Historical data based model and Artificial Neural Network model). However, a great advantage of the regression models is that they could reveal the importance of certain inputs for prediction. For example, Patnaik et al. (2004) concluded that weather was not a strong input for their modelling. In general, variables in transport systems are highly inter-correlated and this could be a deterrent factor for the applicability of regression models.

Non-parametric regression models (NPR)

In addition to the regression models the NPR models are based on a non-predetermined form and thus they are constructed according to information derived from the data. In other words, NPR is a prediction method which does not require the preliminary estimation of certain parameters. Therefore, NPR models are found more suitable for real-time applications. On the other hand, they require larger sample sizes than parametric regression as the data should support model specification as well as the model estimation. One of the widely applied NPR methods is the k nearest neighbour (k-NN), (Vlahogianni et al., 2004). An k-NN model adapted to bus travel time prediction was proposed by Chang et al. (2010). Their study utilizes historical and current information gathered from AVL source. This model uses the current path travel time data for the distance between the same origin and destination stop, considering the multi-interval prediction horizon with an adoptable time lag. The model was found effective, when it was evaluated for accuracy and computing time based on real data. Smith et al. (2002) indicated the desire of large databases for increasing the prediction accuracy. On the other hand, the latter increase could have significant implications on the timeliness of the model.
2.3. RTI GENERATION SCHEMES

execution.

2.3.3 Kalman filter models

Kalman Filter modelling arises from the state-space representations in modern control theory. These type of models are designed to estimate the current state of the system. However, their ability to filter noise could lead to predictions of future states, while also could improve the variables’ estimation (Kalman, 1960). Shalaby and Farhan (2004) proposed a model based on two Kalman filter algorithms, which predicts running and dwell times respectively, in an integrated framework. For the evaluation of their model they used AVL and APC data. The Kalman filter algorithms outperformed traditional prediction models (e.g. regression and neural network) both in real world data and in simulated scenarios. However, it should be noticed that in their regression and neural network model, they included dwell time in link travel time. Cathey and Dailey (2003) developed a three stages model for bus arrival/departure time, which included a track, a filter and a predictor. For filtering, they used Kalman filter in order to estimate the vehicles dynamical states. According to the authors, whenever the described method has as inputs: the set of fleet vehicles, schedule times and geographical route representation, and AVL records could provide accurate predictions.

In general, Kalman filtering algorithms could provide promising estimation of dynamic travel time (Park and Rilett, 1999). However, they are characterized as computationally complex methods and they are able to handle only linear dynamic relationships (Newland et al., 2006; Jazwinski, 2007).

2.3.4 Machine learning models

Machine learning models have a number of advantages in comparison to the statistical methods. Firstly, they are able to handle complex relationships among prediction components, which could arise within large amounts of data. Moreover, these models successfully deal with the non-linear relationships of predicting components, while they are also able to process complex and noisy data (Recknagel, 2001). Machine learning models provide prediction of travel time, without the need to explicitly describe the traffic relationships. The most highly used machine learning models are Artificial Neural Networks (ANN), and Support Vector Machines (SVM).

The motivation of ANN is to replicate the intelligent data processing ability of human brain. For that reason, ANN are constructed as sequences of multiple layers of processing units, called artificial neurons. These artificial neurons are inter-related, with corresponding weights. Chen et al. (2004) proposed an ANN model for the prediction of travel time. This model was able to estimate travel time on each segment along the route by taking into account trips with different patterns (e.g. time-of-day, day-of-week, weather conditions). Although the proposed ANN model outperformed timetables, a dynamic algorithm based on Kalman filtering
technique always outperformed ANN model. In general, ANN models are able to capture complex non-linear relationships between travel time and independent variables. However, the required learning and testing processes constitute deterrent factors which leads to a slow convergence (Hagan et al., 1996).

SVM is a type of supervised learning algorithms which are based on the statistical learning theory. They could be adjusted in order to map the relationships between inputs and outputs for a complex non-linear system. The solution of SVM is always unique and globally optimal since the process of reaching the solution is similar to a linearly constrained quadratic programming problem. Yu et al. (2011) explored the dimensions of different models for the prediction of bus arrival at bus stops with multiple routes. The proposed models were, SVM, ANN, k-NN and linear regression, and they utilized bus running and arrival data from observation surveys. The results indicate that SVM outperformed the rest of the models. However, in this research only data from buses were used in order to estimate the system’s conditions.

2.3.5 Summary of utilized inputs

The following table summarizes the inputs used in the above mentioned RTI generation schemes. In this synthesis, each method is not represented by an exhaustive publication, in comparison with the existing numerous of relative literature. However, chronologically this summary could portray the introduction and incorporation of additional and more accurate information in the prediction systems. Starting from the utilization of historical running time, and later on the detection of location of the approaching vehicle, the latest research embeds real-time running time datasets. This is accomplished with the technological and thus equipment expansion in public transport systems. The fusion of data derive from weather conditions, bus stop information, and dwell time illustrates the need to overcome the traditional focus in travel time and capture potential missing sources of information. For that reason, research is nowadays targeting to find an efficient way to manage the additional significant sources of information in order to generate accurate RTI predictions in low computational cost.
### 2.3. RTI GENERATION SCHEMES

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<th>Real-Time Running Time</th>
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<th>Historical Running Time</th>
<th>Schedule Arrivals</th>
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<th>Bus Stop Information</th>
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(Williams et al., 2003)  
(Lin et al., 1999)  
(Sun et al., 2007)  
(Patnaik et al., 2004)  
(Jeong et al., 2004)  
(Vlahogianni, 2004)  
(Chang et al., 2010)  
(Shalaby et al., 2004)  
(Cathey, 2003)  
(Chen et al., 2004)  
(Yu, 2011)
Chapter 3

Methodology

The objective of this thesis is to formulate and evaluate a methodology for predicting bus arrivals. The motivation arises from the need to overtake the main drawbacks of the current proposed prediction schemes. Specifically, literature suggests numerous of approaches which were found to need high computational effort in order to produce RTI. This is a deterrent factor for real-time applications. Thus, the proposed methods target to offload this computation effort by introducing simple algorithmic steps. A second drawback of existing RTI generators is the limited utilization of real-time running time, passengers demand profiles and bus stop information inputs (Tab. 2.1). The incorporation of real-time running time and historical dwell time constitute core inputs in order to understand the variations of running and dwell time respectively. Furthermore, in the proposed RTI generators bus stop characteristics are also taken into account in order to capture spatial sensitive cases.

The following paragraphs describe the proposed RTI generation methods. The first section demonstrates the steps for identifying the approaching vehicle and basic notations used in all methods. Following the three methods algorithm steps are described. In the last section the performance metrics used for the evaluation of the proposed generators are presented.

3.1 Identification of the Approaching Vehicle - Basic Notations

In order to be able to make a prediction for the next bus arrival at a specific stop in the network, the location of the approaching vehicle is needed. Based on this location the RTI generator will estimate the arrival at further downstream locations. The following paragraphs will present the generic process of identifying an approaching vehicle, which is used in various RTI generators.

In this study, the detection of an approaching bus is vehicle oriented. Specifically, it is based on the real time stamp of the last vehicle that visited the stop, for which the prediction is made, and on an ordered set of bus trips. With the use of real time stamps collected along the route, it is feasible to track which was the last trip
that visited the stop of interest at certain time (or RTI request time). Based on the ordered set of bus trips and the real time location records, the approaching vehicle is tracked.

A mathematical formulation of the above mentioned detection of approaching vehicle, as well as the common RTI generators’ notations, are presented in the following paragraphs.

The RTI generator uses the bus trajectory which could be represented as a vector of time stamps along a list of locations, typically stops. The trajectories of an ordered set of bus trips, (trips denoted as \( K_l \) on line \( l \in L \), where \( L \) is the set of service lines in the network) during a certain time interval can be hence represented as a matrix. This matrix is denoted as \( \pi^\alpha \) where each cell, \( \pi^\alpha_{k,s} \), is the actual time where bus trip \( k \) arrived at location \( s \in S_l \). Such matrix is partially empty for any ongoing trip.

A corresponding matrix denoted \( \pi^t \) contains the timetable trajectories for \( K_l \). This time dependent timetable database is seasonally constructed and indicates planned arrival times at each stop along the route with indication of which stops along each line act as time point stops (TPS). TPS are certain stops along the route which used as regulation stops. In such stops and in cases where the bus runs early, bus drivers have the opportunity to wait till the adjustment with their schedule time. TPSs are subset of the recording locations (\( \hat{s}_l \subseteq S_l \)). The output of the prediction scheme is the corresponding matrix of predicted bus arrivals, \( \pi^p \).

The prediction schemes include the following steps when searching at time \( \tau \) the approaching vehicle at the stop in which the prediction is made for:

**STEP 1**: Find the last bus trip \( k \) that visited stop \( s \). The last bus trip that visited stop \( s \) is denoted as \( k^p \), hence:

\[
k^p = \arg \max_{K_l} \{ \pi^\alpha_{k,s} : \pi^\alpha_{k,s} < \tau \}
\]  

**STEP 2**: Find the last location visited by the successive bus trip. The last location which was visited by the next trip (\( k^p + 1 \)) is denoted as \( m \) and defined as follows:

\[
m = \begin{cases} 
\arg \max_{i=1...s} \{ \pi^\alpha_{k^p+1,i} : \pi^\alpha_{k^p+1,i} < \tau \} & \text{if } \pi^\alpha_{k^p+1,1} \neq \emptyset \\
0 & \text{Otherwise}
\end{cases}
\]  

Despite the existence of ordered set of trips for the whole network, the possibility of rare overtakes occurs. Overtakes could contribute to a more punctual service by dealing with cases such as: bunch effects, collisions, increased dwell times at certain stops. However, many authorities’ regulations, regarding the running of bus service, give a higher penalty in cases where vehicles are found to run earlier than later, in comparison to their timetables. As an example, public transport
3.2. SCHEDULED TRAVEL TIME METHOD

Authorities in Stockholm region set up the criteria for arrival within the time window of 1 minute early and 3 minutes late compared to the timetable (SL, 2009). For that reason, overtakes in the case study network are limited, however they could not be discarded. Consequently, during the implementation of the above tracking of approaching vehicle, potential overtakes are taken into consideration. In other words, in many cases the approaching vehicle is found to be the bus trip $k_p + 2$, or $k_p + 3$ etc, as this was the trip that reached a upstream location $m$ closer to time $\tau$, rather than the expected trip $k_p + 1$.

3.2 Scheduled Travel Time Method

The commonly used method for generating real-time arrival information, (TCRP, 2003), will be evaluated and used as test bed for comparisons against the newly developed methods. This method represents also the currently deployed bus arrival prediction scheme in Stockholm, Sweden. The following paragraphs present the formulation of this prediction scheme. It should be mentioned that this real-time information generation scheme was constructed based on discussions with the information technology department in SL, Stockholm’s public transport authority, but has not been confirmed by the system provider.

This bus arrival prediction scheme, henceforth will be referred as Scheduled Travel Time method (STT), is based on the real-time location of the approaching bus and the corresponding remaining scheduled travel time. In other words, assuming that a passenger with no prior knowledge of approaching buses arrives at a certain stop at a certain time, the arising question is what the RTI provided at this stop, regarding the next approaching vehicle, would be. Being able to monitor vehicles along the route, based on real-time positioning records (§3.1), the system is able to identify the upcoming bus further upstream the corresponding stop (Eq. 3.1-3.2). At this location, the deviation from the schedule could be observed. The prediction scheme presumes that this schedule deviation is maintained until the arrival at the stop for which the prediction is made. The only exception is when buses run early and have a TPS between the current stop location and the relevant downstream location. In this case, as drivers are instructed to hold at these stops, the prediction at the stop of interest will be equal to the timetable. In other words, it is assumed that the current deviation from the scheduled will be sustained in case of non-early trips as well as in case there is no intermediate TPS.

The scheme requires as input the real-time positions of all buses and a time-dependent timetable database. Moreover, the prognosis scheme is based on the following assumptions:

- travel time between bus current location and any downstream location is equal to the schedule travel time; and

- buses never leave TPS (including origin stop) prior to their schedule time.
CHAPTER 3. METHODOLOGY

Following the steps for detection of bus trip \( k^{p+1} \) and its last recorded stop visit at location \( m \), the STT prediction scheme consists of the following process when generating at time \( \tau \) the prediction of the next arrival of line \( l \) at stop \( s \), \( \pi_{l,s}^{p+1} (\tau) \). Specifically, this RTI generator is making a prediction based on the timetable by distinguishing between the two following cases:

**Case A**: When at time \( \tau \), the next trip to visit stop \( s \) has not started yet \((m = 0)\) or the bus is running early \((\pi_{\alpha}^{k_{p+1},m} < \pi_{k_{p+1},m}^{l})\) and there is an intermediate TPS \((\exists m \leq i < s, i \in \hat{s}_l)\) then the predicted arrival time is simply the scheduled time (see Fig. 3.1):

\[
\pi_{l,s}^{p} (\tau) = \pi_{k_{p+1},s}^{p} (\tau) = \pi_{k_{p+1},s}^{l} \tag{3.3}
\]

**Case B**: Otherwise, \((\pi_{\alpha}^{k_{p+1},m} \geq \pi_{k_{p+1},m}^{l} \text{ OR } \nexists m \leq i < s, i \in \hat{s}_l)\), the predicted arrival time is calculated based on the scheduled remaining travel time (see Fig. 3.2):

\[
\pi_{l,s}^{p} (\tau) = \pi_{k_{p+1},s}^{p} (\tau) = \pi_{k_{p+1},m}^{\alpha} + \pi_{k_{p+1},s}^{l} - \pi_{k_{p+1},m}^{l} \tag{3.4}
\]

The following figures illustrate the two cases of STT method. Specifically, Fig. 3.1 presents Case A where the condition of a bus running early, while an intermediate TPS exists, is applied.

### 3.3 Real-Time Travel Time Method

Being able to monitor the real-time location of several buses could provide valuable information regarding the distribution of travel time along the route. Considering the spatial and temporal heterogeneity of travel time at routes, the use of real time information from previous bus trajectories could potentially offer a more accurate estimation of travel time than the aforementioned schedule deviation logic (STT). The following paragraphs will present a newly formulated prediction method which

![Figure 3.1: Illustration of STT method’s case A](image-url)
3.3. REAL-TIME TRAVEL TIME METHOD

\[ \pi_{k^p+1,x}^p (\tau) = \pi_{k^p+1,m}^a + \pi_{k^p+1,t}^l - \pi_{k^p+1,m}^c \]

Figure 3.2: Illustration of STT method’s case B

will utilize real-time positioning data for the estimation of travel time, which consequently constitutes the input of the RTI generator. Henceforth this method will be referred as real-time travel time method (RTTT).

The process begins with a request for RTI regarding the next bus arrival at a certain stop at a certain time. As discussed in previous sections, the tracking of vehicles along the route, based on real-time positioning records, could provide valuable information for the identification of the upcoming bus further upstream the location of RTI request (Eq. 3.1-3.2). From the location of last appearance of the forthcoming vehicle until the stop of interest the travel time is computed based on travel time from the latest buses that traversed the respective segment. Specifically, this travel time is calculated by weighting the travel times of previous buses. The final RTI generation will be based on the upcoming vehicle’s latest position probe plus the computed travel time.

Similarly to the STT method, this prediction scheme classifies cases where a TPS is located between the current stop location and the relevant downstream location. Given this condition, the prediction of travel time from current stop location till the TPS is computed. If this prediction leads to an early arrival (at the TPS), than what the timetable suggests, the RTTT assumes that the bus will wait till the regulation with the timetable. Thus, the prediction will be based on the schedule time of the approaching vehicle at the TPS plus the prediction of travel time from the TPS until the stop in which the prediction is made for.

The scheme requires as input the real-time positions of all buses and a time-dependent timetable database. Moreover, the prognosis scheme is based on the assumption that buses never leave TPS (including origin stop) prior to their schedule time. The following paragraphs present a mathematical formulation of the above prediction scheme.

At first, the way of weighting the travel times of previous buses will be demonstrated. As \( r_{k^p, stopA \rightarrow stopB} \) is denoted the weighted average travel time of a number of preceding buses (e.g. bus trips \( k^p, k^p - 1, ..., k^p - \delta \), on line \( l \) and for the segment defined between \( stop A \) and \( stop B \). In general, the last preceding bus to the target bus will contribute in greater extend to the weighted average travel time than those
found further downstream. A simple weighted method is to assign each preceding bus a weight which corresponds to the inverse of the time interval between the preceding bus and the target bus \( k^p + 1 \). Thus, \( \hat{t}_{k^p+1}^{\text{stopA} \rightarrow \text{stopB}} \) can be attained by the following equations:

\[
\hat{t}_{k^p+1}^{\text{stopA} \rightarrow \text{stopB}} = \sum_{j=0}^{\delta} \frac{1}{\left( \pi_{k^p+1,\text{stopA}} - \pi_{k^p-j,\text{stopA}} \right)} \left( \pi_{\delta,\text{stopB}} - \pi_{j,\text{stopA}} \right) \tag{3.5}
\]

\[
\Gamma = \sum_{j=0}^{\delta} \frac{1}{\left( \pi_{k^p+1,\text{stopA}} - \pi_{k^p-j,\text{stopA}} \right)} \tag{3.6}
\]

Where, \( \Gamma \) is the sum of the weight of each preceding bus, \( \delta \) the number of preceding buses utilized for prediction.

Following the steps for detection of bus trip \( k^p + 1 \) and its last recorded stop visit at location \( m \), the RTTT prediction scheme consists of the following process when generating at time \( \tau \) the prediction of the next arrival of line \( l \) at stop \( s \), \( \pi_{l,s}^p(\tau) \). Specifically, this RTI generator is making a prediction based on the real-time records by distinguishing between the two following cases:

**Case A**: At time \( \tau \), the next trip to visit stop \( s \) is estimated (based on the computed travel time from previous trips) to arrive earlier to TPS, which is located intermediate of \( m \) and \( s \), than what the schedule arrival suggests (\( \exists m \leq i < s, i \in \hat{s}_l \text{ AND } \pi_{k^p+1,m}^p + \hat{t}_{k^p+1,m}^{i \rightarrow s} < \pi_{k^p+1,i}^p \)). In this case the predicted arrival time is calculated based on the schedule arrival of trip \( k^p + 1 \) and the estimated travel time (based on the computed travel time from previous trips) from TPS to the stop \( s \):

\[
\pi_{l,s}^p(\tau) = \pi_{k^p+1,s}^p(\tau) = \pi_{k^p+1,i}^l + \hat{t}_{k^p+1}^{i \rightarrow s} \tag{3.7}
\]

**Case B**: Otherwise (\( \exists m \leq i < s \text{ OR } \exists m \leq i < s, i \in \hat{s}_l \text{ AND } \pi_{k^p+1,m}^p + \hat{t}_{k^p+1,m}^{i \rightarrow i} \geq \pi_{k^p+1,i}^l \)), the predicted arrival time is calculated based on the estimated travel time (based on the computed travel time from previous trips) from stop \( m \) to stop \( s \):

\[
\pi_{l,s}^p(\tau) = \pi_{k^p+1,s}^p(\tau) = \pi_{k^p+1,m}^p + \hat{t}_{k^p+1}^{m \rightarrow s} \tag{3.8}
\]

The following figure illustrates the two cases of RTTT method. Specifically, on the upper part case A where the condition of a bus running early is applied, is presented. The arrows represent the source of inputs which are utilized in the computation process.

**Implementation notes**

In this paragraph, there will be noted a number of special cases where the implementation of the above described general cases are unable to handle.
3.3. REAL-TIME TRAVEL TIME METHOD

Figure 3.3: Illustration of RTTT method's cases
1. As one could notice, STT method is found unable to deal with cases where
the next trip to visit stop s has not started yet ($m = 0$). In such cases
the predicted arrival time is simply the schedule time ($\pi_{pl,s}(\tau) = \pi_{kp+1,s}(\tau) = \pi_{kp+1,m}$)(Eq. 3.3). On the other hand, for the same occasions RTTT prediction
scheme is assuming that the prediction of travel time will be held from the
first stop till the stop s and the process of predicting the arrival time will be
identical to the above case B (Eq. 3.8).

2. The limitation of available real time data should be taken into account in
RTTT. Specifically, the implementation of RTI generator scheme distinguishes
two cases:

(a) When there is lack of previous bus trips for the segment $m \rightarrow TPS$,
the predicted arrival time is calculated based on the scheduled remaining
travel time (§3.2, Case B, Eq. 3.4):

$$\pi_{pl,s}(\tau) = \pi_{kp+1,s}(\tau) = \pi_{kp+1,m} + \pi_{kp+1,s} - \pi_{kp+1,m}$$

(b) When there is lack of previous bus trips for the segments $TPS \rightarrow s$ or
$m \rightarrow s$, the predicted arrival time is simply the scheduled time (§3.2, Case
A, Eq. 3.3):

$$\pi_{pl,s}(\tau) = \pi_{kp+1,s}(\tau) = \pi_{kp+1,s}$$

3. In order to reduce the computational effort of the RTTT method the potential
existence of only one TPS between stops $m$ and $s$ was assumed. The
combination of factors regarding the frequency of lines, the distance among
consecutive stops, as well as the distance between consecutive TPSs on the
case study network (§4), suggests that there is no possibility of existence of
more than one TPS between stops $m$ and $s$. In cases of different networks the
introduction of control for consideration of more than one intermediate TPS
is suggested.

### 3.4 Iterative Forward Running and Dwell Time Method

The aforementioned RTTT method proposes a way to utilize real time information
from previous trajectories in order to get a more accurate estimation of travel time
between two locations. However, it should be noticed that travel time in the latter
case incorporates the corresponding running and dwell times. Specifically, running
time refers to the time spend while the vehicle is moving, including the time for
approaching and departing a stop. Evolving the RTTT prediction scheme, this
section describes a more elaborated method where the prediction is based on:

- the real-time location of the approaching vehicle;
- the prediction of running time based on real-time information of preceding
  buses; and
3.4. ITERATIVE FORWARD RUNNING AND DWELL TIME METHOD

- the dwell time spent at stops based on passengers’ demand profiles.

The following paragraphs will present a newly formulated prediction method which will utilize real-time positioning data and demand profile data for the prediction of running time and dwell time, respectively. In turn, these predictions constitute input for the RTI generator. Henceforth, this method will be referred as iterative forward running and dwell time method (IF_RDT).

The process begins with a request for RTI regarding the next bus arrival at a certain stop at a certain time and, as discussed in previous sections, the tracking of vehicles along the route, based on real-time positioning records, could provide valuable information for the identification of the upcoming bus further upstream the location of RTI request. From the location of last appearance of the forthcoming vehicle (Eq. 3.1-3.2) until the stop of interest the computation of travel time is held by predicting the running and dwell time at the stop level. The latter is a step wise process which consists of the following steps (Fig. 3.4). At first, the headway between the upcoming vehicle and its previous trip is computed. Based on this headway and passengers demand profiles, a prediction of departure time is computed. It should be noticed that every stop along the network is attached with a passenger demand profile, which could deviate along the time-of-the-day. Each period contains a number of passengers, which is assumed to be uniformly distributed through period’s time. On parallel, a prediction of running time till the next stop is held. Thus, relying on the last two predictions, a final prediction of arrival at the next stop is computed. The computed arrival time in contrary to the previous trip appearance at the next stop reveals a new headway. The whole process is repeated till the estimation of arrival reaches the stop where the RTI is expected. The last estimation constitutes the final RTI generation.

Similarly to the STT and RTTT methods, this prediction scheme classifies cases where a TPS is located between the current stop location and the relevant downstream location. In such a case, if during the above described process the estimation of arrival at the TPS is found to be earlier than what the TPS’s timetables suggests, the IF_RDT assumes that the bus will wait until the regulation with the timetable. Thus the step-wise process will continue based on the schedule time of the approaching vehicle at the TPS and consecutive further estimations of dwell and running time, till reaching the stop where the RTI is expected.

The scheme requires as input the real-time positions of all buses and a time-dependent timetable database. Moreover, the passengers demand profile for every stop along the line is needed. The prognosis scheme is based on the assumption that buses never leave TPS (including origin stop) prior to their schedule time. The following paragraphs present a mathematical formulation of the above prediction scheme.

At first, the way of weighting the running times of previous buses will be demonstrated. Albeit that the weighting process follows the same logic like in RTTT method (Eq. 3.5-3.6), the time references should be updated based on the fact that in IF_RDT method the dwell time is computed independently. In other words,
Figure 3.4: IF_RDT algorithmic steps

Travel time refers to the time spent from the actual arrival at a stop A till the actual arrival at a stop B (RTTT method). On the other hand, running time corresponds to the time spent from the departure at stop A till the actual arrival at stop B. For that reason, this prediction scheme introduces the matrix $\pi^d$, where each cell, $\pi^d_{k,s}$, is the departure time of bus trip $k$ at location $s \in S_l$. This matrix is also partially empty for any ongoing trip.

As $\hat{t}_{p+1}^{\text{stopA} \rightarrow \text{stopB}}$ is denoted the weighted average running time of a number of preceding buses (e.g. bus trips $k^p, k^p - 1, ..., k^p - \delta$), on line $l$ and for the segment defined between stop A and stop B. In general, the last preceding bus to the target bus will contribute in greater extend to the weighted average running time than those found further downstream. A simple weighted method is to assign each preceding bus a weight which corresponds to the inverse of the time interval between
3.4. ITERATIVE FORWARD RUNNING AND DWELL TIME METHOD

the preceding bus and the target bus \( k^p + 1 \). Thus, \( \hat{t}_{k^p+1}^{r, \text{stopA} \rightarrow \text{stopB}} \) can be attained by the following equations:

\[
\hat{t}_{k^p+1}^{r, \text{stopA} \rightarrow \text{stopB}} = \sum_{j=0}^{\delta} \frac{1}{(\pi_{k^p+1, \text{stopA}}^d - \pi_{k^p-j, \text{stopA}}^d)} (\pi_{j, \text{stopB}}^a - \pi_{j, \text{stopA}}^d)
\]

(3.9)

\[
\Gamma = \sum_{j=0}^{\delta} \frac{1}{(\pi_{k^p+1, \text{stopA}}^d - \pi_{k^p-j, \text{stopA}}^d)}
\]

(3.10)

Where, \( \Gamma \) is the sum of the weight of each preceding bus, \( \delta \) the number of preceding buses utilized for prediction.

Secondly, the computation of dwell time is based on the anticipated headways between buses and their impact on boarding time of passengers. Hence, dwell time prediction requires as input the headway and the number of passengers arriving based on the demand profile of the respective stop. The prediction of dwell time at a stop \( i \) is noted as \( \hat{t}_i^p \) and computed as follows:

\[
\hat{t}_i^p = (\text{Arrival}_{k^p+1,i}^a - \pi_{k^p,i}^a) \cdot D_s^{\text{Period}} \cdot t^{\text{Boarding}} + C^{\text{Boarding}}
\]

(3.11)

Where, \( D_s^{\text{Period}} \) is the estimated number of passengers (e.g. demand), \( t^{\text{Boarding}} \) is the passenger’s time of boarding coefficient and \( C^{\text{Boarding}} \) is a constant related to non-service lost time at the stop (e.g. opening and closing the doors). \( \text{Arrival}_{k^p+1,i}^a \) refers to one of the actual, estimated or schedule arrival at stop \( i \). The latter depends on the cases, which will be outlined in following paragraphs.

Considering the steps for detection of bus trip \( k^p + 1 \) and its last recorded stop visit at location \( m \), the IF_RDT prediction scheme consists of the following process when generating at time \( \tau \) the prediction of the next arrival of line \( l \) at stop \( s \), \( \pi_{l,s}^p(\tau) \). Specifically, the IF_RDT method is making a prediction based on a step-wise repeating process, which cumulatively computes dwell and travel times along the segment located between stop \( m \) and stop \( s \).

The step-wise process starts by initializing a variable which cumulatively keeps records of the running and dwell times. This variable will be noted as \( \Sigma \), and in the beginning of the process is assigned the actual time where bus trip \( k^p + 1 \) arrived at stop \( m \), \( \pi_{k^p+1,m}^a \). Also a stop counter is initially set equal to the last location visited by bus trip \( k^p + 1 \), \( c = m \). The following two steps are repeated till the stop counter reaches stop \( s - 1 \).

\textbf{Step 1:} The dwell time is computed for stop \( i \), and the variable \( \Sigma \) is updated as follows:

\[
\Sigma := \Sigma + \hat{t}_i^p
\]

(3.12)

It should be noted that for the computation of \( \hat{t}_i^p \), either the actual arrival of trip \( k^p + 1 \) at stop \( m \) (\( \Sigma = \pi_{k^p+1,m}^a \) AND \( i = m \)) or the predicted arrival of trip \( k^p + 1 \) at stop (\( \Sigma \)) is used for \( \text{Arrival}_{k^p+1,i}^a \).
CHAPTER 3. METHODOLOGY

Reaching this step, the product of variable $\Sigma$ is the predicted departure time from stop $i$. In case that stop $i$ works as TPS ($i \in \hat{t}$) and the prediction of departure is earlier than the suggested schedule departure ($\Sigma < \pi_{k^{p+1},i}$) then it is assumed that the bus will wait until regulation with the timetable. In other words, the variable $\Sigma$ will be updated based on the schedule time of trip $k^{p} + 1$ at stop $i$:

$$\Sigma := \pi_{k^{p+1},i}$$  \hspace{1cm} (3.13)

**Step 2:** The running time is calculated for segment defined between stops $i$ and $i+1$, and the variable $\Sigma$ is updated as follows:

$$\Sigma := \Sigma + \hat{t}_{k^{p+1}}^{i \rightarrow i+1}$$ \hspace{1cm} (3.14)

It should be noted that for the computation of $\hat{t}_{k^{p+1}}^{i \rightarrow i+1}$ is used, as $\pi_{k^{p+1},i}$, the predicted departure of trip $k^{p} + 1$ from stop ($\Sigma$).

When the process terminates $\Sigma$ it establishes the predicted arrival time:

$$\pi_{l,s}^{p}(\tau) = \pi_{k^{p+1},s}^{p}(\tau) = \Sigma$$ \hspace{1cm} (3.15)

The following figure illustrates the two steps of IF_RDT method. Specifically, it presents a focus on a short segment of the total route where the existence of TPS is taken into account. The arrows represent the source of inputs utilized in the computation process.

**Implementation Notes**

In this paragraph, they will be noted a number of special cases where the implementation of the above described general cases are unable to handle.

1. As in the RTTT method, IF_RDT is taking into consideration cases where the next trip to visit stop $s$ has not started yet ($m = 0$). Specifically, IF_RDT method assumes that the step-wise computation process starts from the first stop of the route. Thus the initialization of parameters are: $i = 1$, and $\Sigma := \pi_{k^{p+1},1}^{l}$. However, if the record of arrival time of trip $k^{p} + 1$ at the first stop is missing, then the predicted arrival time is simply the schedule time (Eq. 3.3):

$$\pi_{l,s}^{p}(\tau) = \pi_{k^{p+1},s}^{p}(\tau) = \pi_{k^{p+1},s}^{l}$$

2. IF_RDT method determines cases where the process begins ($i = m$) and the bus trip $k^{p} + 1$ has already departed ($\pi_{k^{p+1},m}^{d} \leq \tau$). In such cases the step-wise computation process initializes variable $\Sigma$ with the value of departure time: $\Sigma := \pi_{k^{p+1},m}^{d}$, and proceed direct to above mentioned Step 2. In other words, it is taken into account that the dwell time spent at stop $m$ has already passed.
3.4. ITERATIVE FORWARD RUNNING AND DWELL TIME METHOD

Figure 3.5: Illustration of IF_RDT method
3. In cases where the computation of headway at step 1 is not feasible (e.g. missing records of previous trips) the dwell time is computed based on AVL data and specifically the respective stop’s aggregated waiting time.

4. The limitation of available real time data should be taken into account in IF_RDT. Specifically, when there is lack of previous bus trips for the segment \( i \rightarrow i + 1 \), the estimation of travel time is based on the schedule remaining travel time. Thus at aforementioned step 2 variable \( \Sigma \) will be updated as follows:

\[
\Sigma := \Sigma + \pi^t_{k,p+1,i+1} - \pi^p_{k,p+1,i}
\]

### 3.5 Performance Metrics

In order to proceed in the evaluation and comparison of the above mentioned RTI schemes a series of metrics are formulated. The latter are calculated ex-post and consider both passenger’s and operator’s perspectives. The difference between the aforementioned perspectives is based on the perception of the upcoming bus.

From passenger’s point of view, no importance is attached to the specific trip’s identity, and the accuracy is determined by the difference between the provisioned RTI and the next arrival of line \( l \) at stop \( s \), computed as follows:

\[
e_{p, l,s}^\alpha(\tau) = \pi_{k,\alpha,s}^\alpha(\tau) - \pi_{l,s}^p(\tau)
\]  \hspace{1cm} (3.16)

Where \( k^\alpha \) is the first trip to arrive at stop \( s \), defined as:

\[
k^\alpha = \arg \min_{K_l} \{ \pi_{k,s}^\alpha : \pi_{k,s}^\alpha > \tau \}
\]  \hspace{1cm} (3.17)

This could be interpreted as the difference between the predicted and experienced waiting times for a passenger that arrived at stop \( s \) at time \( \tau \). It should be noticed that \( k^\alpha \) might differ from \( k^p \) (see Eq. 3.1) when an overtaking occurs between stops \( m \) and \( s \).

On the other hand, for operators the prediction is carried out at the vehicle level. The prediction error for the arrival of trip \( k \) at stop \( s \) is assessed by comparing the prognosis at time \( \tau \) against the corresponding actual arrival time along the same vehicle trajectory:

\[
e_{k,s}^p(\tau) = \pi_{k,s}^\alpha(\tau) - \pi_{k,s}^p(\tau)
\]  \hspace{1cm} (3.18)

The prediction error measures will reveal the differences that occur between predicted and observed arrival times. An unbiased and valid prediction scheme will yield a normal distribution of prediction errors with a mean value of zero. Moreover, the variability of prediction errors has to be minimized in order to obtain a reliable prediction scheme. In this study, the prediction errors will be used in order to evaluate and compare the aforementioned RTI schemes.
3.5. PERFORMANCE METRICS

The performance of static information concerning arrivals is used as a benchmark. Such a study could potentially reveal the importance of RTI in addition to the static information. The latter’s accuracy was formulated for both operator’s and passenger’s perspectives. Similarly to the prediction error, the RTI is substituting for the corresponding timetable term, as follows:

\[ e^t_{l,s}(\tau) = \pi^\alpha_{k^\alpha,s}(\tau) - \pi^t_{k^t,s}(\tau) \]  

(3.19)

\[ e^t_{k,s} = \pi^\alpha_{k,s} - \pi^t_{k,s} \]  

(3.20)

Where \( k^t \) is the first trip scheduled to arrive at stop defined as:

\[ k^t = \arg \min_{K_l} \{ \pi^t_{k,s} : \pi^t_{k,s} > \tau \} \]  

(3.21)

It should be noticed that \( k^\alpha \) (Eq. 3.17) might differ from \( k^t \) in case the first arriving bus was scheduled to arrive before the passenger arrived at the stop. The prediction error of static information from operator’s perspective (Eq. 3.20) is equivalent to schedule adherence at the vehicle level.

Furthermore, the extent to which timetables and RTI are effective in assisting passengers to shift their expectations closer to the actual waiting time is assessed. The actual waiting time of a passenger arriving at a stop \( s \) at time \( \tau \) with the intention to board line \( l \) is:

\[ w^\alpha_{l,s}(\tau) = \pi^\alpha_{k^\alpha,s}(\tau) - \tau \]  

(3.22)

While the expected waiting time implied by RTI and the timetable are:

\[ w^p_{l,s}(\tau) = \pi^p_{l,s}(\tau) - \tau \]  

(3.23)

\[ w^t_{l,s}(\tau) = \pi^t_{k^t,s}(\tau) - \tau \]  

(3.24)

In order to present the average magnitude of the errors in the overall set of predictions, the mean absolute error (MAE) was calculated. In this study, MAE consists of the average absolute difference between actual waiting time of a passenger waiting at a stop \( s \) at time \( \tau \) and the related expected waiting time implied by static or real-time information. Although the fact that MAE is a linear score, which means that all the individual differences are weighted equally in the average, it is able to illustrate a global prediction score for the respective source of information (timetables or RTI). The following equations correspond to the computation of MAE for RTI and timetables.

\[ MAE^p = \frac{\sum_{l,s,\tau} |e^p_{l,s}(\tau)|}{\sum_{l \in L} |S_l| \cdot |\tau|} \]  

(3.25)

\[ MAE^t = \frac{\sum_{l,s,\tau} |e^t_{l,s}(\tau)|}{\sum_{l \in L} |S_l| \cdot |\tau|} \]  

(3.26)
Chapter 4

Case Study

Chapter 3 begins with an introduction to the vehicle positioning data, and passengers demand profiles gathered by Stockholm’s regional public transport agency (SL), while also the presentation of the case study network characteristics. The chapter pursues with implementation details regarding the treatment of data and generation of the RTI.

4.1 Data

4.1.1 Vehicle positioning data

The regional public transport agency in Stockholm (SL) has successfully installed GPS systems in the whole bus fleet. Such systems could be used for various scopes, including real-time localization of vehicles, identification (ID) of potential incidents, fleet management, while also RTI systems. Moreover, the GPS real time location probes are used by the authority in order to construct an event based AVL database. The term event based database refers to real time records of bus stop visits by a tracked vehicle. In other words, each AVL record is attached to the GPS probe which was found spatially closer to the bus stop. The transmission of information from the tracked vehicle includes details regarding the trip ID, stop ID, actual and schedule arrival, while also actual and schedule departure.

The performance of the RTI generation methods was analysed based on detailed and comprehensive AVL data. These data were provided by SL and contained the aforementioned vehicle position data for each bus stop. The selected study period consists of records from 15/11/2011-15/11/2011 and 9/1/2012-19/1/2012 in order to exclude the winter holidays. This dataset includes more than one million records.

The trunk bus system of Stockholm, Sweden was selected as the case study network (Fig 4.1). It includes 4 bus lines which compose the backbone of Stockholm inner-city bus network. This network contains more than 200 stops along more than 80 route-km. Each route includes 2-4 time point stops (TPS) located at key public transport transfer locations. The aforementioned lines account for 60% of the total ridership in this area with approximately 120,000 boarding passengers per
day between 7:00-19:00 (SL, 2006). For that reason this research focuses on the same time intervals. Furthermore, these lines are characterized by high frequency, articulated vehicles, designated lines at main streets, traffic signal priority and RTI displays at all stops.

### 4.1.2 Passengers demand profiles

Additionally to AVL system, SL has managed to implement APC recorders in a finite amount of buses in their fleet. This limitation constitutes a deterrent factor regarding the implementation of a more sophisticated system, which could potentially take into account real-time APC data. However, the existing APC system could provide a notable source of information regarding the passengers demand profiles at every stop. Specifically, the APC data contain information regarding dwell time, boarding and alighting passengers, occupancy, speeds, while also stop and route details such as distances.

The demand profiles constructed in this study are based on the number of boarding passengers in a period from 1/9/2011 to 1/12/2011. This period was divided into three subcategories related to four time-of-the-day periods, specifically 06:00-09:00, 09:00-15:00, 15:00-18:00 and 18:00-21:00. Every period contains an aggregated product of boarding passengers derived from at least 30 vehicles.
4.2 Implementation Details

Real-time bus arrival predictions were made in this case study according to the specification of the respective methodology. The RTI generators transformed the real-time bus positioning data (e.g. actual arrival and departure) and the corresponding timetable into a matrix format resulting with $\pi^a$, $\pi^d$ and $\pi^t$, respectively. Concerning the construction of the matrix, the real-time bus positioning data were ordered based on the sequence of scheduled daily trips. In other words, for every single day a pivot table with ordered real time trajectories of the daily scheduled trips was constructed. Cases is which there are missing records or short trips the prediction schemes take special care of the process.

Note that the available AVL data were limited to bus stop visits. Bus positioning information was hence processed in an event-based basis, while the assessment of the RTI performance requires a time-based sampling of the provisioned information. This facilitates the evaluation of the RTI generator across time and space where the time stamps correspond to passenger arrival time at stops.

The prediction schemes presented in previous chapter were implemented in MATLAB®. The algorithms trigger a RTI provision inquiry across the entire network every minute. The RTI generators at time $\tau$ follow then the steps outlined in Chapter 2 and thus utilizing only bus positioning data collected prior to time $\tau$. The implemented algorithms account explicitly for overtaking (as mentioned in partial implementation details). Passengers’ boarding time coefficient ($t^{Boarding}$) and the dwell time constant ($C^{Boarding}$) were assigned the values of 2 and 3 seconds respectively.

The RTI generators provide as output the predicted bus arrival time at each stop and line combination, $\pi^p_{l,s}(\tau)$, for every minute so that $\tau = (7:00, 7:01, ..., 19:00)$. The common assumption that passengers arrive randomly at stops, in the case of high-frequency service, implies that the average statistics over all time instances $\tau$ are equivalent to the average passenger experience. The output produced by the implemented RTI generator enabled the computation of the performance metrics defined above.

The performance of the RTI generators was analyzed by comparing the predicted waiting times with observed waiting times derived from the AVL data. The fundamental analysis unit consists of a cross-network sampling of the prediction provided by the RTI systems. This implies the calculation of the passengers’ and operators’ prediction error metrics across the network with one minute sampling.

Furthermore, 'SL minute' is notoriously known in Stockholm as a particularly long minute because the bus fails to arrive within the projected time window (Fig. 4.2). The design of this study allows to test whether the coined term is empirically justified in the current system (STT). Moreover, 'SL minute' could be used as a performance indicator for the newly developed prediction schemes (RTTT, IF_RDT).
Figure 4.2: Stockholm’s "SL minute" reports (Aftonbladet, 2006; SvD, 2012)
Chapter 5

Results

This chapter demonstrates the results of the three prediction methods. It begins with the prediction accuracy, temporal and spatial analysis of each of the methods in comparison with the rest. Following, a comparison of all RTI generation schemes with static information is held.

5.1 Scheduled Travel Time Method Analysis

5.1.1 Prediction accuracy

In order to evaluate the overall RTI accuracy of the STT bus arrival prediction scheme (§3.2), the distribution of passengers’ prediction error is constructed (Eq. 3.16). In other words, the difference between actual arrival and prediction for the overall network, the whole study period and each time instant is analysed.

In the following Fig. 5.1 passengers’ prediction error (Eq. 3.16) is presented. It follows a normal distribution with a mean value of +15 seconds and a standard deviation of 2 minutes. Moreover, the distribution is positively skewed, indicating that the prediction scheme has a slight systematic bias to underestimate passengers waiting time. More than one third of the inquiries (36%) yielded a prediction error - either positive or negative - of more than 1 minute. Furthermore, 14% and 5% of RTI projections had a prediction error of more than 2 and 4 minutes, respectively. In two thirds of these cases, the prediction error was due to underestimation of the remaining waiting time.

As mentioned in the previous section, STT methodology is applied in reality for the case study network, as well as for the entire Stockholm region. In order to give a quantitative answer about the dimension of the notoriously known "SL minute", the prediction error of the provisioned RTI should be assessed by accounting for the average waiting time. This analysis obtained that the average excessive waiting time per projected minute is 6.2% for the case study system. In absolute terms, the average accessible SL minute lasts in fact 63.7 seconds. However, the relative prediction error depends greatly on the remaining waiting time.
CHAPTER 5. RESULTS

The latter is observed when the predictions obtained by the RTI provision were segmented based on the experienced waiting time - the time lag between their generation and the next bus arrival time. Specifically, the bars in Fig. 5.2 show how the relative difference between the actual waiting time (Eq. 3.22) and the waiting time projected by RTI (Eq. 3.23) vary for different actual waiting times. For very short waiting times the STT scheme overestimates the remaining waiting time, in contrast to an increasingly underestimation observed for waiting times longer than 2 minutes. Particularly, for waiting times longer than 8 minutes, the underestimation reaches almost 10%. For example, a RTI projection of 9 minutes would on average imply that the waiting time would be close to 10 minutes.

In parallel, the reliability of RTI prediction is presented in the above figure as a function of the remaining waiting time. The curve indicates that the RTI prognosis is less reliable for longer prediction horizon. This was expected as longer prediction horizons undermine the possibility to estimate the sequential time disturbances. Since the standard deviation of RTI prediction error increases linearly with the waiting time, the reliability does not increase in relative terms (e.g. coefficient of variation).

5.1.2 Temporal analysis

The time and space heterogeneity in traffic and passenger demand conditions leads the RTI prediction to exercise temporal variations with respect to the day of the week and time of the day. In the following Tab. 5.1 the mean and standard deviation values of the prediction error by day of the week are presented. While the
5.1. SCHEDULED TRAVEL TIME METHOD ANALYSIS

Figure 5.2: STT method’s real-time information accuracy and reliability as function of the remaining time until the next bus arrival

underestimation of waiting times prevails on all days of the week, its extent varies considerably. On Mondays and Tuesdays the RTI predictions were most accurate and reliable. However, the prediction accuracy and reliability deteriorate along the week with the worst performance obtained on Saturdays. Sundays, in contrast, performed like an average weekday. These differences are presumably determined by the extent to which timetables reflect the prevailing traffic conditions. The case study network has a common timetable for all weekdays and separate timetables for Saturdays and Sundays. It should be noted that a high degree of relation between the STT scheme and timetables exists.

A further analysis regarding the temporal variations with respect to time of day was held. Particularly, prediction errors were calculated separately for trips that started at the AM peak (7:00-9:00), Off-Peak (9:00-15:30) and PM peak (15:30-19:00) periods. The last is associated with less accurate and less reliable RTI provision (Tab. 5.2). In contrast the AM peak performs surprisingly well. This may be due to its more homogeneous conditions.

Table 5.1: STT Method’s Prediction Error by Day-of-the-Week (mm:ss)

<table>
<thead>
<tr>
<th></th>
<th>MON</th>
<th>TUE</th>
<th>WED</th>
<th>THU</th>
<th>FRI</th>
<th>SAT</th>
<th>SUN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>00:05</td>
<td>00:10</td>
<td>00:17</td>
<td>00:21</td>
<td>00:22</td>
<td>00:32</td>
<td>00:20</td>
</tr>
<tr>
<td>StD</td>
<td>01:51</td>
<td>01:46</td>
<td>02:18</td>
<td>02:25</td>
<td>02:38</td>
<td>02:52</td>
<td>01:50</td>
</tr>
</tbody>
</table>
CHAPTER 5. RESULTS

Table 5.2: STT Method’s Prediction Error for Time-of-Day Categories (mm:ss)

<table>
<thead>
<tr>
<th>Time-of-day Categories</th>
<th>AM</th>
<th>Off-Peak</th>
<th>PM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>00:11</td>
<td>00:10</td>
<td>00:15</td>
</tr>
<tr>
<td>StD</td>
<td>01:35</td>
<td>01:49</td>
<td>02:12</td>
</tr>
</tbody>
</table>

5.1.3 Spatial analysis

As a continuation of the explanatory variations in this section the performance of RTI, provided by the STT, was further investigated by examining its spatial variation along each of the 8 service routes. The eastbound route of bus line 1 was selected to illustrate the commonly observed patterns. This route consists of 33 stops, of which 3 serve as TPS. Fig. 5.3 illustrates the performance of the STT prediction method along the route. Specifically, the blue curve follows the performance of mean across different stops. At the same time the vertical lines illustrate the relative standard error. The TPS for eastbound route of bus line 1 are: Fridhemsplan, Hötorget and Värtavägen, as noted with star at the bottom of the figure. It could be observed that the average prediction error (Eq. 3.16) fluctuates along the route within the range of ±1.5 minutes.

Regardless the average performance of the RTI method, the plotted route revealed three interesting patterns:

I. RTI predictions become less reliable at further downstream stops. This could be explained by the propagation of uncertainty associated with traffic conditions, dwell time and driver behaviour along the route. It revealed that the aforementioned uncertainty is unsuccessfully captured by the timetables, which constitute the core input for the STT prediction method.

II. The important role that TPS plays in the prediction method is apparent in evolution of RTI accuracy along the route. It is a clear evident that RTI provides the most accurate prediction at TPS locations followed by an immediate substantial increase in the prediction error, which is then reduced gradually until reaching the next TPS. The accurate prediction at TPS is presumably obtained due to drivers’ attempts to adhere to the schedule at these locations where their punctuality is measured (Cats, 2013). In contrast, bus arrivals at stops immediately downstream of TPS are subject to large dwell time variations at TPS due to large passenger flows, holding times and driver shift changes.

III. RTI prediction error is negative on the last stretch of the route following the last TPS. This is presumably attributed to driver behaviour patterns as they wish to prolong their break at the end terminal and thus arrive earlier than the RTI generation suggests. Previous studies (Torres, 2012) that analysed
Figure 5.3: STT method’s real-time information accuracy and reliability along the route, Line 1 eastbound

(*) Indicate a TPS

... driving patterns along the line concluded that drivers tend to drive faster on the last stretch of stops before taking their break.

5.2 Real-Time Travel Time Method Analysis

5.2.1 Prediction accuracy

As described in previous section (§3.2), STT method is using the real time location of the approaching vehicle and the schedule difference. In addition, the RTTT prediction scheme is based on the real time location of the approaching vehicle and utilizes the travel time information from previous recorded trips, which were conducted at the same route (§3.3). In order to understand the contribution of previous bus trips in predicting vehicle arrivals a sensitivity analysis was held. This analysis tried to investigate the optimum number of previous trips, which could be utilized in order to provide information related to travel time. Furthermore, a qualitative analysis held related to the performance of RTTT scheme versus the
CHAPTER 5. RESULTS

As in the previously mentioned STT method, the evaluation of the overall RTI accuracy of the RTTT bus arrival prediction method is held by constructing the distribution of passengers’ prediction error (Eq. 3.16). These distributions correspond to scenarios with different number of utilized trips in RTTT method, and are compared with each other, while also against the STT’s prediction error distribution. Specifically, for the RTTT method the performance of scenarios that utilized 1 to 5, while also 10 previous trips will be presented.

The following Fig. 5.4 summarizes the prediction error distributions. The error for the RTTT prediction scheme follows a normal distribution for all the scenarios. Fig. 5.5 presents the corresponding means and standard deviations. The mean value for all scenarios is slightly increased in comparison with the STT method. However, the standard deviation illustrates a better concentration of error values around 0. The latter is also visible in the figure with higher percentage of error around 0 and less in the tales of the distributions. Moreover, all RTTT scenarios distributions are positively skewed, indicating that the prediction scheme, independent of the number of utilized trips, has a slight systematic bias to underestimate passengers waiting time.

The closest observation of error concentration reveals important details regarding the success ratio of the newly applied methodology. Fig. 5.6 presents a gradual decrease of inquiries, which yielded a prediction error - either positive or negative - of more than 1 minute while the utilized buses are increased. Specifically, from 36% in the STT prediction scheme the passengers’ prediction error drops to 25.5% with the use of 10 previous bus trips in the RTTT prediction scheme. Furthermore, the focus on percentages of prediction error of more than 2 and 4 minutes respectively reveals that the RTTT method succeeds to deal with cases where the current deployed method was substantially inaccurate. In these cases, using 10 previous buses outperformed the rest of scenarios. Overall for the scenarios of the RTTT method, the two thirds of the above mentioned cases, the prediction error was due to underestimation of the remaining waiting time.

The sensitivity analysis for the RTTT method reveals that the marginal benefit diminishes after the utilization of 5 buses. Fig. 5.5 demonstrates a stabilization of mean and standard deviation values around 20 and 90 seconds respectively. Moreover, Fig. 5.5 illustrates consolidation of values despite the introduction of more than 5 buses. As the aim of a prediction scheme is to reduce the overall computation effort, the scenario of 5 utilized trips is revealed as the outperforming scenario for RTTT method.

The prediction error of the provisioned RTI should be assessed by accounting for the average waiting time. For the RTTT the average excessive waiting time per projected minute is 8% for the case study system. In other words, the average 'SL minute' lasts in fact 64.8 seconds, or 1 second more in comparison with the relative 'SL minute' from the STT system. However, the relative prediction error depends greatly on the remaining waiting time.

The predictions obtained by the two different methods (STT and RTTT) were
5.2. REAL-TIME TRAVEL TIME METHOD ANALYSIS

Figure 5.4: RTTT and STT methods’ real-time information prediction error

(*) Indicate the number of utilized previous trips
CHAPTER 5. RESULTS

Figure 5.5: RTTT and STT methods’ real-time information prediction error mean and standard deviation

Figure 5.6: RTTT and STT methods’ real-time information prediction error of more than \(|1|, |2| \text{ and } |4| \text{ minutes respectively}

(*#) Indicate the number of utilized previous trips
5.2. REAL-TIME TRAVEL TIME METHOD ANALYSIS

segmented based on the experienced waiting time - the time lag between their
generation and the next bus arrival time. It should be noted that for the RTTT
prediction method the utilization of 5 previous bus trips was chosen.

The bars in Fig. 5.7 show how the relative difference between the actual waiting
time (Eq. 3.22) and the waiting time projected by RTI (Eq. 3.23) vary for different
actual waiting times for the two different methods. It could be observed that the
RTTT prediction scheme increasingly underestimates the remaining waiting time,
except for the perfect estimation, which held in the short prediction horizon of less
than half a minute. In comparison with the STT system, the proposed RTTT pre-
diction method succeeds to eliminate the regions of overestimated remaining waiting
time (waiting times shorter than 2 minutes). On the other hand, for waiting times
longer than 2 minutes RTTT increasingly underestimates the remaining waiting
time, to a greater extent than the STT method does. Specifically, among the two
methods the percentage of inaccuracy increased by 3% for waiting times longer than
8 minutes.

The reliability of RTI prediction is also visible in the above figure as function of
the remaining waiting time. The curve indicates that the RTI prognosis becomes
less reliable the longer the prediction horizon, as it is unable to handle the sequential
time disturbances. Since the standard deviation of RTI prediction error increases
linearly with the waiting time, the reliability does not increase in relative terms (e.g.
coefficient of variation). However, the RTTT prediction method was found to be

![Figure 5.7: STT and RTTT methods’ real-time information accuracy and reliability as function of the remaining time until the next bus arrival](image-url)
more reliable throughout the entire range of remaining waiting times. In particular, it proved superior in the region of long remaining waiting times.

5.2.2 Temporal analysis

The time and space heterogeneity in traffic and passenger demand conditions leads the RTI prediction to exercise temporal variations with respect to the day of the week and time of the day. In order to evaluate the performance of the newly developed RTTT method the temporal variations with respect to the day of the week and time of the day will be analysed. These variations will be compared against the corresponding ones from the STT prediction scheme. It should be noted that for the RTTT prediction method the utilization of 5 previous bus trips per prediction is used throughout this analysis.

In the following Tab. 5.3, the mean and standard deviation values of the prediction error by day of the week for the two different methods are presented. For both methods, while the underestimation of waiting times prevails on all days of the week, its extent varies considerably. In overall terms the RTTT method is found more reliable all along the week. However, an inaccuracy in working days is revealed. Both prediction accuracy and reliability deteriorate along the week with the worst performance obtained on Fridays and Saturdays. Sundays, in contrast, performed like an average weekday. As described in STT’s section, these differences are presumably determined by the irregularity and hence, less predictable traffic and travel patterns occurred in end of the week.

Table 5.3: STT and RTTT Methods’ Prediction Error by Day-of-the-Week (mm:ss)

<table>
<thead>
<tr>
<th></th>
<th>MON</th>
<th>TUE</th>
<th>WED</th>
<th>THU</th>
<th>FRI</th>
<th>SAT</th>
<th>SUN</th>
</tr>
</thead>
<tbody>
<tr>
<td>STT</td>
<td>Mean</td>
<td>00:05</td>
<td>00:10</td>
<td>00:17</td>
<td>00:21</td>
<td>00:22</td>
<td>00:32</td>
</tr>
<tr>
<td></td>
<td>StD</td>
<td>01:51</td>
<td>01:46</td>
<td>02:18</td>
<td>02:25</td>
<td>02:38</td>
<td>02:52</td>
</tr>
<tr>
<td>RTTT</td>
<td>Mean</td>
<td>00:15</td>
<td>00:17</td>
<td>00:23</td>
<td>00:26</td>
<td>00:30</td>
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</tr>
<tr>
<td></td>
<td>StD</td>
<td>01:29</td>
<td>01:28</td>
<td>01:52</td>
<td>02:00</td>
<td>02:14</td>
<td>02:05</td>
</tr>
</tbody>
</table>

A further analysis regarding the temporal variations with respect to time of day was held. Particularly, prediction errors were calculated separately for trips that started at the AM peak (7:00-9:00), Off-Peak (9:00-15:30) and PM peak (15:30-19:00) periods. The last is associated with less accurate and less reliable RTI provision (Tab. 5.4) for both prediction methods. In contrast the AM peak performs surprisingly well. This may be due to its more homogeneous conditions. RTTT method is found slightly inaccurate but significantly more reliable for all time-of-day categories, in comparison to the STT method.
5.2. REAL-TIME TRAVEL TIME METHOD ANALYSIS

Table 5.4: STT and RTTT Methods’ Prediction Error for Time-of-Day Categories (mm:ss)

<table>
<thead>
<tr>
<th>Time-of-day Categories</th>
<th>AM</th>
<th>Off-Peak</th>
<th>PM</th>
</tr>
</thead>
<tbody>
<tr>
<td>STT</td>
<td>Mean</td>
<td>00:11</td>
<td>00:10</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>01:35</td>
<td>01:49</td>
</tr>
<tr>
<td>RTTT</td>
<td>Mean</td>
<td>00:20</td>
<td>00:17</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>01:27</td>
<td>01:24</td>
</tr>
</tbody>
</table>

5.2.3 Spatial analysis

As a continuation of the underlying sources of variations in this section, the performance of RTI, provided by the RTTT, was further investigated by examining its spatial variation along each of the 8 service routes. As in STT method, the eastbound route of bus line 1 was selected to illustrate the commonly observed patterns. Fig. 5.5 illustrates the performance of the STT and RTTT prediction methods along this route. For the RTTT prediction method, the scenario of utilizing 5 previous bus trips per prediction is been used. Specifically, the blue dotted and continuous orange lines follow the performance of the mean values across different stops for STT and RTTT method respectively. In parallel, the vertical blue and orange lines illustrate the standard error accordingly. The average prediction error (Eq. 3.16) for the RTTT prediction method fluctuates along the route within the range of less than half a minute. The latter forms an overall better estimation of the bus arrivals in comparison to the relative fluctuation of ±1.5 minutes occurred in the STT system. Furthermore, for the given route the running time prediction method only lightly underestimates the bus arrivals.

Regardless of the average performance of the RTI methods, the plotted route revealed three interesting patterns:

I. For the RTTT method, the RTI predictions become more reliable at further downstream stops. Such a progress is exactly the opposite of the relative RTI predictions from the STT system, where they become less reliable at further downstream locations. This could be explained by the increase of more comprehensive records as vehicles progress throughout the route (e.g. numerous of short trips are scheduled from the first TPS till the last stop). On the other hand, the lack of informative records (e.g. partial trips, trips that has not started yet [§3.3 Implementation notes 1,2]) and the short segment, which is used in order to compute the travel time for the stop in which the prediction is made for, produce a higher uncertainty on the first stretch of stops.

II. The important role that TPS plays in the prediction method is apparent in
Figure 5.8: STT and RTTT methods’ real-time information accuracy and reliability along the route, Line 1 eastbound

(*) Indicate a TPS

the evolution of RTI accuracy along the route. Comparing the two methods, RTTT is found to provide most accurate predictions one stop downstream at TPS. This is followed by an immediate substantial increase in the prediction error, which is then reduced gradually until reaching the next TPS area. On the other hand at one stop downstream the TPS, the mean prediction error fluctuates considerably less under RTTT compared with STT. The accurate prediction at location precisely after the TPS is presumably obtained due to drivers’ attempts to adhere to the schedule at these locations where their punctuality is measured (Cats, 2013). In other words, the RTI produced by RTTT method, is able to capture the schedule recovery and provide a more accurate estimation of arrivals at further downstream locations. This explanation could also be enhanced by the fact that uncertainty is reduced after the TPS. Furthermore, the RTTT prediction method succeeds to capture the large dwell time variations at TPS due to large passenger flows, holding times and driver shift changes at stops immediately downstream of TPS.
III. RTI prediction error for the RTTT method is almost eliminated on the last stretch of the route following the last TPS. This is a strong indication that the new method is able to capture driver behaviour patterns. These patterns are illustrated in the STT prediction scheme and occurred as a result of drivers’ willingness to prolong their break at the end terminal and thus arrive earlier than the RTI generation suggests.

5.3 Iterative Forward Running and Dwell Time Analysis

5.3.1 Prediction accuracy

As described in previous sections, the STT method uses the real time location of the approaching vehicle and the schedule difference, while the RTTT prediction scheme is based on the real time location of the approaching vehicle and utilizes the travel time information from previous recorded trips, which were conducted at the same route segment. IF_RDT method is also based on the real time location of the approaching vehicle and computes the prediction based on the running time information from previous recorded trips and the dwell time spend at stops. This case study will focus on the contribution of previous bus trips in predicting vehicle arrivals. Demand profiles are assumed to remain constant, based on aggregated number of passengers at each stop and time-of-the-day, as described in previous section (§3.4). In order to understand the contribution of previous bus trips in predicting vehicle arrivals a sensitivity analysis was conducted. This analysis tried to investigate the optimum number of previous trips, which could be utilized in order to provide information related to running time. Furthermore, a qualitative analysis held related to the performance of IF_RDT scheme versus the STT and RTTT methods.

As in the previously mentioned methods, the evaluation of the overall RTI accuracy of the IF_RDT bus arrival prediction method is held by constructing the distribution of passengers’ prediction error (Eq. 3.16). These distributions correspond to scenarios with different amount of utilized trips in IF_RDT method, and are compared among each other, while also against the STT’s and RTTT’s (scenario which utilizes 5 previous trips) distributions. Specifically, for the IF_RDT method they will be presented the performance of scenarios that utilized 1 to 5, while also 10 previous trips.

The following Fig. 5.9 summarises the above cited distributions. The error for the IF_RDT prediction scheme follows a normal distribution for all the scenarios with a significant shift on the right part of the distribution. The latter is indication of a systematic overall underestimation. Fig. 5.10 presents the corresponding means and standard deviations. The mean value for all scenarios is significantly increased in comparison with aforementioned prediction systems (STT and RTTT). Moreover, the standard deviation illustrates a slightly better concentration of error values around 0, despite not being at the same level as the RTTT method. Furthermore, all the distributions from the IF_RDT method are positively skewed, indicating that
CHAPTER 5. RESULTS

the prediction scheme, independently of the utilized trips, has a strong systematic bias to underestimate passengers waiting time.

The closest observation of error concentration reveals important details regarding the success ratio of the newly applied methodology. Fig. 5.11 presents a gradual decrease of inquiries, which yielded a prediction error - either positive or negative - of more than 1 minute while the utilized buses are increased. Specifically, from 36% in the STT prediction scheme the passengers’ prediction error shortly drops to 34% with the use of 10 previous trips in the IF_RDT prediction scheme. Furthermore, the focus on the percentages of prediction error of more than 2 and 4 minutes reveals that the IF_RDT method performed almost identical to the STT system. Overall, for this method and for the four fifths of the above mentioned cases, the prediction error was due to underestimation of the remaining waiting time.

The sensitivity analysis for the IF_RDT method reveals, as in the RTTT case, that the marginal benefit diminishes after the utilization of 5 buses. Fig. 5.10 demonstrates a stabilization of mean and standard deviation values around 40 and 110 seconds respectively. Moreover, Fig. 5.11 illustrates consolidation of values regardless of the introduction of more than 5 buses. As the aim of a prediction scheme is to reduce the overall computation effort, the scenario of 5 utilized trips is revealed as the outperforming scenario for IF_RDT method.

The prediction error of the provisioned RTI should be assessed by accounting for the average waiting time, as seen in the previous methods. For the IF_RDT the average excessive waiting time per projected minute is 16.4% for the case study system. In other words, the average ‘SL minute’ lasts in fact 69.8 seconds. In other words IF_RDT method ‘SL minute’ is found 6 and 5 seconds longer in comparison with the relative from the STT and RTTT systems. However, the relative prediction error depends greatly on the remaining waiting time.

The predictions obtained by the three different methods (STT, RTTT and IF_RDT) were segmented based on the experienced waiting time - the time lag between their generation and the next bus arrival time. It should be noted that for both RTTT and IF_RDT methods it was chosen the utilization of 5 previous trips per prediction.

The bars in Fig. 5.12 show how the relative difference between the actual waiting time (Eq. 3.22) and the waiting time projected by RTI (Eq. 3.23) vary for different actual waiting times for the three different methods. It could be observed that the IF_RDT prediction scheme significantly underestimates the remaining waiting time, except of the short region of less than half a minute. In comparison with the STT system the proposed IF_RDT prediction method succeed to eliminate the regions of overestimated remaining waiting time (waiting times shorter than 2 minutes). On the other hand, for waiting times longer than half minute, IF_RDT increasingly underestimates the remaining waiting time in even greater proportion than RTTT method. Specifically, for waiting time longer than half a minute the relative difference between actual and predicted is increased by more than 10%.

Fig. 5.12 also displays the reliability of RTI as function of the remaining waiting time. The curves indicate that the RTI prognosis becomes, as expected, less reliable
5.3. ITERATIVE FORWARD RUNNING AND DWELL TIME ANALYSIS

Figure 5.9: IF_RDT, RTTT and STT methods’ real-time information prediction error

(*#) Indicate the number of utilized previous trips
CHAPTER 5. RESULTS

Figure 5.10: IF_RDT, RTTT and STT methods’ real-time information prediction error mean and standard deviation

Figure 5.11: IF_RDT, RTTT and STT methods’ real-time information prediction error of more than |1|, |2| and |4| minutes respectively

(*#) Indicate the number of utilized previous trips
5.3. ITERATIVE FORWARD RUNNING AND DWELL TIME ANALYSIS

Figure 5.12: RT_RDT, STT and RTTT methods’ real-time information accuracy and reliability as function of the remaining time until the next bus arrival

the longer the prediction horizon is. Since the standard deviation of RTI prediction error increases linearly with the waiting time, the reliability does not increase in relative terms (e.g. coefficient of variation). IF_RDT scheme is found more reliable all along the remaining waiting time, in comparison with STT method. On the other hand, IF_RDT scheme is found more reliable in contrast to the RTTT method for remaining waiting times equal to less than 7 minutes.

5.3.2 Temporal analysis

The time and space heterogeneity in traffic and passenger demand conditions leads the RTI prediction to exercise temporal variations with respect to the day of the week and time of the day. In order to evaluate the performance of the newly developed IF_RDT method, the temporal variations with respect to the day of the week and time of the day are analysed. These variations are compared against the corresponding ones from the STT and RTTT prediction schemes. It should be noted that for the IF_RDT and RTTT prediction methods the utilization of 5 previous bus trips per prediction is been used.

In the following Tab. 5.5, the mean and standard deviation values of the prediction error by day of the week for the three different methods are presented. For all methods, while the underestimation of waiting times prevails on all days of the week, its extent varies considerably. In overall terms the IF_RDT method is found
significantly inaccurate all along the week. However, this method is found more reliable than the STT method and slightly less reliable than the RTTT method. Great exception consists of Thursdays where the IF_RDT method is found notably more accurate on one hand and less reliable on the other. Both prediction accuracy and reliability deteriorate along the week with the worst performance obtained on Fridays and Saturdays. Sundays, in contrast, performed like an average weekday. As described in previous sections, these differences are presumably determined by the irregularity and hence, less predictable traffic and travel patterns occurred at the end of the week.

Table 5.5: IF_RDT, STT and RTTT Methods’ Prediction Error by Day-of-the-Week (mm:ss)

<table>
<thead>
<tr>
<th></th>
<th>MON</th>
<th>TUE</th>
<th>WED</th>
<th>THU</th>
<th>FRI</th>
<th>SAT</th>
<th>SUN</th>
</tr>
</thead>
<tbody>
<tr>
<td>STT</td>
<td>Mean</td>
<td>00:05</td>
<td>00:10</td>
<td>00:17</td>
<td>00:21</td>
<td>00:22</td>
<td>00:32</td>
</tr>
<tr>
<td></td>
<td>StD</td>
<td>01:51</td>
<td>01:46</td>
<td>02:18</td>
<td>02:25</td>
<td>02:38</td>
<td>02:52</td>
</tr>
<tr>
<td>RTTT</td>
<td>Mean</td>
<td>00:15</td>
<td>00:17</td>
<td>00:23</td>
<td>00:26</td>
<td>00:30</td>
<td>00:31</td>
</tr>
<tr>
<td></td>
<td>StD</td>
<td>01:29</td>
<td>01:28</td>
<td>01:52</td>
<td>02:00</td>
<td>02:14</td>
<td>02:05</td>
</tr>
<tr>
<td>IF_RDT</td>
<td>Mean</td>
<td>00:39</td>
<td>00:42</td>
<td>00:48</td>
<td>00:33</td>
<td>00:53</td>
<td>00:58</td>
</tr>
<tr>
<td></td>
<td>StD</td>
<td>01:36</td>
<td>01:31</td>
<td>01:53</td>
<td>02:56</td>
<td>02:16</td>
<td>02:08</td>
</tr>
</tbody>
</table>

A further analysis regarding the temporal variations with respect to time of day was held. Particularly, prediction errors were calculated separately for trips that started at the AM peak (7:00-9:00), Off-Peak (9:00-15:30) and PM peak (15:30-19:00) periods. The last is associated with less accurate and less reliable RTI provision (Tab. 5.6) for all prediction methods. In contrast, the AM peak performs surprisingly well. This may be due to its more homogeneous conditions. For all time-of-day categories the IF_RDT method is found less accurate and slightly less reliable than the RTTT method.

Table 5.6: STT and RTTT Methods’ Prediction Error for Time-of-Day Categories (mm:ss)

<table>
<thead>
<tr>
<th>Time-of-day Categories</th>
<th>AM</th>
<th>Off-Peak</th>
<th>PM</th>
</tr>
</thead>
<tbody>
<tr>
<td>STT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>00:11</td>
<td>00:10</td>
<td>00:15</td>
</tr>
<tr>
<td>StD</td>
<td>01:35</td>
<td>01:49</td>
<td>02:12</td>
</tr>
<tr>
<td>RTTT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>00:20</td>
<td>00:17</td>
<td>00:21</td>
</tr>
<tr>
<td>StD</td>
<td>01:27</td>
<td>01:24</td>
<td>01:48</td>
</tr>
<tr>
<td>IF_RDT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>00:41</td>
<td>00:41</td>
<td>00:35</td>
</tr>
<tr>
<td>StD</td>
<td>01:32</td>
<td>01:52</td>
<td>02:05</td>
</tr>
</tbody>
</table>
5.3. ITERATIVE FORWARD RUNNING AND DWELL TIME ANALYSIS

Figure 5.13: IF_RDT, STT and RTTT methods’ real-time information accuracy and reliability along the route, Line 1 eastbound

(*) Indicate a TPS

5.3.3 Spatial analysis

As a continuation of the explanatory variations, in this section the performance of RTI provided by the IF_RDT, was further investigated by examining its spatial variation along eastbound route of bus line 1. Fig. 5.13 illustrates the performance of the STT, RTTT and IF_RDT prediction methods along the route. For both RTTT and IF_RDT methods, the scenario of utilizing 5 previous bus trips per prediction is been used. Specifically, the blue and orange dotted while also the continuous green lines follow the performance of the mean values across different stops for STT, RTTT and IF_RDT method, respectively. At the same time the vertical blue, orange and green lines illustrate the standard error accordingly. The average prediction error (Eq. 3.16) for the IF_RDT prediction method fluctuates along the route within the range of less than one minute. This illustrates a systematic significant underestimation of the bus arrivals for every single stop.

Regardless of the average performance of the RTI methods, the plotted route revealed two interesting patterns:
CHAPTER 5. RESULTS

I. For the IF_RDT method, the RTI predictions become more reliable at further downstream stops. Such a progress is exactly the opposite of the relative RTI predictions from the STT system, where they become less reliable at further downstream locations. This could be explained by the increase of the more comprehensive records as vehicles progress throughout the route (e.g. numerous of short trips are scheduled from the first TPS till the last stop). On the other hand, the lack of informative records and the short segment, which is used in order to compute the running time for the stop in which the prediction is made for, produces higher uncertainty on the first stretch of stops.

II. The important role that TPS plays in the prediction method is apparent in the evolution of RTI accuracy along the route. Similarly to RTTT, IF_RDT is found to provide most accurate predictions one stop downstream at TPS. This is followed by a slight increase in the prediction error. The error is then reduced gradually until reaching the next TPS area. The accurate prediction at locations precisely after the TPS, is presumably obtained due to drivers’ attempts to adhere to the schedule at these locations where their punctuality is measured (Cats, 2013). In other words, the RTI produced by IF_RDT method, is able to capture the schedule recovery and provide a more accurate estimation of arrivals at further downstream locations. This explanation could also be enhanced by the fact that uncertainty is reduced after the TPS. Furthermore, the IF_RDT prediction method succeeds to capture the large dwell time variations at TPS due to large passenger flows, holding times and driver shift changes at stops immediately downstream of TPS.

5.4 Comparison with Static Information

The dissemination of RTI concerning arrival times aims to reduce the uncertainty associated with waiting time for public transport services. This could potentially give the opportunity to passengers to adapt their travel choices accordingly. On the other hand a perfectly punctual public transport system would hypothetically make RTI provision redundant as static information will suffice. The potential added-value of RTI derives from its utilization of recently transmitted probes concerning public transport dynamics as opposed to static information. In the following paragraphs, the performance of RTI produced by three generation methods will be investigated.

Firstly, observing Fig. 5.14, the distribution of schedule adherence (Eq. 3.20) is strongly skewed towards late arrivals with a long right tail. Only 10% of all arrivals are within an interval of ±30 seconds compared to the timetable. Hence, the remaining share of the RTI provisioned waiting times, which coincide with those derived from the timetable, do so simply because the RTI prediction scheme reserves to the schedule under certain circumstances. This occurs when the next bus has not
5.4. COMPARISON WITH STATIC INFORMATION

Figure 5.14: Static information accuracy (vehicle level)

started yet its trip or in cases where the bus runs early and there is an intermediate TPS.

The following Fig. 5.15-5.17 demonstrate the differences between RTI provisions (Eq. 3.23), produced by three generation methods (STT, RTTT, IF_RDT), and the corresponding timetable information (Eq. 3.24). Regarding, the STT system, in 20% of the cases real-time and static means yielded the exact same information with respect to the remaining time to the next bus arrival. This could be either thanks to a punctual service or due to deficiencies of the prediction method. Deficiencies mostly refer in cases where the prediction is unable to compute a RTI (e.g. cases of missing records or the trip has not started yet), so the provision is the same like in the timetable.

On the other hand, for both RTTT and IF_RDT methods the real-time and static means differ systematically. Regarding the RTTT method, which as illustrated in previous section performs considerably better than the other methods, the cases where the real-time and static mean values yielded the exact same information with respect to the remaining time to the next bus arrival is limited to almost 6%. This could enhance the opinion that the likelihood of perfect punctuality in the system is rather low.

In order to investigate the added-value of RTI, the distributions of expected waiting time based on the timetable and RTI (Eq. 3.23-3.24) for the different prediction systems are constructed. The Fig. 5.18 illustrates the aforementioned
Figure 5.15: Real-time information (STT) vs. static information

Figure 5.16: Real-time information (RTTT) vs. static information
distributions in contrast with the distribution of the actual waiting times (Eq. 3.22). The average waiting time, which is the mean actual waiting time derived from the study network during the whole study period, equals to 4 minutes and 12 seconds where 80% of the passengers wait less than 5 minutes. It is worthwhile to note that the average actual waiting time is 57% longer than the value that would have been obtained from a perfectly regular bus arrival. Since the RTI generation procedure followed a uniform temporal distribution, the number of observations is linearly proportional to the headway.

At first, one could indicate that waiting time expectation derived from the timetable result in a considerable underestimation of waiting times. The comparison of static information and actual arrivals reveals an overestimation of the likelihood of waiting times shorter than 5 minutes. This could be explained by the fact that the expected waiting time based on the timetable could be realized only in case the service is perfectly punctual. The concentration of instances from 0 to 5 minutes is expected as the planned headway for the lion share of the day is between 4 to 6 minutes for the case study lines.

On the other hand, the distributions of expected waiting time based on RTI, produced by the STT and RTTT methods, follow closely the distribution of actual waiting time. The mean absolute error of the timetable is $MAE^t = 146 \text{ sec}$ (Eq. 3.26), while the average deviations of RTI (Eq. 3.25) from the aforementioned systems are less than half $MAE^{STT} = 68 \text{ sec}$ and one third as long $MAE^{RTTT} = $
Figure 5.18: Waiting time distributions - actual and expected based on static or real-time information (from IF_RDT, RTTT and STT methods)
5.4. COMPARISON WITH STATIC INFORMATION

51 sec-, respectively. Specifically, the derived expected waiting time for the RTTT method is found closer to actual waiting time for waiting times less than 1 minute and for the range of 5 to 8 minutes. This could explain its better performance in mean absolute error.

The average deviation of RTI from IF_RDT system is lying to \( MAE^{IF\_RDT} = 63 \) sec. The IF_RDT method’s expected waiting time follows closely the distribution of waiting time determined by static information for waiting times less than 3 minutes. The reason that IF_RDT and timetable distribution of waiting time is following closely each other could be found on the methodological approach of IF_RDT scheme. The latter is constructed based on real-time running time information which is derived from previous trips and aggregated dwell time at a stop level. Considering the well performed RTTT method, it is proved that the aggregated dwell time component used in IF_RDT was unable to capture the variability of time spend at stops. The average dwell time prediction needs to be further calibrated in order to be able to follow the uncertainty of time spend at stops and avoid replicating the average conditions of the system. Specifically, the usage of the constant common values \( (t^{boarding}, t^{boarding}) \) potentially results a systematic bias in this implementation of this prediction scheme.

As one could observe, RTI enables passengers to shift their expectations considerable closer to their experienced waiting time. Regarding the STT, the difference between waiting time expectations derived from the timetable and RTI is equivalent to 30.95% of the average waiting time. On the other hand, this difference is greater in the case of RTTT and IF_RDT method, with their value reaching 37.70% and 32.94% for the respective methods. The latter is a strong indication that the incorporation of real-time inputs in the prediction scheme could potentially benefit passengers’ decision process.

Notwithstanding, approximately 5% of RTI provision cases, in the case of STT, yield negative values which correspond to cases where the stop sign displays that the next bus should arrive “Now” while it has not reached the stop yet. It is presumed that this phenomenon contributes significantly to the “SL minute” reputa- tion. However, this percentage of negative values is significantly dropped in RTTT and IF_RDT systems, with the negative values making 3.9% and 3.4% of the instances, respectively.

The value of RTI is not limited only to passengers. RTI prediction schemes could also be used by operators to project the progress of their fleet. The information produced by these schemes could project the downstream vehicle trajectory and thus could support the decisions taken by control centre dispatchers. The deviation between RTI predictions (Eq. 3.18), from the three different schemes, and the timetable (Eq. 3.20) at the vehicle-level is presented in the following figures. For all prediction methods, the added value of RTI over the planned timetable is greater for operators than for passengers as reflected in the difference between Fig. 5.15-5.17 and Fig. 5.19-5.21, respectively. This is due to passengers indifference concerning whether a certain bus is the earlier bus running late or the later bus arriving early. Nonetheless, operators are interested not only in the inter-arrival
Figure 5.19: Real-time information (STT) vs static information ( operators)

distribution but also in the order of occurrences and how well does it match the planned vehicle scheduling. The comparison between the two perspectives reveals that for all the three proposed prediction methods and operators figures there is a significant concentration of observations in the positive tail of the distribution. Particularly, the predictions of arrivals are systematically longer than the expected schedule ones. The latter constitutes a strong indication that buses are found in most of the cases late compared with the planned timetables. These results could be beneficial for operators as they could investigate the causes of these delays and take operational actions such as fleet management and prevent overtakes.

Regarding the STT system, in more than 25% of the cases the difference between real-time and static information is equal to zero. This means that they both provide exactly the same information with respect to the remaining time until the next bus arrival. Additionally, for both RTTT and IF_RDT methods the real-time and static mean values differ systematically. As described in a previous paragraph, in many cases the STT is unable to provide RTI and relies greatly on timetables. This could likely explain the divergence among the different systems.

It should be noted that the RTI generation implementation for the three proposed methods is passenger oriented. In other words, the prediction of arrival and the computation of actual arrival is based on the vehicle that is expected to arrive first in the stop of interest. This aforementioned trip is attached with a schedule time at this stop, which could be different than the planned one. The RTI gen-
5.4. COMPARISON WITH STATIC INFORMATION

Figure 5.20: Real-time information (RTTT) vs static information (operators)

Figure 5.21: Real-time information (IF_RDT) vs static information (operators)
erators in this research do not aim to construct the trajectories of each individual vehicle and thus the information of actual arrival of the planned schedule trip is not available. That was the reason that the comparison of passengers’ and operators’ perspectives is based on the difference between predicted and schedule timing and not the directly divergence between actual arrival times.
Chapter 6

Conclusions

6.1 Discussion

Nowadays, ITS based systems are increasingly funded and implemented by agencies to various transportation fields. Public transport systems are not exempted from this trend, with advanced information and communication technologies being embedded in order to improve passengers’ level of service, public transport planning, infrastructure maintenance and operations. The aforementioned systems help public transport agencies to obtain details regarding vehicle travel time, vehicle location, speed, passengers on board and dwell time. Based on these details the generation of RTI for passengers and operators is feasible. In particular, the RTI related to the prediction of remaining time until the arrival of the next vehicle is the most commonly provisioned information and the main focus of research. In addition to the static information (e.g. timetables), the information provision from RTI takes into account the real conditions of the public transport system, and thus could potentially achieve more accurate predictions of vehicle arrivals. Furthermore, these accurate predictions could potentially benefit passengers in the decision process of their trip planning.

This thesis investigates the RTI provision for bus systems. The motivation arises on the challenge to capture the high travel and dwell time variability, which exist in such a public transport network. A bus system, in contrast to e.g., a subway system, is exposed to significant supply and demand fluctuations derived from numerous factors such as traffic conditions, passengers demand, service vehicle/road characteristics. Previous studies have considered a wide range of statistical tools which aimed to develop accurate and reliable predictions. These tools, as summarized in Tab. 2.1, utilize different input sources. However, the proposed approaches need high computation effort in order to produce RTI. This is a deterrent factor for real time applications. A second drawback of the proposed methods is the limited usage of inputs regarding real-time travel time, passengers demand profiles and bus stop characteristics. Thus, the aim of this thesis is to create a methodological approach which will keep in a limited level the computation effort and integrate the
aforementioned important source of information.

Three different prediction schemes are proposed. All methods start the generation of RTI based on the real-time identification of the approaching vehicle. The first one (STT), which also constitutes one of the most widely used RTI generators in real-world applications, bases its prediction on the remaining scheduled travel time, while the second one (RTTT), is using real-time records by previous trips in order to compute the travel time for the same scope. The last method (IF_RDT) is generating the prediction of running time based on real-time information of preceding buses and the dwell time spent at stops based on demand profiles. All methods take explicitly into account the existence of TPS along the bus trip.

The performance of RTI provision methods was evaluated for the trunk lines network in Stockholm’s inner-city. Specifically, AVL records from these lines were formulated in order to provide the input for the RTI methods and, in parallel, the empirical data for the assessment of the corresponding predictions.

The results of this analysis indicate that RTI produced by STT method underestimates the remaining waiting time by 6.2% on average ("SL minute" lasts 63.7 sec) and 64% of all prediction errors are lying within ±1 minute interval. This is considered to be a reasonable level of performance given the limited utilization of real-time vehicle positioning data embedded in the generator. However, the RTI prognosis from this method was particularly unreliable; the longer the prediction horizon, on Thursday to Saturday, during after peak period, further downstream along the route and immediately following a TPS. The outcome of the RTTT suggests the utilization of 5 previous trips in order to compute the travel time. In this case the average excessive waiting time per projected minute reaches 8% for the case study system ("SL minute" equals to 64.8 sec). However, the percentage of all predictions errors, which lay within ±1 minute interval, drops significantly to 74%. This result reveals the remarkable contribution of real-time information for computing travel time. The RTTT prognosis, in comparison with the STT method, was more reliable all along the prediction horizon, along the week and during the whole day. Its reliability announced superior in the majority of locations in the along the route analysis. The last method developed in this thesis (IF_RDT) failed to provide accurate predictions. The results revealed a systematic significant underestimation of waiting time for all the explanatory categories (e.g. temporal, time-of-day and spatial analysis). This critical underestimation is attached with a relatively low unreliability. This is an indication of introduction of a systematic bias. Thus, the need for further calibration of constant parameters related to dwell time is demonstrated.

The performance of each of the RTI generators was further evaluated by comparing its projections with the respective expectations that could be derived from the static information and the rest of the methods. It was found that the difference between passengers’ waiting time expectations derived from the timetable and STT method is equivalent to 30.95% of the average waiting time. On the other hand, this difference is greater in the case of RTTT and IF_RDT method, with the corresponding values reaching 37.70% and 32.94%, respectively. The latter percentages
6.2 DIRECTIONS FOR FURTHER RESEARCH

strongly indicate that the incorporation of real-time inputs in the prediction scheme could potentially benefit passengers’ decision process.

In order to address the passengers’ benefit, the time gain for average demand and waiting time conditions was computed. Firstly, the study considers the daily number of passengers for the case study network which is equal to 122,361 pass/day (Kuerban, 2012) and the mean actual waiting time of 4 minutes and 12 seconds. Thus, the average actual waiting time for one year is $3.13 \cdot 10^6$ hours. Based on the aforementioned percentages and the method for RTI provision, passengers could gain: $0.95 \cdot 10^6$ hours, $1.18 \cdot 10^6$ hours or $1.03 \cdot 10^6$ hours when they use RTI instead of the static information for the STT, RTTT and IF_RDT schemes, respectively. Furthermore, as Isacsson and Swardh (2007) indicate in their study the value of commuting time is assumed to be equal to 94 SEK per hour and the waiting time is equivalent to twice this value (188 SEK/h). Thus, in money terms passengers gain per year: $1.8 \cdot 10^8$ SEK, $2.2 \cdot 10^8$ SEK or $1.9 \cdot 10^8$ SEK with the use of STT, RTTT or IF_RDT RTI provision systems instead of the timetables. It should be considered that the framework of the proposed methods is based on already installed tracking equipment. Stockholm, while also numerous of other cities have equipped their public transport vehicles with GPS. Hence, by switching from STT to RTTT method the social benefit reaches more than 40M SEK per year, considering the limited cost associated with implementing the new algorithm and the zero investment costs for additional equipment.

This thesis investigated the potential contribution of real-time public transport data in the real-time arrival information system. As second step, it considers both the recent downstream running time information, while also anticipated headways and their impact on downstream dwell times. The contribution of this research is not limited to the detailed evaluation of the widely used schedule travel time method. It proposes also a robust method, which outperforms the aforementioned STT with low computation effort. In parallel, it provides the milestone for the introduction of dwell time component in calculation process of RTI.

6.2 Directions for Further Research

The proposed methods illustrate alternative approaches of utilizing real-time data. However, the limitation of available real-time datasets regarding dwell time gives a new target for future studies. Specifically, the replacement of aggregated demand profiles with data provided by systems like APC will potentially result in more accurate and timely predictions of dwell time at stops. Alternatively, the average dwell time prediction need to be further calibrated in order to be able to follow the uncertainty of time spend at stops and avoid replicating the average conditions of the system.

Furthermore, the current analysis based its evaluation of the existing and proposed methods on an event-based vehicle positioning dataset, rather than time-based. In case that the penetration rate of vehicle position data and the dissemi-
nation from the RTI generator to stop displays is more frequent, a further analysis of RTI performance is suggested. It should be noted that Stockholm belongs to the case where a bus generates three times more positioning probes than stop-visit records along an average trip.

Future studies could also investigate the potential integration of real-time traffic data (such as taxi GPS records) and passenger counts in the RTI generation. Moreover, the proposed schemes could generate other travel attributes such as in-vehicle time or crowding levels. Delving into a passengers’ behaviour aspect, another future direction can evaluate the performance of RTI in a way that reflects passengers perceptions (e.g. late arrivals are viewed more negatively than early arrivals).
References


REFERENCES


REFERENCES


Appendix A

Methodology in Block Diagrams
For given:
- line \( l \)
- direction \( d \)
- date
- stop \( s \)
- time \( \tau \)

\[ m = \text{NaN} \]

\( \text{TRUE} \)

\( \text{FALSE} \)

\( k^{p+1} \) run early & exists intermediate TPS between \( s \) and \( m \)

Prediction = Schedule Time

Prediction = Schedule remaining travel time

TRUE

FALSE

Find the last bus trip that visited stop \( s \): \( k^p \)

Find the last stop visited by bus trip \( k^{p+1} \): \( m \)

\( m = \text{NaN} \)

Figure A.1: Block diagram illustration for STT method (§3.2)
For given: line l, direction d, date, stop s, time τ
m=NaN
TRUE
FALSE
Prediction = Schedule Time

Find the last bus trip that visited stop s:
k

Find the last stop visited by bus trip k+1:
m

Find previous trips which conducted the segment m→s:
Exist TPS between s and m
TRUE
FALSE
No Previous Trips

Estimation of earlyness:
Find previous trip which conducted the segment TPS→s
TRUE
FALSE
No Previous Trips

Prediction = Weighted Travel Time of Previous Trips
FALSE
No Previous Trips

Prediction = Remaining Travel Time
FALSE
No Previous Trips

Prediction = Schedule Time at TPS + Weighted Travel Time of Previous Trips

Figure A.2: Block diagram illustration for RTTT method (§3.3)
APPENDIX A. METHODOLOGY IN BLOCK DIAGRAMS

For given:
- line l, direction d, date, stop s, time τ

m = NaN → TRUE

Σ = Actual arrival of kp+1 at m, i=m

FALSE → No Schedule time of kp+1 at m

TRUE → Prediction = Schedule Time

m = i → m+1

Σ = Schedule time of kp+1 at m, i=m

FALSE → No Schedule time of kp+1 at m

FALSE → Prediction = I

I = Schedule remaining travel time

I = I + Weighted Running Time of Previous Trips

FALSE → No Previous Trips

TRUE → Find previous trips which conducted the segment TPS→s

Find previous record in stop i for the computation of Headway

FALSE → TRUE

No Headway

FALSE → TRUE

I+1 = Dwell time (based on aggregated number of passengers)

I+2 = Dwell time (based on passengers’ demand levels)

I = Actual departure of kp+1 at m

FALSE → TRUE

TRUE → FALSE

I = Schedule departure time at stop i

Find previous trips which conducted the segment TPS→s

FALSE

Figure A.3: Block diagram illustration for IF_RDT method (§3.4)
Appendix B

Network’s Spatial Analysis
APPENDIX B. NETWORK’S SPATIAL ANALYSIS

IF_RDT, STT and RTTT methods’ real-time information accuracy and reliability along the case study network. Star (*) indicates a TPS.

Figure B.1: Line 1 westbound
Figure B.2: Line 2 southbound

Figure B.3: Line 2 northbound

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APPENDIX B. NETWORK’S SPATIAL ANALYSIS

Figure B.4: Line 3 southbound

Figure B.5: Line 3 northbound

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Figure B.6: Line 4 southbound

Figure B.7: Line 4 northbound
Appendix C

Publication
REAL-TIME BUS ARRIVAL INFORMATION SYSTEM—AN EMPIRICAL EVALUATION

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Abstract—Waiting time uncertainty is one of the main determinants of public transport reliability and overall level-of-service. The dissemination of real-time information concerning vehicle arrivals is often considered an important measure to reduce unreliability. Moreover, the prediction of downstream vehicle trajectories could also benefit real-time control strategies. In order to adequately analyze the performance of real-time bus arrival information system, the generated predictions have to be compared against empirical bus arrival data. A conventional real-world bus arrival prediction scheme is formulated and applied on the trunk lines network in Stockholm. This scheme was found to systematically underestimate the remaining waiting time by 6.2% on average. Prediction error accuracy and reliability varies considerably over time periods, along the route and as a function of the prognosis horizon. The difference between passengers’ waiting time expectations derived from the timetable and real-time information is equivalent to 30% of the average waiting time.

I. INTRODUCTION

Public transportation systems are increasingly equipped with information and communication technologies in order to improve the level of service and facilitate fleet management [1]. Advanced Public Transportation Systems (APTS) such as Automatic Vehicle Location (AVL) were first used for improving operations and management. Later on, these systems were also utilized to provide real-time information (RTI) to passengers [2]. In the context of public transport systems, RTI can refer to information on service disruptions, crowding conditions, prescriptive journey planners or the remaining time until the arrival of the next vehicle. The latter is the most commonly provisioned information and the main focus of research.

Previous studies analyzed the impact of RTI provision on various aspects of travellers’ experience including the level of satisfaction [3], perceived waiting time [4,5] as well as actual waiting time [6]. The benefits from deploying RTI systems are not limited to reduced uncertainty and trip departure time choice. RTI can also facilitate path choice changes that would yield time savings [7,8].

The generation of RTI can be based on historical data or real-time AVL data. The latter can potentially result in more accurate estimations of current traffic conditions. Previous studies applied various methods for bus arrival predictions as regression models, artificial neural networks (ANN), Kalman filter and statistical pattern recognition [9-12]. These methods follow the general prescription proposed by Cathey and Dailey [13].

In contrast to the extensive literature concerned with the development of bus arrival prediction schemes which involve the application of computationally-intensive statistical methods, there is lack of research on the performance of real-world systems. This paper aims to bridge this gap by investigating the performance of a commonly deployed RTI generation scheme.

A conventional timetable-based real-time bus arrival prediction scheme is evaluated based on empirical analysis. Unfortunately, RTI dissemination systems often do not store historical provisions. In the lack of unmediated access to RTI provision, the prediction scheme has been implemented and applied for an AVL database. The generated predictions are then compared against the ground-truth bus arrival data.

The rest of the paper is organized as follows. The RTI generation method is formulated in Section 2 along with the respective performance metrics from passengers’ and operators’ perspectives. Section 3 presents the case study and discusses how the RTI generator was implemented for this system. The results of our analysis are presented in Section 4 where the generated arrival predictions are compared with empirical bus arrival data while considering temporal and spatial variations. This paper concludes with an overall assessment of the current system and the potential for the development of more elaborative prediction schemes.

II. METHODOLOGY

A. Real-Time Information Generation Scheme

The bus arrival prediction scheme evaluated in this study is based on the real-time location of the approaching bus and the corresponding remaining scheduled travel time. It requires therefore the real-time positions of all buses and a time-dependent timetable database. The latter is seasonally constructed and indicates planned arrival times at each stop along the line. Moreover, it indicates which stops along each line act as stops where the timetable is regulated, also known as time point stops (TPS). Drivers are instructed to hold at these stops in case they run early compared with the timetable in order to improve service punctuality.

The prognosis scheme is based on the following assumptions: (a) The travel time between bus current location and any downstream location is equal to the scheduled travel time; (b) Buses never leave TPS (including origin stop) prior to their scheduled time.

The combination of these assumptions implies that buses maintain their schedule deviation with the exception of buses that run early and have a TPS between the current location and the relevant downstream location, since they will be able to correct their schedule deviation and hence to arrive on-time.

Bus trajectory could be represented as a vector of time stamps along a list of locations, typically stops. The trajectories of an ordered set of bus trips denoted \( K_{t} \) on line...
during a certain time interval can be hence represented as a matrix, where $L$ is the set of service lines in the network. Let us denote this matrix as $\pi^a$ where each cell, $\pi^a_{s,k}$, is the actual time where bus trip $k$ arrived at location $s \in S_l$. This matrix is partially empty for any ongoing trip.

A subset of the recording locations for line $l$ ($S_l \subseteq S_l$) serve as TPS. A corresponding matrix denoted $\pi^b$ contains the timetable trajectories for $K_l$. The output of the prediction scheme is the corresponding matrix of predicted bus arrivals, $\pi^p$.

The prediction scheme consists of the following steps when generating at time $t$ the prediction of the next arrival of line $l$ at stop $s$, $\pi^p_{s,l}(t)$:

a) Find the last bus trip $k$ that visited stop $s$—let us denote by $k^p$ the last bus trip that visited stop $s$, hence:

$$k^p = \arg \max_{k \in K_l} \{\pi^a_{s,k} : \pi^a_{s,k} < t\}$$

b) Find the last location visited by the next bus trip—let us denote by $m$ the last location that was visited by the next trip ($k^p + 1$), defined as follows:

$$m = \begin{cases} \pi^a_{m,s,k} = \emptyset & \text{arg} \max_{m=1,2} \{\pi^a_{s,k} : \pi^a_{s,k} < t\} \\ Otherwise & 0 \end{cases}$$

c) Make a prediction based on the timetable—The scheme distinguishes between the two following cases:

Case A—At time $t$, the next trip to visit stop $s$ has not started yet ($m = 0$) or the bus is running early ($\pi^a_{s,k+1,m} < \pi^a_{s,k+1,m}$) and there is an intermediate TPS ($\exists m \leq i < s, i \in S_l$) then the predicted arrival time is simply the scheduled time:

$$\pi^p_{s,l}(t) = \pi^a_{s,k+1,s} = \pi^a_{s,k+1,s}$$

Case B—Otherwise ($\pi^a_{s,k+1,m} \geq \pi^a_{s,k+1,m}$ OR $\exists m \leq i < s, i \in S_l$), the predicted arrival time is calculated based on the scheduled remaining travel time:

$$\pi^p_{s,l}(t) = \pi^a_{s,k+1,s} = \pi^a_{s,k+1,s} + \pi^a_{s,k+1,m} - \pi^a_{s,k+1,m}$$

In other words, it is assumed that the current deviation from the scheduled will be sustained in case of non-early trips as well as in case there is no intermediate TPS.

### B. Performance Metrics

The RTI performance is assessed by a series of metrics that are calculated ex-post and consider both passengers’ and operators’ perspectives. In the case of the latter, the prediction is carried out at the vehicle-level. The prediction error for the arrival of trip $k$ at stop $s$ is therefore assessed by comparing the prognosis generated at time $t$ against the corresponding actual arrival time of the same trip:

$$e^p_{s,k}(t) = \pi^a_{s,k} - \pi^p_{s,k}(t)$$

From passengers’ perspective, however, no importance is attached to the specific trip’s identity, and the accuracy is determined by the difference between the provisioned RTI and the next arrival of line $l$ at stop $s$, calculated as follows:

$$e^q_{s,k}(t) = \pi^a_{s,k} - \pi^q_{s,k}(t)$$

Where $k^a$ is the first trip to arrive at the stop, defined as:

$$k^a = \arg \min_{k \in K_l} \{\pi^a_{s,k} : \pi^a_{s,k} > t\}$$

This could be interpreted as the difference between the predicted and experienced waiting times for a passenger that arrived at stop $s$ at time $t$. Note that $k^a$ might differ from $k^p$ when an overtaking occurs between $m$ and $s$.

The prediction error measures enable to identify the difference between predicted and observed arrival times. An unbiased and valid prediction scheme will yield a normal distribution of prediction errors with a mean value of zero. Moreover, the variability of prediction errors has to be minimized in order to obtain a reliable prediction scheme.

The performance of static information concerning arrivals is used as a benchmark. Static information accuracy from operators’ and passenger’s perspectives — $e^q_{s,k}$ and $e^q_{s,k}(t)$, respectively — was formulated similarly by substituting the RTI prediction for the corresponding timetable term, as follows:

$$e^q_{s,k} = \pi^a_{s,k} - \pi^q_{s,k}$$

$$e^q_{s,k}(t) = \pi^a_{s,k} - \pi^q_{s,k}(t)$$

Where $k^q$ is the first trip scheduled to arrive at the stop, defined as:

$$k^q = \arg \max_{k \in K_l} \{\pi^a_{s,k} : \pi^a_{s,k} > t\}$$

Note that $k^q$ might differ from $k^t$ in case the first arriving bus was scheduled to arrive before the passenger arrived at the stop. The prediction error of static information from operators’ perspective (4) is equivalent to schedule adherence at the vehicle-level.

Furthermore, the extent to which timetables and RTI are effective in assisting passengers to shift their expectations closer to the actual waiting time is assessed. The actual waiting time of a passenger arriving at stop $s$ at time $t$ with the intention to board line $l$ is:

$$w^a_{s,l}(t) = \pi^a_{s,k}(t) - t$$

While the expected waiting time implied by RTI and the timetable are:

$$w^p_{s,l}(t) = \pi^p_{s,k}(t) - t$$

$$w^q_{s,l}(t) = \pi^q_{s,k}(t) - t$$

The mean absolute error performance measure can be then calculated as follows:

$$MAE^t = \frac{\sum_s |w^a_{s,l}(t) - w^q_{s,l}(t)|}{\sum_s |w^a_{s,l}(t)|}$$

$$MAE^p = \frac{\sum_s |w^a_{s,l}(t) - w^p_{s,l}(t)|}{\sum_s |w^a_{s,l}(t)|}$$

### III. Case Study

#### A. Network

The performance of the RTI generation method was analyzed based on detailed and comprehensive AVL data. These data were provided by SL, the regional public transport agency, and contained vehicle positioning data for each bus stop visit. The selected study period consists of records from 15/11/2011-15/12/2011 and 9/1/2012-19/1/2012 in order to exclude winter holidays. This dataset includes more than one million records.

The trunk bus system of Stockholm, Sweden, was selected as the case study network. It consists of 4 bus lines which compose the backbone of Stockholm inner-city bus network (Fig. 1). This network contains more than 200 stops along more than 80 route-km. Each route includes 2-4 TPSs located at key public transport transfer locations. These lines
account for 60% of the total ridership in this area with approximately 120,000 boarding passengers per day between 7:00-19:00. These lines are characterized by high frequency, articulated vehicles, designated lanes at main streets, traffic signal priority and RTI displays at all stops.

‘SL minute’ is notoriously known in Stockholm as a particularly ‘long’ minute because the bus fails to arrive within the projected time window. The design of this study allows to test whether the coined term is empirically justified.

\[ \mu_6/ \text{PLQXWH} \] LV QRWRULRXVO NQRZQ

B. Implementation Details

Real-time bus arrival predictions were reproduced for the case study data. The RTI generator converted the real-time bus positioning data and the corresponding timetable into a matrix format resulting with \( \pi^u \) and \( \pi^r \), respectively. A high value \( (M \geq \max \pi_{k,s}^u) \) was assigned to non-served stops in the case of partial trips.

Note that the available AVL data was limited to bus stop visits. Bus positioning information was hence processed in an event-based basis, while the assessment of the RTI performance requires a time-based sampling of the provisioned information. This facilitates the evaluation of the RTI generator across time and space where the time stamps correspond to passenger arrival time at stops.

The prediction scheme was implemented in MATLAB. The algorithm triggers a RTI provision inquiry across the entire network every minute. The RTI generator at time \( \tau \) follows then the steps outlined in Section 2 and thus utilizing only bus positioning data collected prior to \( \tau \). The implemented algorithm accounts explicitly for overtaking.

The prediction scheme is positively skewed, indicating that the prediction scheme overestimates the waiting time. More than one third of the inquiries (36%) yielded a prediction error – either positive or negative – of more than 1 minute. Furthermore, 14% and 5% of RTI projections had a prediction error of more than 2 minutes and 4 minutes, respectively. In two thirds of these cases, the prediction error was due to an underestimation.

The prediction error of the provisioned RTI should be assessed by accounting for the average waiting time. The average excessive waiting time per projected minute is 6.2% for the case study system. Hence, the average SL minute lasts in fact 63.7 seconds. However, the relative prediction error depends greatly on the remaining waiting time.

The predictions obtained by the RTI provision were segmented based on the experienced waiting time - the time lag between their generation and the next bus arrival time. The bars in Fig. 3 show how the relative difference between the actual waiting time (6) and the waiting time projected by RTI (7) vary for different actual waiting times. It could be observed that the prediction scheme overestimates the remaining waiting time for very short waiting times while it increasingly underestimates it for waiting times longer than 2 minutes. For waiting times longer than 8 minutes, the underestimation approaches 10%. For example, a RTI projection of 9 minutes would on average imply that the waiting time would be 10 minutes.

The reliability of RTI predictions is also presented in Fig. 3 as function of the remaining waiting time. The curve indicates that the RTI prognosis becomes, as expected, less reliable the longer the prediction horizon. Since the standard deviation of RTI prediction error increases linearly with the waiting times derived from the AVL data.

IV. Results

A. Prediction Accuracy

Fig. 2 presents the overall RTI accuracy as reflected by the distribution of passengers’ prediction error (3). It follows a normal distribution with a mean value \(+15\) seconds and a standard deviation of 2 minutes. Moreover, the distribution is positively skewed, indicating that the prediction scheme has a slight systematic bias to underestimate passengers’ waiting time. More than one third of the inquiries (36%) yielded a prediction error – either positive or negative – of more than 1 minute. Furthermore, 14% and 5% of RTI projections had a prediction error of more than 2 minutes and 4 minutes, respectively. In two thirds of these cases, the prediction error was due to an underestimation.
waiting time, the reliability does not increase in relative terms (e.g. coefficient of variation).

![Image of a graph showing real-time information accuracy and reliability as a function of waiting time until the next bus arrival.]

**Figure 3. Real-time information accuracy and reliability as a function of the remaining time until the next bus arrival.**

### B. Temporal Analysis

The RTI prediction accuracy exercises temporal variations over days of the week and times of day. Table I presents mean and standard deviation values of the prediction error by day of the week. While the underestimation of waiting times prevails on all days of the week, its extent varies considerably. RTI predictions were the most accurate as well as the most reliable on Monday and Tuesday. Both prediction accuracy and reliability deteriorate along the week with the worst performance obtained on Saturdays. Sundays, in contrast, performed like an average weekday. These differences are presumably determined by the extent to which timetables reflect the prevailing traffic conditions. Saturday in particular is subject to irregular and hence less predictable traffic and travel patterns. It should be noted that the case study network has a common timetable for all weekdays and separate timetables for Saturdays and Sundays.

<table>
<thead>
<tr>
<th></th>
<th>MON</th>
<th>TUE</th>
<th>WED</th>
<th>THU</th>
<th>FRI</th>
<th>SAT</th>
<th>SUN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>00:05</td>
<td>00:10</td>
<td>00:17</td>
<td>00:21</td>
<td>00:22</td>
<td>00:32</td>
<td>00:20</td>
</tr>
<tr>
<td>SD</td>
<td>01:51</td>
<td>01:46</td>
<td>02:18</td>
<td>02:25</td>
<td>02:38</td>
<td>02:52</td>
<td>01:50</td>
</tr>
</tbody>
</table>

The temporal variations with respect to time of day were also analyzed. Prediction errors were calculated separately for trips that started at the AM peak (7:00-9:00), off-peak (09:00-15:30) and PM peak (15:30-19:00) periods. The latter is associated with less accurate and less reliable RTI provision (Table II). In contrast, the AM peak period performs surprisingly well. This may be due to its more homogenous conditions.

<table>
<thead>
<tr>
<th>Time-of-Day Categories</th>
<th>AM</th>
<th>Off-Peak</th>
<th>PM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>00:11</td>
<td>00:10</td>
<td>00:15</td>
</tr>
<tr>
<td>SD.</td>
<td>01:35</td>
<td>01:49</td>
<td>02:12</td>
</tr>
</tbody>
</table>

**C. Spatial Analysis**

The performance of RTI was further investigated by examining its spatial variation along each service route. The eastbound route of bus line 1 was selected to illustrate the commonly observed patterns. This route consists of 33 stops, of which 3 serve as TPS. Fig. 4 presents the performance of the prediction method along the route. It could be observed that the average prediction error (3) fluctuates along the route within the range of ±1.5 minutes.

![Image of a graph showing real-time information accuracy along the route, Line 1 eastbound; star indicate a TPS.]

**Figure 4. Real-time information accuracy along the route, Line 1 eastbound; star indicate a TPS.**

Three patterns are evident across routes. First, RTI predictions become less reliable at further downstream stops. This could be explained by the prorogation of uncertainty attributed to traffic conditions, dwell time and driver behavior along the route. Second, the important role that TPS plays in the prediction method is apparent in evolution of RTI accuracy along the route. It is evident that RTI provides the most accurate prediction at TPS, followed by an immediate substantial increase in the prediction error which is then reduced gradually until the next TPS. The accurate prediction at TPS is presumably obtained due to drivers’ attempts to adhere to the schedule at these locations where their punctuality is measured [14]. In contrast, bus arrivals at stops immediately downstream of TPS are subject to large dwell time variations at TPS due to large passenger flows, holding times and driver shift changes. Third, RTI prediction error is negative on the last stretch of the route following the last TPS. This is attributed to driver behavior patterns as they wish to prolong their break at the end terminal and thus arrive earlier than the RTI generation suggests.

**D. Comparison with Static Information**

The dissemination of RTI concerning arrival times aims to reduce the uncertainty associated with waiting time for public transport services. A perfectly punctual public transport system ($e_{k,s}(t) = 0 \forall k,s,t$) would hypothetically make RTI provision redundant as static information will suffice. The potential added-value of RTI emerges from its utilization of recently transmitted probes concerning public transport dynamics as opposed to static information.

Fig. 5 plots the difference between RTI provisions (7) and the corresponding timetable information (8). Note that this is equivalent to the difference between the respective
prediction errors, (5) and (3). In 20% of the cases, real-time and static means yielded the exact same information with respect to the remaining time to the next bus arrival. This could be either thanks to a punctual service or due to deficiencies of the prediction method. The distribution of schedule adherence (4) is strongly skewed towards late arrivals with a long right tail (Fig. 6). Only 10% of all arrivals are within an interval of ±15 seconds compared with the timetable. Hence, the remaining share of the RTI provisioned waiting times, which coincide with those derived from the timetable, do so simply because the RTI prediction scheme reserves to the schedule under certain circumstances. This occurs when the next bus has not started yet its trip or in cases where the bus runs early and there is an intermediate TPS (Section 2).

The added-value of RTI was further analyzed by constructing the distributions of expected waiting time based on the timetable (7) and RTI (8). Fig. 7 contrasts these distributions with the distribution of the actual waiting times (6). The average waiting time is 4 minutes and 12 seconds where 80% of the passengers waiting less than 5 minutes. It is worthwhile to note that the average actual waiting time is 57% longer than the value that would have been obtained from a perfectly regular bus arrival. Since the RTI inquiries follow a uniform temporal distribution, the number of observations is linearly proportional to the headway.

It is evident that waiting time expectation derived from the timetable result with a considerable underestimation of waiting times. The expected waiting time based on the timetable could be realized only in case the service is perfectly punctual and therefore results in an overestimation of the likelihood of waiting times shorter than 5 minutes. This is expected as the planned headway for the lion share of the day is between 4-6 minutes for the case study lines.

The distribution of expected waiting time based on RTI (8) on the other hand follows closely the distribution of actual waiting time (6). The mean absolute error of the timetable (9) is \( MAE_I = 146 \) sec, while the average deviation of RTI (10) is less than half as long -\( MAE_P = 68 \) sec. RTI enables therefore passengers to shift their expectations considerably closer to their experienced waiting time. The difference between waiting time expectations derived from the timetable and RTI is equivalent to 30% of the average waiting time. Notwithstanding, approximately 5% of RTI provision cases fail and provide negative values which correspond to cases where the stop sign displays that the next bus should arrive “Now” while it has not reached the stop yet. It is presumed that this is the phenomenon which contributes significantly to the ‘SL minute’ reputation.

RTI prediction schemes could also be used by operators to project the progress of their fleet. The projection of downstream vehicle trajectory can support the decisions taken by control center dispatchers. The deviation between RTI predictions (2) and the timetable (4) at the vehicle-level is presented in Fig. 8.
The added value of RTI over the planned timetable is greater for operators than for passengers as reflected in the difference between figures 5 and 8. This is due to passengers’ indifference concerning whether a certain bus is the earlier bus running late or the later bus arriving early. Unlike passengers, the operator is interested not only in the inter-arrival distribution but also in the order of occurrences and how well does it match the planned vehicle scheduling.

V. CONCLUSIONS

The assessment of RTI performance requires the comparison of generated arrival predictions with the respective actual arrival times. This paper reports the formulation, implementation and evaluation of a commonly used timetable-based prediction scheme. This scheme utilizes real-time vehicle positioning data concerning only the next approaching vehicle while the remaining travel time is calculated based on a time-dependent timetable. Performance metrics concerning the prediction error accuracy and reliability and their impact on expected waiting time were formulated from both passengers’ and operators’ perspective. Equivalent measures were developed for the timetable in order to facilitate the investigation of the added-value induced by RTI.

The performance of RTI provision was applied for the trunk lines network in Stockholm’s inner-city. The results of this analysis indicate that RTI underestimates the remaining waiting time by 6.2% on average and 64% of all predictions are within ±1 minute error interval. This is considered by the authors to be a reasonable level of performance given the limited utilization of real-time vehicle positioning data embedded in the current prediction scheme. However, the RTI prognosis was particularly unreliable the longer the prediction horizon, on Thursday-Saturday, during the afternoon peak period, further downstream along the route and immediately following a TPS.

The performance of RTI was further evaluated by comparing its projections with the respective expectations that could be derived from the static timetable. It was found that the difference between passengers’ waiting time expectations derived from the timetable and RTI is equivalent to 30% of the average waiting time. The added-value of RTI is even more pronounced for operators since vehicle trajectory predictions utilize instantaneous schedule deviation data at the individual vehicle-level.

In the absence of disseminated RTI records, the analysis consisted on generating RTI projections by mimicking the prediction scheme. This implied an event-based vehicle positioning data availability rather than time-based. In case that the penetration rate of vehicle positioning data and the dissemination from the RTI generator to stop displays is more frequent, our analysis will result in an underestimation of the RTI performance. This is indeed the case in Stockholm where a bus generates three times as many probes as stop-visit records along an average trip.

The deficiencies identified in this analysis could be addressed by the further development of RTI prediction schemes. Previous studies have considered a wide range of statistical tools that can obtain more accurate and reliable predictions by using recent vehicle positioning data for calculating the remaining travel time to downstream stops rather than relying on the timetable [9-12]. Future research should try to close the large gap between the current state of the practice and the advanced state of the art by proposing incremental and applicable improvements to currently deployed prediction schemes.

ACKNOWLEDGMENT

The data used in this study was kindly provided by SL, Stockholm’s public transport authority. The real-time information generation scheme was formulated based on discussions with the information technology department in SL but has not been confirmed by the system provider.

REFERENCES