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CTS Working Paper 2013:25

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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.

Keywords: Public transport; Real-time information; Reliability; Prediction

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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_l on line

$l \in L$ 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 π^a where each cell, $\pi^a_{k,s}$, 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 ($\hat{s}_l \subseteq S_l$) serve as TPS. A corresponding matrix denoted π^t contains the timetable trajectories for K_l. The output of the prediction scheme is the corresponding matrix of predicted bus arrivals, π^p.

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

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:

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

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:

$$m = \begin{cases} if\ \pi^a_{k^p+1,1} \neq \emptyset & arg\ \max_{i=1\dots s}\{\pi^a_{k^p+1,i}: \pi^a_{k^p+1,i} < \tau\} \\ Otherwise & 0 \end{cases}$$

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

Case A –At time τ, the next trip to visit stop s has not started yet ($m = 0$) OR the bus is running early ($\pi^a_{k^p+1,m} < \pi^t_{k^p+1,m}$) and there is an intermediate TPS ($\exists\ m \le i < s, i \in \hat{s}_l$) then the predicted arrival time is simply the scheduled time:

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

Case B - Otherwise ($\pi^a_{k^p+1,m} \ge \pi^t_{k^p+1,m}$ OR $\nexists$ m ≤ i < $s, i \in \hat{s}_l$), the predicted arrival time is calculated based on the scheduled remaining travel time:

$$\pi^p_{l,s}(\tau) = \pi^p_{k^p+1,s}(\tau) = \pi^a_{k^p+1,m} + \pi^t_{k^p+1,s} - \pi^t_{k^p+1,m} \quad (1)$$

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 τ against the corresponding actual arrival time of the same trip:

$$e^p_{k,s}(\tau) = \pi^a_{k,s} - \pi^p_{k,s}(\tau) \quad (2)$$

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:

$$e^p_{l,s}(\tau) = \pi^a_{k^a,s}(\tau) - \pi^p_{l,s}(\tau) \quad (3)$$

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

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

This could be interpreted as the difference between the predicted and experienced waiting times for a passenger that arrived at stop s at time τ. 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 - $e^t_{k,s}$ and $e^t_{l,s}(\tau)$, respectively - was formulated similarly by substituting the RTI prediction for the corresponding timetable term, as follows:

$$e^t_{k,s} = \pi^a_{k,s} - \pi^t_{k,s} \quad (4)$$

$$e^t_{l,s}(\tau) = \pi^a_{k^a,s}(\tau) - \pi^t_{k^t,s}(\tau) \quad (5)$$

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

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

Note that k^a 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 τ with the intention to board line l is:

$$w^a_{l,s}(\tau) = \pi^a_{k^a,s}(\tau) - \tau \quad (6)$$

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

$$w^p_{l,s}(\tau) = \pi^p_{l,s}(\tau) - \tau \quad (7)$$

$$w^t_{l,s}(\tau) = \pi^t_{k^t,s}(\tau) - \tau \quad (8)$$

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

$$MAE^t = \overline{\left|w^a_{l,s} - w^t_{l,s}\right|} = \frac{\sum_{l,s,\tau}\left|e^t_{l,s}(\tau)\right|}{\sum_{l \in L}|S_l| \cdot |\tau|} \quad (9)$$

$$MAE^p = \overline{\left|w^a_{l,s} - w^p_{l,s}\right|} = \frac{\sum_{l,s,\tau}\left|e^p_{l,s}(\tau)\right|}{\sum_{l \in L}|S_l| \cdot |\tau|} \quad (10)$$

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.

Figure 1. Stockholm's inner-city trunk lines routes

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 π^{a} and π^{t}, respectively. A high value ($M \gg max\, \pi_{k,s}^{a}$) 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 τ follows then the steps outlined in Section 2 and thus utilizing only bus positioning data collected prior to τ. The implemented algorithm accounts explicitly for overtaking.

The algorithm provides as output the predicted bus arrival time at each stop and line combination, $\pi_{l,s}^{p}(\tau)$, for every minute so that $\tau = (7{:}00, 7{:}01, \ldots, 19{:}00)$. 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 τ 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 generator was analyzed by comparing the predicted waiting times with experienced waiting times derived from the AVL data. The fundamental analysis unit consists of a cross-network sampling of the prediction provided by the RTI system. This implies the calculation of the passengers' and operators' prediction error metrics across the network with one minute sampling.

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.

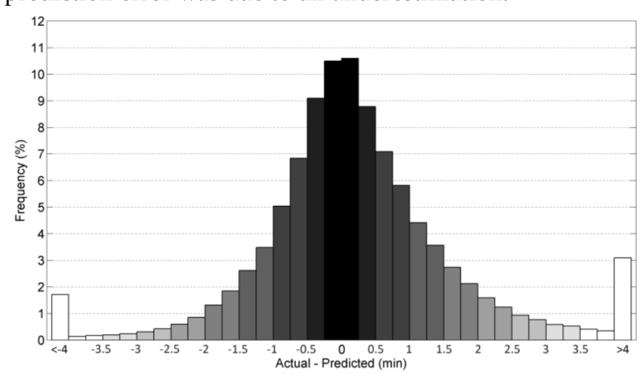

Figure 2. Real-time information prediction error

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 time, the reliability does not increase in relative terms (e.g. coefficient of variation).

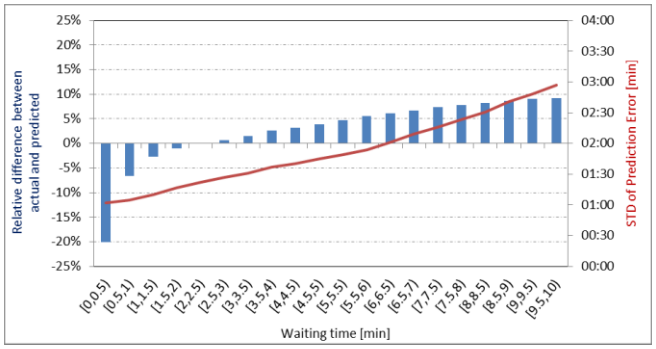

Figure 3. Real-time information accuracy and relaibility as function of the remaining time until the next bus arrival

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 I. PREDICTION ERROR BY DAY-OF-THE-WEEK (MM:SS)

	MON	**TUE**	**WED**	**THU**	**FRI**	**SAT**	**SUN**
Mean	00:05	00:10	00:17	00:21	00:22	00:32	00:20
StD	01:51	01:46	02:18	02:25	02:38	02:52	01:50

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 II. PREDICTION ERROR FOR TIME-OF-DAY CATEGORIES (MM:SS)

	Time-of-day Categories		
	AM	***Off-Peak***	***PM***
Mean	00:11	00:10	00:15
St.D.	01:35	01:49	02:12

C. Spatial Analysis

The performance of RTI was further investigated by examined 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.

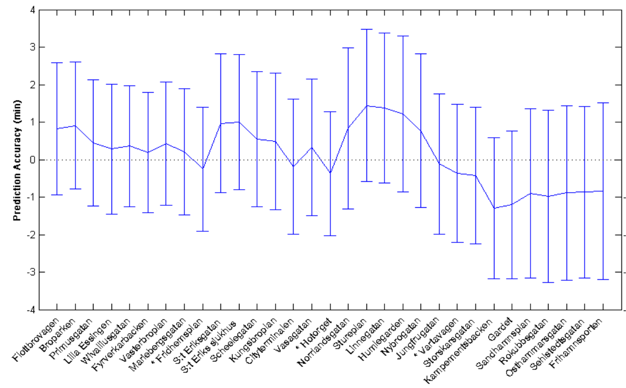

Figure 4. Real-time information accuracy along the route, Line 1 eatbound;star indicate a TPS

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 ($e_{k,s}^{t}(\tau) = 0 \;\forall k, s, \tau$) 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).

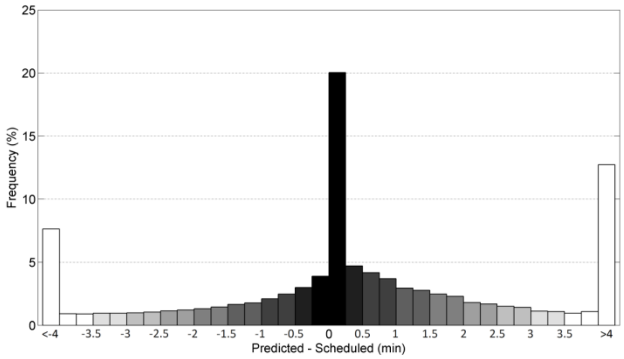

Figure 5. Static vs. real-time information

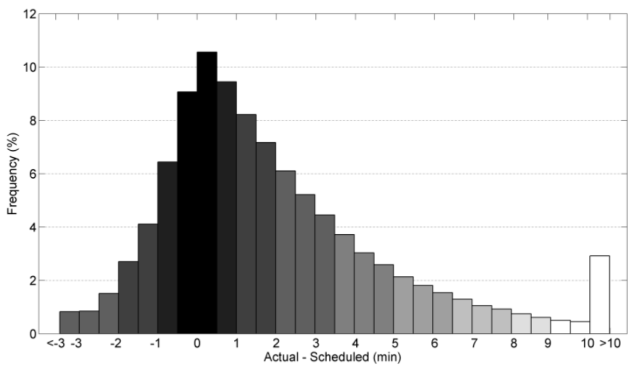

Figure 6. Static information accuracy (vehicle-level)

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 $MAE^t = 146\,sec$, 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.

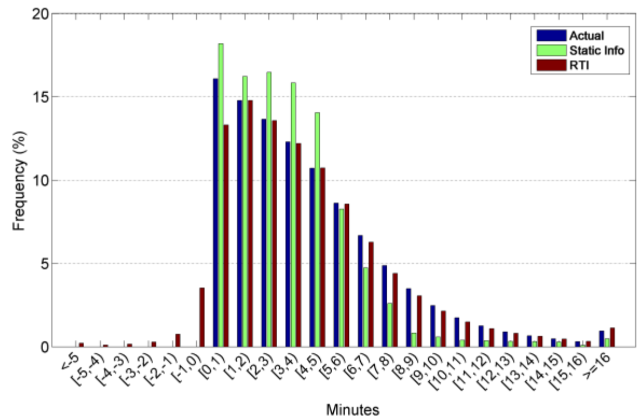

Figure 7. Waiting time distributions – actual and expected based on static or real-time information

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.

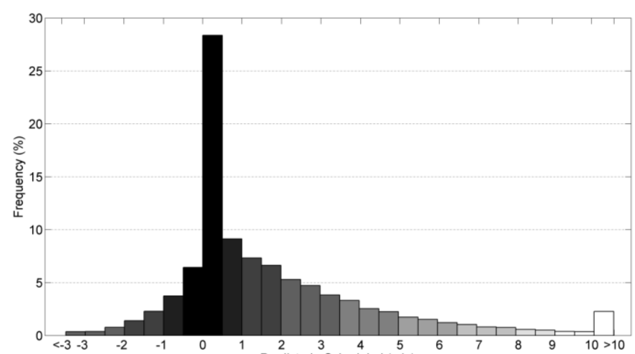

Figure 8. Real-time information vs static information (operators)

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.

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