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Determinants of Bus Riding Time Deviations: Relationship between Driving Patterns and Transit Performance

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Abstract: Urban bus services are subject to high levels of uncertainty and disturbances. Methods to determine the timetable are designed to absorb variations in riding times between stops by allocating additional travel time. The propagation of service unreliability along the route could be restrained by drivers' adjustment at stops and between stops. This paper analyzes the main determinants of bus riding times deviations based on automatic vehicle location (AVL) data from four trunk lines in Stockholm, Sweden. The analysis indicates that drivers can and do adjust their speeds in response to instantaneous real-time schedule adherence information, although these adjustments depend on the underlying control scheme: locations where the performance is measured. A model for bus riding time deviations was estimated with autoregressive effects, performance indicators, link characteristics, and trip attributes as the explanatory factors. The results can support the development of travel time prediction and real-time control strategies that take drivers' response to operations into account. This highlights the importance of the human factor in designing control schemes and the corresponding transit performance evaluation. **DOI: 10.1061/JTEPBS.0000201.**

Author keywords: Public transportation; Delay time; Bus vehicles; Time factors; Driver behavior; Scheduling.

Introduction

Service reliability is a key factor for both service users and providers since it influences door-to-door travel times as well as the capability to maintain the planned timetable. Transit operations are subject to several sources of uncertainty that could negatively impact service reliability. This is particularly true for the bus operation environment. The underlying causes of service variability are the inherent stochastic demand and supply processes such as passenger arrival process, traffic conditions, and driver behavior. The interactions between these processes impact schedule deviations from the planned timetable of departure times from the first stop, riding times between stops, and dwell times at stops. These deviations are further reinforced by the interaction between delayed vehicles, headways, passenger flows, and dwell times at stops. This positive feedback loop results in the well-known bunching phenomenon because delays propagate along the trip as well as from one trip to the other through trip chaining.

There are various methods to determine the scheduled running time, i.e., the combination of subsequent riding and dwell times (Strathman et al. 2002). These methods are designed to balance between, on one hand, the need to allocate sufficient time to allow buses to maintain the schedule and, on the other hand, the need to minimize resources while adhering to labor and safety constraints. Timetables have to be revised on a regular basis to account for changing traffic and transit conditions. Service providers are commonly evaluated and penalized based on their on-time performance (Jansson and Pyddoke 2010). Consequently, timetable design and its punctual execution have substantial economic implications and are subject to negotiations between service providers and the respective transit authority as part of the tendering process.

The propagation of service unreliability along the route could be restrained by drivers' adjustments at stops and between stops through speed adjustments and holding, respectively. In order to improve their prospects of adhering to the schedule, drivers are often required to regulate their departure time from stops in case of early arrivals. This common schedule-based holding control strategy helps distribute the operational uncertainty over several segments with their boundaries defined by the set of stops where holding may take place. These stops are known as time point stops (TPSs). The extent to which drivers can adjust their speeds is, of course, restricted by traffic conditions, traffic signals, and safety concerns. Nevertheless, the analysis of Cats et al. (2012, 2011) provides indications that drivers do adjust their cruising speeds just before approaching TPSs in order to make it within the desired time window.

Timetables are therefore not merely a reflection of running times. Driver performance has a mutual relationship with transit operations and control. This is indeed one of the reasons for performance evaluation—to impact driver behavior in a favorable manner. Ingemarson (2010) compared the running times of Trunk Lines 1 and 4 in Stockholm, Sweden, before and after the introduction of priority measures and congestion charging. She found that riding speeds remained unchanged even though traffic flows decreased by 20%. It is important to interpret these results in the context of the schedule-based control strategy that was at the time used in Stockholm. As long as the timetables did not reflect the updated traffic conditions, buses did not exploit them. This highlights the importance of analyzing riding time deviations (RTDs) at the link level in order to get a better understanding of the mutual relationship between driving patterns and transit performance.

The aim of this paper is to analyze the main determinants of bus riding time deviations. The performance of high-frequency lines

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that operate under a schedule-based control scheme is analyzed based on detailed automatic vehicle location (AVL) data. The autoregressive relations of link riding time deviations of consecutive links and subsequent trips are analyzed. Distinctive patterns emerge for different lines for the relationship with the riding time deviation experienced by the previous trip. In contrast, a more homogenous pattern prevails for the relationship with schedule adherence, arguably due to the common underlying behavioral mechanisms. A linear regression model for bus riding time deviations is presented with link characteristics, trip attributes, and performance-related variables as the explanatory factors. The autoregressive impact of previous trip travel time and proximity to the next control stop are some of the unique contributions of this study. The results provide transit operators and agencies with insights into the interrelation between timetable design, driver performance, and schedule adherence. Moreover, these interrelations can be used to for improving real-time bus arrival time prediction (Cats and Loutos 2016) and the design of methods for combating bus bunching that rely on such predictions (Moreira-Matias et al. 2016). The impacts of such measures can then be quantified and monetarized by relating changes in travel time and travel time variability to service users and providers costs (Fadaei and Cats 2016).

The remainder of this paper is organized as follows: first, the literature on bus travel time models and the impact of drivers on transit performance is reviewed, followed by a brief presentation of the main concepts that are used throughout the analysis and related hypotheses. The case study lines is then described and an analysis of their schedule adherence and how riding time deviations evolve spatially and temporally is performed, assessing the plausibility of autoregressive effects. The estimated model is thereafter presented and discussed. This paper concludes with practical recommendations and suggestions for future studies.

Literature Review

There is an agreement in the literature that the main determinants of bus running times at the route level are route length, passenger activity at stops, and the number of traffic signals (e.g., Abkowitz and Engelstein 1984; Berkow et al. 2009). Feng et al. (2015) examined the impact of traffic signals and traffic volumes on bus stop-to-stop travel time. Comi et al. (2017) investigated the relationship between bus traffic and the temporal congestion variability of the relevant background car traffic.

The effect of driver heterogeneity on running times at the route level was studied by Strathman et al. (2002) and Mishalani et al. (2008). Both studies incorporated driver-specific coefficients in their bus running time model, which had a significant contribution to the explanatory power of the total running time model. Strathman et al. (2002) calculated that driver-specific variations account for 17% of running time variation. Furthermore, drivers' experience was found to have a significant effect on running times, with experienced drivers having shorter running time. The same result was reported by El-Geneidy et al. (2011) at the TPS-segment level.

Previous studies obtained contradictory findings with respect to the impact of an initial delay on running times. Some studies found that a late departure from the origin stop is associated with shorter running times along the route (El-Geneidy and Vijayakumar 2011; Tetreault and El-Geneidy 2010), while others reported no significant effect (Strathman et al. 2002; El-Geneidy et al. 2006). At the TPS-segment level, an analysis by El-Geneidy et al. (2011) found that each second of schedule deviation from the first stop on the segment is associated with 0.21-s longer running time along this segment. Mishalani et al. (2008) compared the explanatory power of a model that considers the impact of schedule deviation at the origin stop on the total trip running time with an alternative autoregressive model that considers the relation with the total running time of the previous trip. They found that in the case of buses that perform a round trip, a short running time on the first trip is followed by a longer than planned running time on the back trip. Furthermore, successive trips also exercised a negative relation. Mishalani et al. concluded that the model that considers the initial delay is preferred over the autoregressive model.

Few recent studies explicitly considered the relations between driver behavior and transit performance. Lin and Bertini (2004) formulated the drivers' speed adjustment in response to schedule deviations as a Markov chain model. Their model was developed under the assumption that all links have an equal travel time and exercise a uniform degree of schedule recovery. R. M. Johnson et al. ("'The War for the Fare': How Driver Compensation Affects Bus System Performance," Working Paper No. 11744, National Bureau of Economic Research, Cambridge, MA) demonstrated the importance of driver behavior to transit performance by comparing two operations environments in Santiago, Chile: fixed wage versus per-passenger payment for drivers. They found that the latter were more active in maintaining a regular service due to their interest in avoiding bunching, which implies lower revenues. This led to a lower deterioration of service reliability. However, passengers' satisfaction with service quality and driving safety indicators were higher for lines that are operated with fixed-wage drivers. Moreover, drivers that were paid per passenger reported a higher level of stress and were involved in more traffic accidents.

The determinants of travel time variability were investigated by Mazloumi et al. (2010). They found that a log-normal distribution characterizes the running time distribution, while total trip travel times are distributed symmetrically due to holding times at intermediate TPSs. Schedule deviation was found to be a significant determinant of travel time variation. They also found that trips that run early exercise higher levels of travel time variability. These findings were then embedded into a travel time day-to-day variability prediction model by Mazloumi et al. (2011). The prediction method was applied at the TPS-segment level and included the schedule deviation at each TPS. In contrast, Jeong and Rilett (2005) concluded that it is infeasible to incorporate the schedule recovery phenomenon when estimating bus arrival time prediction models. The results of these studies indicate that drivers' reaction to schedule may introduce a systematic source of variation into running times, but its investigation may require a more detailed level of analysis such as stop-to-stop riding times. Analyzing bus operations at the link level, Ma et al. (2015) estimated regression models with travel time, buffer time, and the coefficient of variation of travel time as dependent variables with planning, operational, and environmental factors as explanatory variables. The ratio of mode speed to free-flow speed, number of traffic signals, and passenger demand at stops were found to be the most important contributors.

An analytical model that formulates the progression of service reliability along a bus route was developed by Ji et al. (2010). The impacts of driver behavior on dwell and running times was represented through their covariance with schedule deviation. Their analysis was restricted for the case that the covariance between the schedule deviations of consecutive trips from the same stop is negligible. They estimated the contribution of riding times between stops to account for 50% of the deterioration of transit reliability along the line. Moreover, in cases of transit reliability improvement, 40% of the improvement was attributed to riding time changes, indicating that drivers indeed adjust their speeds in the benefit of transit performance. They concluded that riding time adjustments could be as important as holding at TPSs.

All of the preceding studies were conducted at either the route or TPS-segment level. Hence, the dependent variable was always a combination of riding time between stops and dwell time at stops. While the main determinants of stop-specific dwell times have been studied extensively (TCRP 2003), less attention has been given to determinants of riding time between stops, which accounts for the lion's share of bus travel time. Furthermore, the aggregate level of analysis prohibits the identification of more refined determinants such as link attributes and the evolution of schedule deviation. In their conclusions based on an analysis of the London road network, Cheng et al. (2012) stressed that to adequately capture autocorrelations, the analysis needs to be performed at a sufficiently detailed level. The aim of this paper is to study the determinants of bus riding time deviations through a high-resolution analysis of riding times between subsequent stops, which enables accounting for link characteristics and instantaneous adjustments by drivers. Such an analysis will be instrumental for bus operations purposes such as timetable design (e.g., by identifying the distortions in the allocation of riding times along the route), dispatching, and control. The next section presents the main notions that will be used throughout this paper.

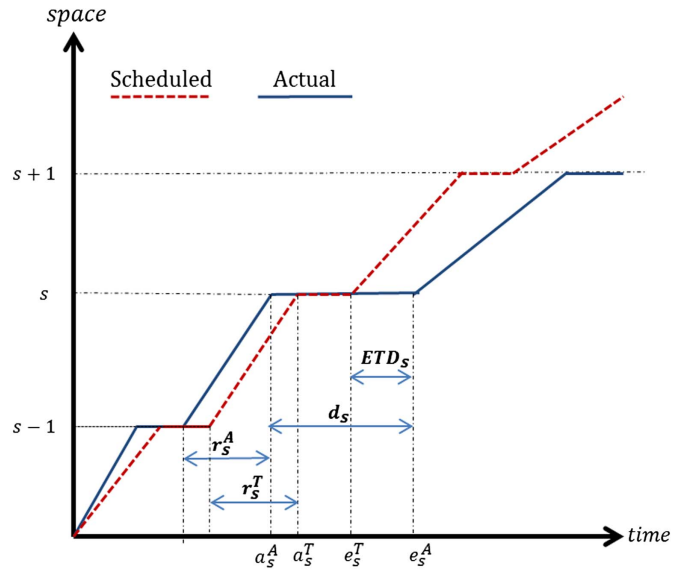

Fig. 1. Bus trajectory.

Concepts and Definitions of Riding Time Deviations

Bus line l is defined by a sequence of stops $l = (s_1, s_2, \ldots)$. The ordered set of vehicle trips on line l during a certain time interval $(t, t+\tau)$ is denoted K_l. Fig. 1 provides an illustration of an actual bus trajectory and a corresponding scheduled trajectory. The bus trajectory of a given trip is constructed by registering consecutive arrival times, a, and exit (departure) times, e, from each stop along the route. The superscripts A and T refer to actual and scheduled time records, respectively.

Bus trajectories, as displayed in Fig. 1, can be decomposed into riding times between stops and dwell times at stops using the time-space diagram. Riding times consist of the time from the departure from the upstream stop to the arrival at the subsequent downstream stop. The actual riding time of trip $k \in K_l$ that traverses a link that starts at stop $s-1$ and ends at stop s is denoted $r_{k,s}^A$ and is defined as follows:

$$r_{k,s}^A = a_{k,s}^A - e_{k,s-1}^A \tag{1}$$

where $a_{k,s}^A$ and $e_{k,s}^A$ = actual arrival and exit (departure) time records of bus trip $k \in K_l$ from bus stop $s \in l$, respectively. Riding times vary between different trips due to traffic conditions on links and at intersections as well as driving styles.

The dwell time at stop s for trip k, denoted $d_{k,s}$, varies between lines, trips, and days, depending on passengers' activity, vehicle type, and driver operations. The actual exit time of trip k from stop s could be decomposed as follows:

$$e_{k,s}^A = e_{k,s_1}^A + \sum_{s'=s_1+1}^{s} (r_{k,s'}^A + d_{k,s'}^A) \tag{2}$$

where stop s_1 is the first stop along trip k and e_{k,s_1}^A is the corresponding exit time from the origin stop; and s' = stop index.

The riding time deviation for trip k on the link that ends at stop s is defined as the difference between the actual and the scheduled riding time between consecutive stops

$$\mathrm{RTD}_{k,s} = r_{k,s}^A - r_{k,s}^T = (a_{k,s}^A - e_{k,s-1}^A) - (a_{k,s}^T - e_{k,s-1}^T) \tag{3}$$

In other words, $\mathrm{RTD}_{k,s}$ is equivalent to the contribution of this link to a positive or negative deviation from the schedule for a certain trip. The deviation from the schedule upon exiting stop s is defined as follows:

$$\mathrm{ETD}_{k,s} = e_{k,s}^A - e_{k,s}^T \tag{4}$$

Finally, the actual headway at stop s is defined as the time interval between the actual exit times of trip k and the preceding trip

$$h_{k,s}^A = e_{k,s}^A - e_{k-1,s}^A \tag{5}$$

The purpose of this analysis is to identify and analyze systematic deviations from the scheduled riding time. The impacts of past RTDs on future deviations could be twofold: temporal autoregressive on subsequent trips and spatial autoregressive on consecutive links. First, prevailing local traffic conditions may induce lasting deviations from the schedule on consecutive trips due to the preservation of traffic conditions. Hence, RTDs are expected to be dependent on the immediately preceding performance: $\mathrm{RTD}_{k,s} = f(\mathrm{RTD}_{k-1,s})$. Second, the effects of traffic spillbacks may also result in correlated schedule deviations on succeeding links, hence $\mathrm{RTD}_{k,s} = f(\mathrm{RTD}_{k,s-1})$. In addition, consistently short or long riding times compared with the timetable could also be attributed to a driving style that is sustained along the line, suggesting a fixed effect at the trip level. The decoupling of these two effects requires detailed data concerning traffic conditions and driver-specific information.

Simultaneously, there are forces that may act in the opposite direction and cause the reversion of existing trends. Bus drivers' efforts to adhere to the schedule could be manifested at stops—by shortening or lengthening their dwell times—or through speed adjustments between stops. In the case of the latter, drivers act as a counterforce to traffic conditions thereof, implying $\mathrm{RTD}_{k,s} = f(\mathrm{ETD}_{k,s})$. The schedule deviation refers to exit time and hence already accounts for the potential dwell time adjustments related to schedule recovery.

The mutual relationship between driving patterns and transit performance is analyzed by investigating the link-level and trip-level autoregressive effects and the timetable adherence effect on riding time deviations. These effects are empirically analyzed in the following section and their impact is estimated in the section thereafter.

Riding Time Deviation Analysis

The concepts and definitions presented in the previous section were applied and analyzed for a set of high-frequency bus lines in Stockholm, Sweden. First, the case study properties are presented along with a description of the data sources that were utilized. Second, the spatial variation of speed and schedule deviations are investigated. Third, in order to gain better understanding of temporal variations in riding times, the two underlying effects discussed in the previous section—namely, traffic conditions and schedule adherence—are further analyzed in the final subsection. This analysis sheds light on the spatial and temporal variations in riding times prior to the estimation of multiple regression models.

Case Study Description

The backbone of the bus network in inner-city Stockholm, Sweden, consists of four trunk lines (Fig. 2). These lines account for approximately 60% of the total number of bus trips in this area and are characterized by high frequency, articulated vehicles, designated lanes at main arterials, signal priority, and real-time arrival information at stops. The planned headway for all these lines is 4–6 min between 07:00 and 19:00.

The performance of the inner-city trunk lines was analyzed based on detailed and comprehensive AVL data for regular operations. The AVL data include information on each bus stop visit that occurred throughout the data collection period. Every time a bus visited a stop, an AVL record was generated with information on the respective line, trip, vehicle, and stop and the corresponding actual and scheduled departure time based on a trajectory analysis. Since the service provider did not indicate scheduled arrival times in the timetable, riding time deviations were calculated in relation to the scheduled departure time only, hence including the dwell time.

The data were made available by SL, Stockholm's public transportation agency.

The database used in this study consists of two periods: from November 15 to December 15, 2011, and January 9 to January 19, 2012, in order to exclude seasonal holidays. Both periods were characterized by high passenger demand and traffic congestion. The analysis considered four distinguished time periods: morning peak (07:00–09:00), off-peak (09:00–15:00), and afternoon peak (15:00–19:00) during weekdays, and all day (07:00–19:00) for weekends. Timetables have been designed to account for the varying traffic and passenger demand conditions. In total, 1,145,324 records corresponding to 40,253 bus trips were used for this analysis, where each record corresponds to a bus stop visit.

At the time data were collected in 2011–2012, the control strategy was to regulate bus departures from two to four TPSs along each route (marked in Fig. 2). These stops were selected based on network configuration as well as function as the main transfer stops from the underground system. Some of these stops were also

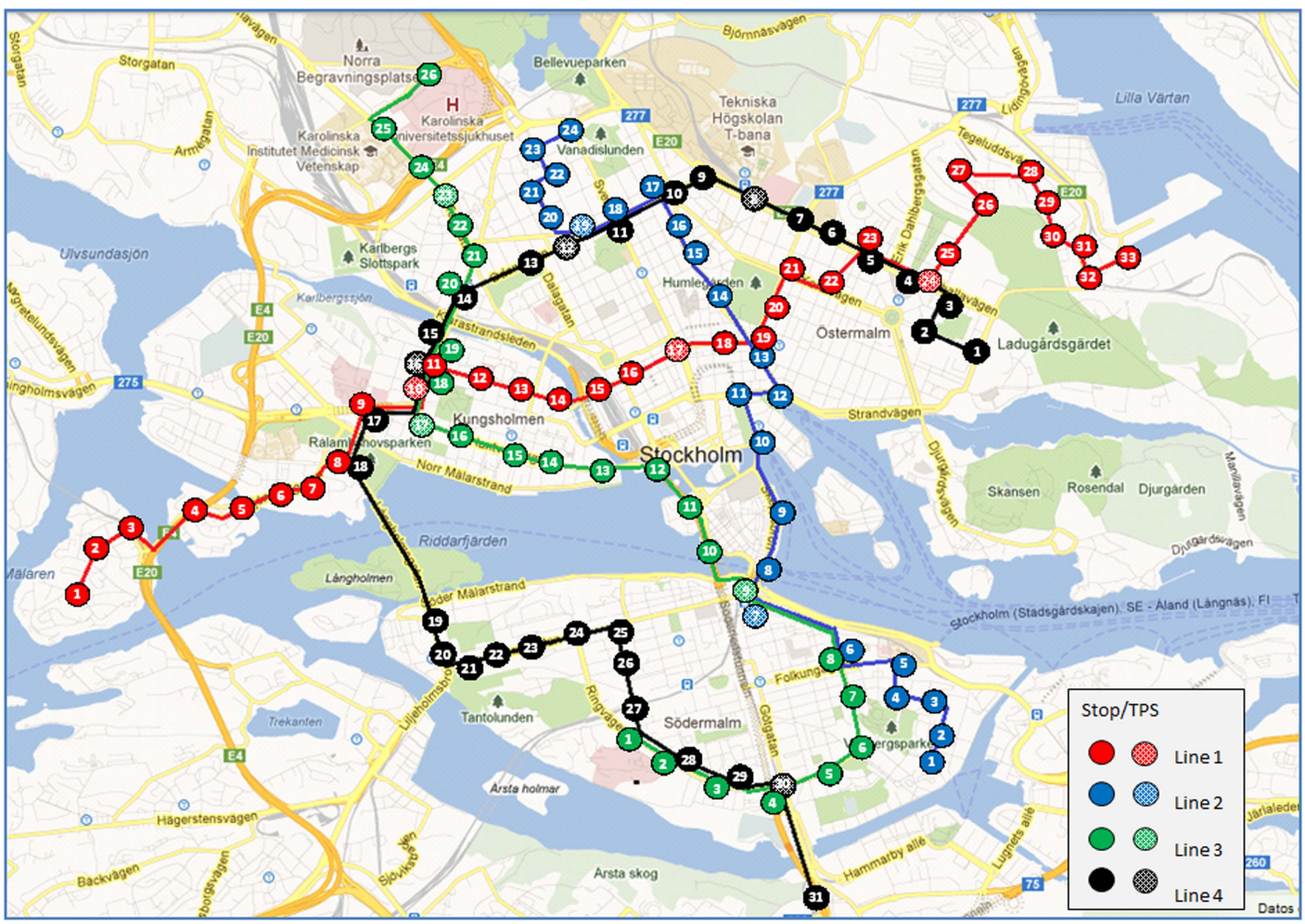

Fig. 2. Stockholm inner-city trunk lines routes. (Map data ©2018 Google.)

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used as a relief point where drivers may start or end their driving block.

All buses in Stockholm are equipped with a computer called BusPC that is located in the driver's cabin. The screen shows the three next TPSs or terminals and the scheduled time at these stops. A measure of schedule adherence is continuously displayed. The measure is calculated based on the current location of the bus at the half-minute level. A plus sign indicates that the bus is running ahead of the schedule and a minus sign indicates that the bus is running behind schedule. This display enables drivers to monitor their performance and promptly adjust their behavior in order to improve their schedule adherence.

During the analysis period, the agreement between the regional transit authority and the incumbent bus operator used on-time performance as the main measure of performance. On-time performance is defined as the share of departures from TPSs that are within the time window of [−1, +3 min] with respect to the timetable. Drivers are trained and encouraged to obtain high on-time performance at TPSs. However, the operator does not provide any incentives at the individual driver level.

Evolution of Deviations from Schedule along the Route

Riding times between stops account for 70%–75% of the travel time for all the analyzed routes and time periods. For each of the eight route directions, the speed profile along the route was first analyzed. The analysis revealed that the eight routes have similar commercial speed, i.e., operational speed consisting of both riding and dwell times, distributions of all of them having a mean speed in the range of 18–20 km/h and a coefficient of variation of approximately 0.25. Moreover, there was no significant difference between speed distributions for different time-of-day periods, while an increase of 2–3 km/h can be observed on weekends. However, speed distributions at the link level vary considerably over links along each route with the mean and coefficient of variation of speed ranging between 8 and 41 km/h and 0.08 and 0.95, respectively.

Fig. 3 presents the distribution of RTDs for the entire data set in the form of a histogram. As described previously, the scheduled time also includes dwell time and therefore the distribution of RTDs is slightly skewed to the left. The average RTD value is −27 s, which is almost equal to the average dwell time of 24 s. After considering the dwell time, the distribution is symmetrical with 67% of the deviations within [−0.5, +0.5 min] difference and 87% within [−1, +1 min] difference.

The accumulation of running time deviations in combination with dwell times may result in systematic schedule deviations. Fig. 4 presents the schedule deviation along the case study routes averaged over all trips. TPSs are marked with dashed vertical lines. A recurring pattern is evident—buses tend to first run behind schedule and then reduce their lateness shortly before approaching a TPS. This suggests that TPSs are effective in enforcing drivers to better adhere to the schedule by adjusting their riding times. In contrast, TPSs that are located toward the end of the route are not effective in holding buses that run ahead of schedule. Drivers are reluctant to hold at these stops because the last stretch is dominated by alighting passengers as well as its impact on layover time (known as the coffee effect in the industry) at the end terminal, as was observed by Cats et al. (2012).

Correlation Analysis of Link Riding Time Deviations

As an exploratory step, key correlations of link RTDs were examined:

1. The temporal autoregressive effect of subsequent trips on RTD on the same link, $r_{\mathrm{RTD}_{k,s},\mathrm{RTD}_{k-1,s}}$, is positive and significantly different from 0 at the 99.9% confidence level for all routes. This implies that riding time deviations tend to sustain themselves. As expected, the autoregressive relation manifests itself to a larger extent during peak periods (correlation coefficients of 6.5% and 5.8% for the morning and afternoon peaks, respectively) than for other periods (2.7% for midday off-peak and 1.4% for weekends). Very distinctive patterns emerge for different routes because they are subject to different traffic conditions. No pronounced differences were found for different time-of-day periods. Fig. 5 shows the autoregressive effect at the link level between consecutive trips along both directions of Line 1, which was selected for illustration purposes. Bars on the x-axis indicate the presence of a dedicated bus lane. The autoregressive effect is particularly pronounced when driving in mixed traffic.
2. A potential spatiotemporal autoregressive effect pertains to the correlation between riding time deviations of the same trip on consecutive links, $r_{\mathrm{RTD}_{k,s-1},\mathrm{RTD}_{k,s}}$. These deviations may be dependent because of queue propagation or a particular driving style. However, the correlations between the riding times of a certain trip on consecutive links were not found to be significantly different from 0 at the 95% confidence level for 90% of the links. All of the correlations were lower than 0.3. Hence, it can be concluded that riding time deviations on consecutive links do not vary jointly because queue propagation and distinguished driving styles do not prevail in most cases.
3. The relation between riding time and the respective cumulative schedule deviation is negative, $r_{\mathrm{RTD}_{k,s},\mathrm{ETD}_{k,s-1}} = [-0.17, -0.04]$ and significantly different from 0 at the 99% confidence level for all routes and time periods. Hence, late buses traverse the successive link faster than early buses do. These results are in line with the findings of Cats et al. (2012), who found that speeds are positively correlated with scheduled adherence, suggesting that drivers can and do continuously adjust their speed in order to reduce their deviation from the scheduled time. However, the extent of these adjustments varies considerably from one link to the other, with strong correlations occurring at segments just prior to TPSs.

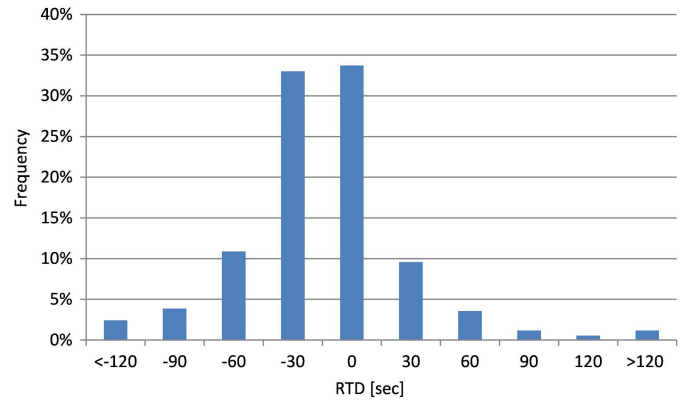

Fig. 3. Riding time deviations.

Riding Time Deviation Model

Method

Minimum least-squared multiple linear regression models for riding time deviations at the link level were estimated. To this end, four sets of independent variables were compiled: performance related, link characteristics, and time and line indicators. Table 1 lists

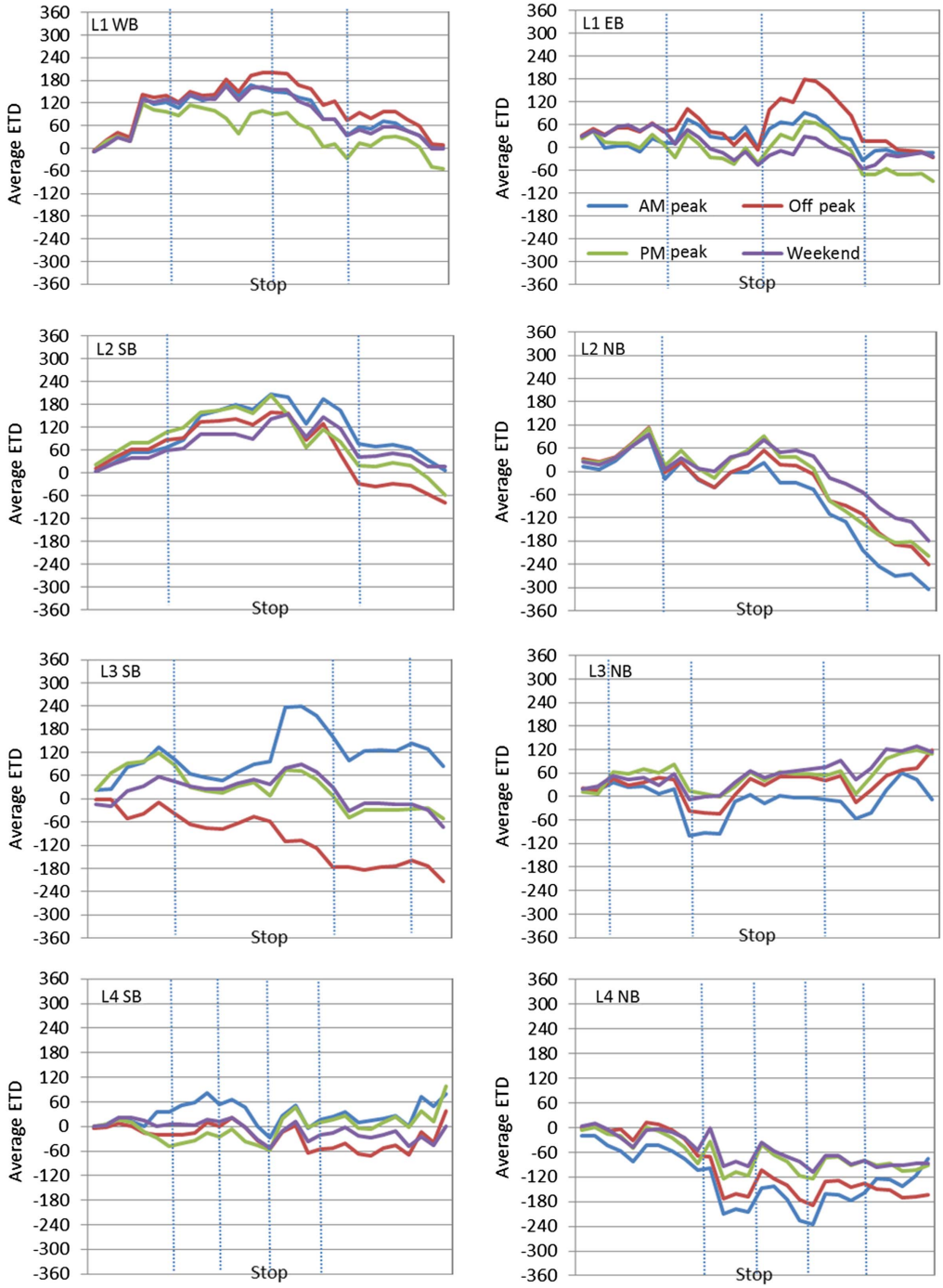

Fig. 4. Average schedule deviations ($\overline{\mathrm{ETD}_s}$) along the route in seconds.

all the independent variables that were considered in this analysis and Table 2 reports the corresponding summary statistics.

The set of performance-related variables includes the autoregressive and cumulative schedule deviation effects discussed in the previous sections. In addition, the actual headway from the preceding bus, $h^A_{k,s}$, could be relevant if the operator actively maintains regular headways on these high-frequency services. The operator indicated in joint discussions that based on their field observations such attempts are made by drivers on a voluntarily basis or in response to intervention of traffic dispatchers in the control room.

The second set of variables consists of link-specific characteristics. Static properties that characterize the driving conditions on a certain link are reflected in historical travel times and therefore should be accounted for in the timetable design and incorporated into the planned riding time. However, inadequate timetable design may result in systematic biases—either underestimation or overestimation—of riding times. Hence, if link characteristics are significant determinants of RTD and induce substantial systematic deviations, then their impact has to be assessed and timetables should be revisited. The following link characteristics were recorded based on field observations: number of right and left turnings, number of signalized and unsignalized intersections (including pedestrian crossings), the presence of a dedicated bus lane, and whether there is an adjacent parking lane or not. In addition, the segment distance was included in the analysis to assess

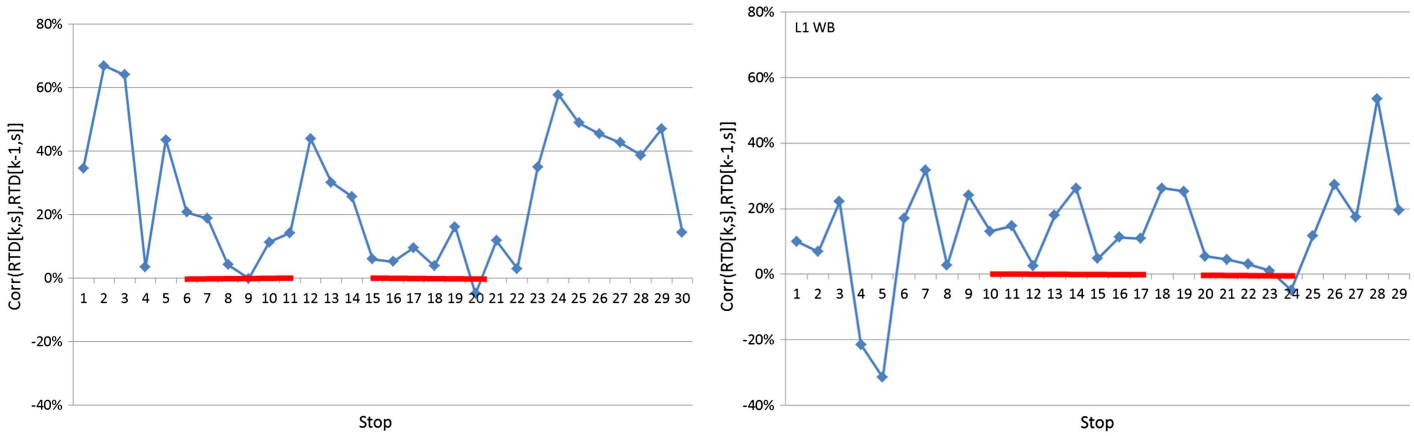

Fig. 5. Autoregressive relation at the link level $(x, y) = (\mathrm{RTD}_{k,s}, \mathrm{RTD}_{k-1,s})$ along Line 1: consecutive riding time deviations between 07:00 and 19:00.

Table 1. Description of independent variables

Variable category	Variable name	Description
Performance	$\mathrm{RTD}_{k-1,s}$	Riding time deviation of the previous bus trip on the same link (s)
	$\mathrm{ETD}^{-}_{k,s-1}$	Earliness in the beginning of the link (s)
	$h^{A}_{k,s-1}$	Time interval between consecutive trips (s)
Link	NSTPS_s	Number of stops between the current location and the next TPS
	SInter_s	Number of signalized intersections and traffic lights on this link
	UInter_s	Number of unsignalized intersections on this link
	RTurn_s	Number of right turns on this link
	LTurn_s	Number of left turns on this link
	BLane_s	Dummy variable for dedicated bus lane on this link
	$\mathrm{Distance}_s$	Total length of the link (m)
	$\mathrm{Parking}_s$	Dummy variable for an adjacent parking lane on this link
	$\mathrm{Pedestrian}_s$	Number of unsignalized pedestrian crossings on this link
Time	AMpeak_k	Dummy variable for morning peak period, weekdays (07:00 and 09:00)
	$\mathrm{OFFpeak}_k$	Dummy variable for off-peak period, weekdays (09:01 and 14:49), used as the reference variable[a]
	PMpeak_k	Dummy variable for evening peak period, weekdays (15:00 and 19:00)
	$\mathrm{Weekend}_k$	Dummy variable for weekends
Line	$\mathrm{L1}_k$	Dummy variable for Line 1
	$\mathrm{L2}_k$	Dummy variable for Line 2
	$\mathrm{L3}_k$	Dummy variable for Line 3, used as the reference variable[a]
	$\mathrm{L4}_k$	Dummy variable for Line 4

[a]Reference level in model estimation, values fixed to zero.

to what extent timetables correctly account for it. Furthermore, the number of remaining downstream stops until the next TPS along the route was expected to be positively correlated with RTD based on previous analysis.

The third and fourth sets of variables are time and line specifics. Part of the RTD variability could stem from various attributes that are consistent over links of the same trip. The data unfortunately do not allow for the identification of individual drivers. Time periods and line-specific indicators were included in the estimation where Line 3 and off-peak weekday periods were used as the reference values.

Table 2. Summary statistics of the independent variables

Variable	Mean	Standard deviation
$\mathrm{RTD}_{k-1,s}$ (s)	−11.85	33.22
$\mathrm{ETD}^{-}_{k,s}$ (s)	−13.42	35.08
NSTPS_s	3.32	2.54
$h^{A}_{k,s}$ (s)	364.50	249.14
SInter_s	1.55	1.17
$\mathrm{NoPriority}_s$	0.0266	0.2249
TTurn_s	0.75	0.93
BLane_s	0.11	0.31
$\mathrm{Distance}_s$ (m)	380.71	168.46
AMpeak_k	0.15	0.36
PMpeak_k	0.37	0.48
$\mathrm{Weekend}_k$	0.18	0.38
$\mathrm{L1}_k$	0.29	0.45
$\mathrm{L2}_k$	0.20	0,40
$\mathrm{L4}_k$	0.31	0.46

Estimation and Analysis

Model selection was based on a backward estimation approach by iteratively reducing the number of variables. Independent variables were assessed based on statistical tests for the null hypothesis that the coefficient is equal to 0. The multiple linear regression model was first specified without the lagged deviation for riding times, $\mathrm{RTD}_{k-1,s}$, as an explanatory variable in order to investigate whether an autoregressive effect prevails after the inclusion of all other independent variables. The residual analysis indicated that the errors were not independent and an autocorrelation pattern was detected. Thereafter, the autoregressive lagged term was introduced as an explanatory variable. Lagged terms for other performance variables (ETD and h) were estimated and found insignificant. Other explanatory variables—link, time, and line specific—did not carry an autoregressive effect.

The estimation process suggests that schedule deviation may be an explanatory variable only when buses run early. It is more plausible for drivers to adjust by slowing down (or prolonging dwell time) than by speeding up, and therefore the response to earliness is more pronounced than the response to lateness. As a result, the relation between $\mathrm{ETD}_{k,s-1}$ and $\mathrm{RTD}_{k,s}$ is more pronounced for

negative $\mathrm{ETD}_{k,s-1}$ values, which correspond to buses that run early. This may also be attributed to the incentive scheme present during the analysis period that penalizes early departures more heavily than late departures. In addition, the coefficients of right and left turns yield values that are significantly different from 0 but are not significantly different from each other and therefore the total number of turnings, TTurn_s, was used in further estimations. This process resulted with the following model:

$$\begin{aligned}\mathrm{RTD}_{k,s} = {} & \beta_0 + \beta_{1\cdot} \cdot \mathrm{RTD}_{k-1,s} + \beta_2 \cdot \mathrm{ETD}^-_{k,s-1} + \beta_3 \cdot h^A_{k,s} \\ & + \beta_4 \cdot \mathrm{NSTPS}_s + \beta_5 \cdot \mathrm{SInter}_s + \beta_6 \cdot \mathrm{NoPriority}_s \\ & + \beta_7 \cdot \mathrm{TTurn}_s + \beta_8 \cdot \mathrm{BLane}_s + \beta_9 \cdot \mathrm{Distance}_s \\ & + \beta_{10} \cdot \mathrm{AMpeak}_k + \beta_{11} \cdot \mathrm{PMpeak}_k + \beta_{12} \cdot \mathrm{Weekend}_k \\ & + \beta_{13} \cdot \mathrm{L1}_k + \beta_{14} \cdot \mathrm{L2}_k + \beta_{15} \cdot \mathrm{L4}_k + \varepsilon_{k,s} \end{aligned} \tag{6}$$

where β = estimated coefficients; and $\mathrm{ETD}^-_{k,s-1}$ takes only negative values of $\mathrm{ETD}_{k,s}$ and 0 otherwise.

Traffic signals along the trunk line corridors in Stockholm are equipped with an adaptive control system. Buses that run ahead of schedule by more than 120 s are not entitled to priority at the intersection. The variable $\mathrm{NoPriority}_s$ captures this interaction by counting the number of signals for nonprioritized buses as follows:

$$\mathrm{NoPriority}_s = \begin{cases} \mathrm{SInter}_s & \text{if } \mathrm{ETD}^-_{k,s-1} < -120 \\ 0 & \text{otherwise} \end{cases}$$

The error term that accounts for the unobserved explanatory variables, measurement errors, and random noise is $\varepsilon_{k,s}$, which is normally distributed with a mean value of 0.

Table 3 presents the estimated values of the coefficient and the corresponding t-statistic in parentheses. All statistical tests were for the null hypothesis that coefficients are equal to 0. All of the estimated coefficients were significant at the 99% level. The model explains approximately 25% of the variation in riding time deviations.

The coefficients were interpreted as the change in seconds in riding time deviation associated with a unit change in the explanatory variable. The negative constant value was arguably attributed to the reference to scheduled departure time. The link-level autoregressive factor was found to have a significant positive impact on RTD. Approximately 5% of the RTDs experienced by the preceding bus on the same link was sustained on the immediate successive trip.

The model suggests that drivers do not adjust promptly their riding times to better adhere to the schedule. In fact, drivers that are ahead of schedule even tend to increase their deviation by riding a shorter time than scheduled on the successive link. This could be interpreted as an indication of an underlying driving style in particular drivers that consistently drive too fast and do not respect the timetable. In addition, buses that run with long headways from the preceding bus result with longer RTDs. Given the range of headways exercised by the cast study lines, the impact of headway on RTD may amount to 6 s per link or 3 min for the entire route. The impact of headway on riding times does not, therefore, counteract the bunching phenomenon, but rather further contributes to it and reinforces the positive feedback loop between headway, passenger flows, and dwell time at stops. Furthermore, running behind schedule has no significant effect on the following RTD. This is in line with the results reported in the section "Correlation Analysis of Link Riding Time Deviations." However, drivers do adjust their riding times when in proximity to a TPS. The further away they are from a downstream TPS, the longer is the RTD. This pattern was observed in the analysis of the evolution of deviations from the schedule in the previous section. This occurs even though drivers have continuous access to information on their schedule adherence. The same pattern was reported by Ji et al. (2010) for the case that drivers have only information concerning scheduled times at TPSs.

Table 3. Riding time deviations model

Variable	Coefficient	t-statistic
Constant	−8.97	−36.69
$\mathrm{RTD}_{k-1,s}$	0.05	40.34
$\mathrm{ETD}^-_{k,s}$	−0.18	−110.80
NSTPS_s	2.73	127.56
$h^A_{k,s}$	0.005	23.28
SInter_s	2.64	51.11
$\mathrm{NoPriority}_s$	7.85	26.35
TTurn_s	3.14	49.56
BLane_s	−5.42	−28.97
$\mathrm{Distance}_s$	−0.11	−311.29
AMpeak_k	2.21	13.98
PMpeak_k	−1.94	−16.43
$\mathrm{Weekend}_k$	4.36	30.06
$\mathrm{L1}_k$	1.53	9.25
$\mathrm{L2}_k$	−17.37	−93.64
$\mathrm{L4}_k$	2.41	15.28
Observations	706,879	
R^2	0.257	
Adjusted R^2	0.257	

The coefficients of the physical link-specific characteristics indicate a systematic error in estimating their contribution to the riding time in the timetable design process. Interestingly, the coefficients of all of these attributes suggest that their impact is underestimated. Each traffic light adds a delay of approximately 3 s to the RTD. In case the bus runs very early and hence is not entitled to signal priority, a longer delay of more than 7 additional seconds is associated with each traffic light. In addition, each turning is associated with 3 additional seconds. The presence of a dedicated bus lane is associated with a reduction of the riding time by 5.5 s more than is reflected in the timetable. Although these values may seem small, since the analysis was carried out at the link level, each of these biases translates to 6%–8% of the scheduled running time. The number of unsignalized intersections and the presence of an adjacent parking lane did not have a significant effect on RTD.

Longer links negatively affect RTD, with each additional 100 m being associated with a decrease of 11 s in the respective RTD. The variation in links length is considerable even in the context of our case study, which exhibits relatively homogenous operations conditions, ranging from 142 to 1,264 m. The latter corresponds to a long bridge connecting a major public transportation interchange hub on the southern fringe of inner-city Stockholm. A further investigation suggested that the timetable allocates too much time for long links. The possibility to reach a higher speed and maintain it on a longer segment is also part of the motivation behind stop consolidation (e.g., Tetreault and El-Geneidy 2010). However, it is also likely that this result is related to the traffic characteristics of these links because their less urban character is the very reason for having a lower stop density.

Various time periods exercise different systematic deviations from the schedule. Riding times during the morning peak period, as one might expect, deviate more from the schedule than in the off-peak period. The opposite trend was found for the afternoon peak period, which is characterized by more homogenous traffic conditions due to the greater dispersion of travel demand. However, weekends have the highest deviation from the schedule, with an

Table 4. Separate riding time deviations model and summary statistics of the independent variables for bus lane links and mixed traffic links

Variable	Bus lanes		Mixed traffic	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	−8.13	−10.87	−14.34	−61.52
$\mathrm{RTD}_{k-1,s}$	0.27	47.26	0.14	71.28
$\mathrm{ETD}^{-}_{k,s}$	−0.07	−11.04	−0.13	−76.20
$\mathrm{ETD}^{+}_{k,s}$	0.01	5.53	—	—
NSTPS_s	2.51	32.24	3.48	141.12
$h^A_{k,s}$	0.004	4.95	0.011	38.61
SInter_s	7.55	44.44	3.95	71.80
TTurn_s	9.50	39.99	3.95	57.57
$\mathrm{Distance}_s$	−0.16	−155.7	−0.10	−249.9
AMpeak_k	3.16	6.91	1.58	8.94
PMpeak_k	−2.07	−6.13	0.44	3.28
$\mathrm{Weekend}_k$	1.86	4.39	2.74	16.70
$\mathrm{L4}_k$	18.79	38.26	−1.23	−8.67
Observations	79,145		627,734	
R^2	0.374		0.145	
Adjusted R^2	0.373		0.145	

excessive deviation of more than 4 s per link compared with off-peak periods on weekdays. This may be an indication that the shorter scheduled riding times on weekends are unrealistic even though the average speed is higher. However, discussions with the operator raised an alternative explanation. Most of the weekend crew consists of part-time and reserve drivers who are less experienced and adhere to the schedule less. Finally, the line-specific coefficients indicate that all other things being equal, the timetable of Line 2 still contains much more slack than any of the other lines (as visible in Fig. 3).

The presence of a dedicated lane is expected to have a profound impact on the determinants of riding time and drivers' ability to adjust their speed. Fig. 5 indicated that the autoregressive relation might be different for dedicated bus lanes than for mixed-traffic links. In order to adequately assess this, two additional multiple linear regression models were estimated for the subsets of the data set, which consists of bus lane links (11% of all data records) and mixed traffic links, separately.

The estimated models along with the corresponding summary statistics are presented in Table 4. Model specification is the same as presented in Eq. (6) with two changes: (1) the inclusion of $\mathrm{ETD}^{+}_{k,s}$, which takes only positive values of $\mathrm{ETD}_{k,s}$ and 0 otherwise; and (2) the exclusion of $\mathrm{L1}_k$ and $\mathrm{L2}_k$, which were found to be insignificant. All of the estimated coefficients are significant at the 99% confidence level. In the case of bus lane links, the model explains approximately 37% of the variation in riding time deviations on bus lanes. In contrast, less than 15% of the dependent variable variations are explained for mixed-traffic links. Hence, the explanatory variables can better predict riding time deviations on bus lanes than in mixed traffic. This is expected because riding times in mixed traffic are subject to greater uncertainty. When driving in dedicated lanes, drivers that are ahead of schedule tend to and often can reinforce their earliness rather than better adhere to schedule. However, this driving pattern is considerably less pronounced—by an order of two—than when driving in mixed traffic. A similar effect occurs for late drivers on links with dedicated bus lanes but to a much smaller extent. Delay attributed to signalized intersections and turnings is longer for buses driving in dedicated lanes than in mixed traffic, possibly due to the more complicated signal programs and intersection layouts that are required. RTDs are systematically longer for Line 4 than for other lines unlike in the case of mixed-traffic conditions. Other variables exhibit similar patterns to those reported for the general model.

Conclusion

Urban bus riding times are subject to high levels of uncertainty and disturbances. Methods to determine the timetable are designed to account for this inherent variability by allocating sufficient time for riding times between stops. A high schedule adherence is desired because it positively influences the passenger level of service and the operational costs associated with crew assignment. This study investigated the main determinants of bus RTDs through a high-resolution analysis of riding times between subsequent stops, which enables accounting for link characteristics and instantaneous adjustments by drivers.

The analysis performed in this study indicated that drivers can and do adjust their speeds based on time-dependent service performance. Importantly, these adjustments depend on the underlying TPS layout—locations where the performance is measured. More specifically, it indicates that drivers do take advantage of the real-time scheduled adherence information that is provided to them, but their reaction is determined by the control scheme design. This result is also relevant in the current mode of operations in the case study network, which since 2014 has shifted into regularity-based operations (Cats 2014). Driver speed adjustments are key for regulating service and proactively avoiding bus bunching from emerging.

The RTD per link can be partially explained by the RTD experienced by the previous trip when riding on the same link. This autoregressive effect over subsequent trips traversing the same link was found to be significant for three of the four studied lines, with a positive correlation between consecutive trips presumably due to the prevailing local traffic conditions. This is reflected in the distinctive patterns that emerged for different lines. A positive autoregressive effect was also found on consecutive links in the case of negative deviations. Further investigation is needed in order to determine whether this is due to driver-specific driving style or because of the correlation between traffic conditions on consecutive links.

The analysis of link-specific attributes such as the presence of a dedicated bus lane and number of turnings and signals indicates that the current timetable systematically underestimates their impact on driving time deviations. RTDs on bus lane links exercise a higher autocorrelation at the link level but lesser tendency to reinforce an existing deviation from the schedule. Nevertheless, the majority of the RTD variation remains unexplained, a testimony to the unsystematic randomness that characterizes the uncertain bus operations environment.

The model of bus riding time deviations presented in this paper could be further enhanced in several ways. First, the RTD analysis is intimately linked to the dwell time. Bus drivers could potentially adjust their dwell time in order to better adhere to the schedule. Moreover, deviations from the schedule can also influence dwell time variations due to the relationship between headways, number of waiting passengers, and dwell times. In order to explain overall travel time variations, the interaction between RTD, schedule deviation, and dwell times needs to be investigated. Second, autoregressive riding times were used in this study as a proxy to local traffic conditions. However, traffic data such as link-specific flows and speeds as well as weather data could be matched against AVL records to adequately capture the impacts of various traffic conditions. Third, previous studies (Strathman et al. 2002; Mishalani et al. 2008) have shown that driver-specific impacts play an

important role. Information related to their duty such as downstream relief could also enhance the model. Fourth, quantile regression can be used for analyzing the impacts of various determinants on the distribution of riding time deviations as opposed to only its central tendency (Ma et al. 2017).

The results of this study could support transit performance improvements in several ways. First, schedule adherence could be improved by adjusting future timetable planning based on the observed systematic biases. Second, the impact of alternative measures such as changing the configuration of TPSs could be assessed. Third, an improvement in headway variability can also reduce travel time variability. This is especially true for headways that are much longer than the planned headway, which are associated with longer travel times and therefore are consequential for fleet size and operational costs.

The results of this study emphasize the importance of the human factor in designing a control scheme and the corresponding transit performance evaluation. The assessment of alternative strategies therefore needs to account for the human factor impacts (Cats et al. 2012; Hlotova et al. 2014). The common way of measuring on-time performance at several stops along the route led to the observed driving pattern. Hence, the operator may revise the location of TPSs in order to maximize their impact. Alternatively, extending the performance evaluation to all stops could encourage drivers to adjust their speed more evenly. This has proven effective in a series of field experiments in Stockholm, Sweden (Cats 2014). Furthermore, the real-time information display in the driver cabin could be enriched by incorporating real-time predictions concerning downstream traffic conditions that were shown to be a key determinant of riding time deviations. This will enable drivers to become more proactive in their adjustments. Drivers could be further encouraged by designing adequate incentive schemes. Moreover, the analysis of driver behavior and their adherence to control strategies can be incorporated in real-time bus arrival time prediction, the design of real-time control strategies, and enriching the representation of driver behavior in transit simulation models.

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