Potential of Low-Frequency Automated Vehicle Location Data for Monitoring and Control of Bus Performance

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The potential of low-frequency bus localization data for the monitoring and control of bus system performance is investigated in this paper. It is shown that data with a sampling rate as low as 1 min, when processed appropriately, can provide ample information. Accurate estimates of stop arrival and departure times are obtained; these estimates in turn allow the analysis of headways and travel times. A three-parameter gamma family of distributions is fitted for headways at the stops along a bus line. The evolution of the parameters demonstrates critical points on the line where bus bunching is significantly increased. Moreover, this analysis allows differentiating problems associated with varying passenger demand from uncertainties associated with traffic conditions. Furthermore it is shown that expected travel time and travel time variability can be calculated from low-frequency localization data. Finally, the way in which the results can be used to calibrate a simulation model that can test bus control strategies is presented. The methods are applied and validated to data obtained from Bus Route Number 1 in Boston, Massachusetts.

Modern advanced traveler information systems are capable of providing information on expected travel times for all modes and origin–destination pairs in real time by incorporating many different data sources, including past measurements of vehicle trajectories, passenger demands, and current traffic conditions. However, collecting these data is still costly and many data sources are not universally available. In particular automatic fare collection or boarding and alighting counts are currently not available in many systems, while automated vehicle location (AVL) information is widespread.

However, many AVL systems provide location-at-time data with a low sampling frequency (on the order of 1 min). In this situation travel time prediction and bus arrival time prediction can be based only on such AVL data sets. NextBus is a major provider of AVL data services to transit agencies across North America and offers those agencies web services so that the agencies can release their data to the public. The agencies control the amount, quality, and frequency of the updates, and many agencies choose to provide low-frequency data because of budget constraints. These AVL data are also used by transit agencies to evaluate their transit system performance, diagnose service bottlenecks, and improve the system level of service (*1, 2*).

The main limitation of AVL data is measurement errors resulting from the Global Positioning System (GPS) devices and recording or transmission errors. The low sampling frequency implies that stop dwell times and en route travel times are not trivial to separate. Linear interpolation methods that are often used [see, e.g., Byon et al. (*3*) and Cortés et al. (*4*)] distort travel speed and headway measurements significantly. For that reason better alternatives are desirable. In this paper, therefore, a new methodology is introduced for the resampling of low-frequency location-at-time AVL records.

Analysis of transit service quality is performed with the resampled data. Among all the service quality measurements, headway distribution (*5, 6*), adherence to schedule, and in-vehicle travel time are the most studied (*7*). For high-frequency urban transit service, headway distribution is the measurement directly related to operations (*5, 8*). It determines passengers' experienced waiting time and could be effectively improved by operational strategies such as holding and stop skipping (*9, 10*). Here the choice was made to study the variation in the distribution of headway across the entire route as a proxy of the deterioration in service quality.

In this paper the goals are threefold:

- To provide a more accurate data preprocessing methodology that enhances low-frequency AVL data (see section on data preprocessing),
- To show that the obtained data can be used to evaluate bus service quality (including travel time uncertainty) and diagnose service bottlenecks (see section on analysis of service quality), and
- To use the acquired statistics to calibrate a bus movement model, which subsequently can be used to evaluate different control strategies for mitigating bus-bunching effects (see section on calibration of a bus movement model).

To achieve these goals, first map matching is performed on low-frequency location-at-time AVL data to assign transit vehicles to their route shapes. Second, resampling is done incorporating buses' actions of traveling on route segment and staying at stops. Stop arrival and departure times are inferred. On the basis of the interpolated data, statistics of in-vehicle travel time are then derived and the way bus headway deviation propagates along the route is shown. Bottlenecks are identified and the underlying causes are investigated. Methods to estimate route travel time and travel time variability are provided. Finally the way the results could be used to calibrate bus movement models is shown.

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DATA PREPROCESSING

Location-at-time AVL data provided by the NextBus service are used in this paper. NextBus provides data for a large number of U.S. and Canadian transit companies [including California's LA Metro, Massachusetts Bay Transit Authority (MBTA), New York City Metropolitan Transportation Authority, San Francisco Muni in California, and the Toronto Transit Commission in Canada]. The NextBus server is polled every 60 s and returns the bus locations. In addition, schedule and route information is given in the form of General Transit Feed Specification (GTFS) format introduced by Google. Locations of bus stops from the GTFS are used to derive arrival and departure times from the AVL records.

To illustrate the methodology, an analysis is done on the AVL records between May 1, 2011, and June 15, 2011, from Route 1 of the MBTA, in total 4,624 trips during weekdays and 796 trips on weekends. MBTA Route 1 runs from Dudley Station in Boston, Massachusetts, to Harvard University in Cambridge, Massachusetts. The data used contain outbound runs records, which have 33 stops starting at Dudley Station and ending at Quincy Street at Harvard Street. The average distance between stops is about 250 m. A map of MBTA Route 1 is shown in Figure 1. Significant stops are indicated; between Stops 8 and 9 the route turns into a main arterial. Between Stops 18 and 19 there are three intersections and the bus transfers with a metro line there. At Stops 12 and 25 large traffic volumes during peak hours are observed.

The scheduled headway during morning peak hours is 8 to 9 min, and during the afternoon peak, it is 7 to 8 min; at off-peak times a 12- to 13-min interval is scheduled.

Map Matching

The first step in the data preprocessing is map matching; see Quddus et al. for an up-to-date review (*11*).

In the data set at hand, map matching has to deal with the following most frequent problems:

1. Wrong temporal order. Time stamp and location pairs appear to be in the wrong order, which makes buses appear to be going backward along the shapes.
2. No matching from the shape. The locations provided in AVL records are far from the route shape. Such points occur in particular at the start or the end of trips.
3. Wrong interval. Some trips have only a few data points recorded at irregular intervals, which may indicate that the buses are out of service or that the GPS devices are broken.

It was found that on average 97.6% of the observations could be map matched directly. For the 2.4% erroneous observations, 0.6% could be fixed by using obvious heuristics, which were mainly wrong temporal order observations; 1.8% of the observations were finally discarded, two-thirds of which corresponded to "no matching from the shape."

Resampling Procedure

The output of the map-matching procedure is sequences of $(t_{i,j}, x_{i,j})$ pairs ($t_{i,j}$: time stamp for *j*th observation of trip *i;* $x_{i,j}$: distance along

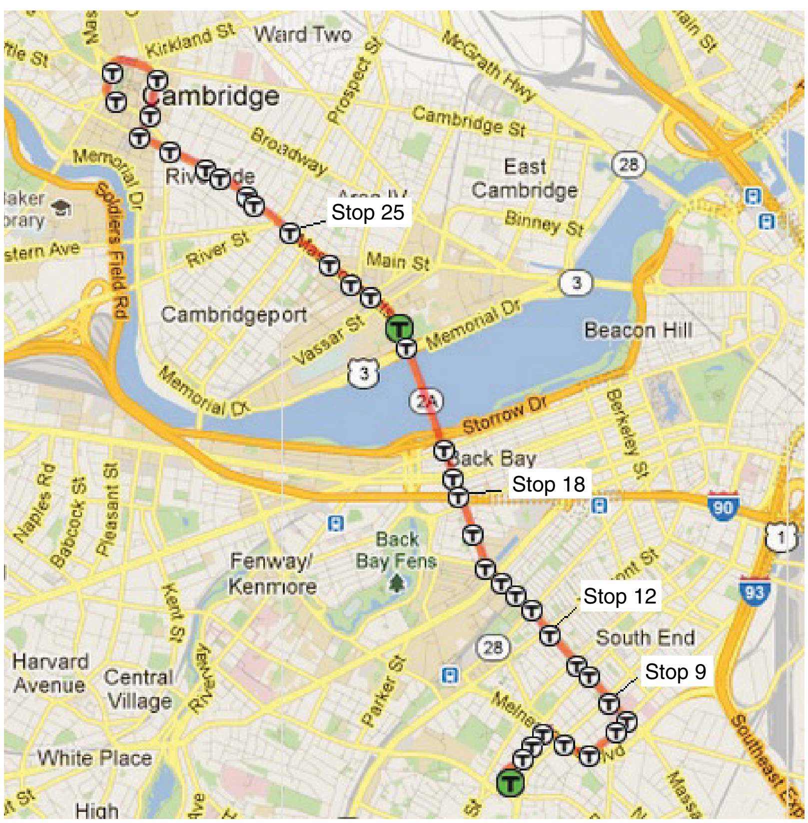


FIGURE 1 MBTA Route 1 with significant stops marked. (Source: Google maps).

shape) for all trips on a given shape for a given route. Since the GPS tracks of the AVL data are available only approximately every 60 s, a resampling scheme has been used to obtain information on arrival and departure times at stop locations. For the resampling, time is viewed as a function of the distance along the route shape. Two approaches could be followed: interpolation (e.g., linear) and smoothing methods (e.g., spline smoothing). The disadvantage is that the result reflects the properties of the interpolation scheme, which might not be desirable. For example, in the case of three consecutive observations of a bus—the middle one occurring while the bus was at a stop s [defined as a small interval $(X(s) - G, X(s) + G)$ around the stop location $X(s)$ according to the shape of length $2G = 30$ m, where G is half the length of the bus stop platform] and the remaining two while the bus was on the road—linear interpolation implies that the bus is at the stop for only a short duration. For spline smoothing the stopping time will depend heavily on the smoothing parameter. This behavior clearly is undesirable.

As an alternative, explicit modeling of bus travel explains time $t(x)$ as a function of distance along shape x. The simplest model for bus movement is constituted by assuming constant speed v_s for the travel between stops s and $s + 1$, leading to travel time $\widehat{\mathrm{TT}}_{i,s} = (X(s+1) - X(s) - 2G)/v_s$ for trip i on route segment s and nonnegative stopping times $\widehat{\mathrm{ST}}_{i,s}$ inside the stop. A shape with S stops (not counting the start of the trip) has $2S$ parameters. For this model, $\widehat{\mathrm{TT}}_{i,s}$, $\widehat{\mathrm{ST}}_{i,s}$, and the time $t_{i,1}$ of the start of the trip fully determine the trajectory of the bus according to

$$\hat{t}(x) = t_{i,1} + \sum_{s:X(s)<x} \left(\widehat{\mathrm{TT}}_{i,s} + \widehat{\mathrm{ST}}_{i,s}\right) + \frac{x - X(s) - G}{X(s+1) - X(s) - 2G} \widehat{\mathrm{TT}}_{i,s+1}$$

for each $x \notin (X(s) - G, X(s) + G)$ not in a stop. Inside the stops linear progression between entering the interval and exiting the interval can be assumed without loss of generality.

To be useful, this model needs to be calibrated with real-world data. In that respect the following observation will be used: for an observer that searches for the location of a bus at a random time instant, the chance to find the bus in an interval of 10 m, say, is proportional to the share of time the bus spends in this interval during the observation period. The same holds true for more frequent sampling of bus location. Figure 2 provides a snapshot of the location of bus observations on Route 1 in the inbound direction (i.e., in the direction of Harvard).

It can be seen that at some stops buses are found more frequently. Other spikes occur at traffic lights, which can be related to average dwell time percentages $\overline{\mathrm{ST}}_s$ inside the stop intervals as well as on the segments between the stops.

To calibrate this model, the observations are split into two groups: observations in the stops $(X(s) - G, X(s) + G)$ are called in-stop observations and denoted as $z_{i,k}$, $k = 1, \dots, K$ (number of in-stop observations) with corresponding time $t_{i,k}$ and stop $s_{i,k}$. The remaining ones are called on-road observations and denoted as $y_{i,l}$, $l = 1, \dots, L$ (number of on-road observations) with corresponding time $t_{i,l}$ and segment $s_{i,l}$. In-stop observations impose restrictions as $\hat{t}(X(s_{i,k}) - G) \le t_{i,k}$ and $\hat{t}(X(s_{i,k}) + G) \ge t_{i,k}$, that is, the trip must arrive at the stop before being observed in the stop and depart after being observed there. The on-road observations should be replicated as well as possible by using the model. From the assumption of constant speed between stops it is clear that there will be no perfect match in particular in situations in which the bus needs to wait at a traffic light.

At the same time the aim is for the model to match the dwell time profile as closely as possible. Therefore the resampling is achieved by finding the parameters minimizing the squared distance to the scaled (with the actual total travel time TTT_i for the whole trip) dwell time profile and the weighted on-road observations subject to the restrictions on arrival and departure times implicit in the on-stop observations:

$$\min L\left(t_{i,1}, \widehat{\mathrm{TT}}_{i,s}, \widehat{\mathrm{ST}}_{i,s}, s = 1, \dots, S\right) = \sum_{l=1}^{L} \left(t_{i,l} - \hat{t}(y_i, l)\right)^2 + w \sum_{s=1}^{S} \left(\widehat{\mathrm{ST}}_{i,s} - \mathrm{TTT}_i * \overline{\mathrm{ST}}_s\right)^2$$

subject to

$$\hat{t}\left(X(s_{i,k}) - G\right) \le t_{i,k}$$

$$\hat{t}\left(X(s_{i,k}) + G\right) \ge t_{i,k}, \; k = 1, \dots, K$$

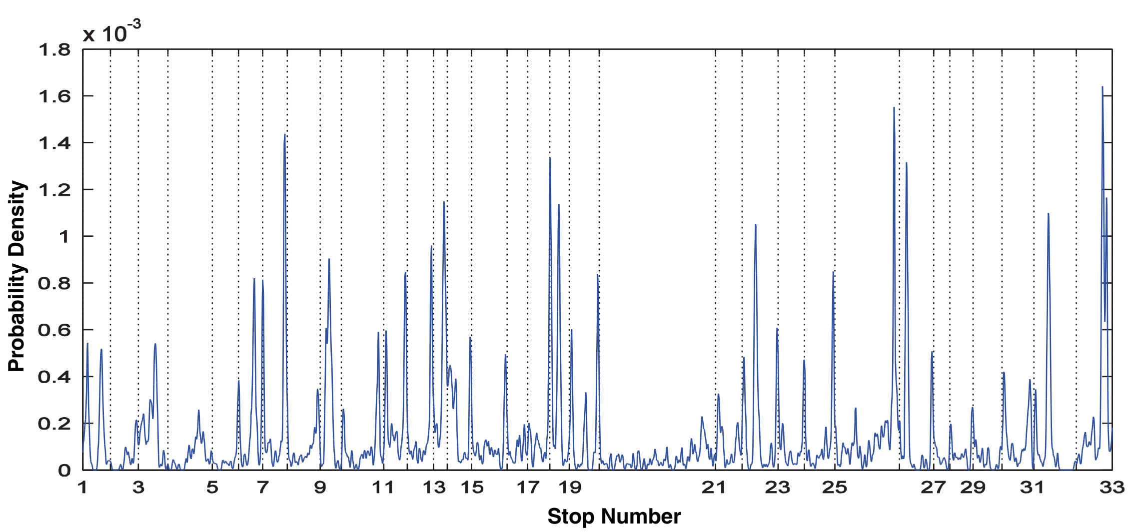


FIGURE 2 Kernel density estimator for observed location of Route 1 buses in Boston in inbound direction (dashed lines = stops).

$$\widehat{\mathrm{TT}}_{i,s} \geq \frac{X(s+1)-X(s)-2G}{V} \qquad s=1,\ldots,S$$

$$\widehat{\mathrm{ST}}_{i,s} \geq \frac{2G}{V} \qquad s=1,\ldots,S$$

Here $w > 0$ is a weighting factor. Large w results in closer fit to the average dwell times; small w puts emphasis on being close to measured observations. V imposes a maximal travel speed, which leads to a linear least squares problem with linear restrictions that can be efficiently solved by using general purpose optimizers.

The resampling procedure uses the assumption that the expected dwell times are identical for all buses, that is, that there are no systematic deviations from the expectations. This is not realistic for a full day, although it appears tenable for small time intervals across different days. Consequently one calculates the resampling separately for a segmentation of the day into 10 time intervals.

Below the resampling procedure is validated by using synthetic as well as real-world data.

Validation with Synthetic Data

To validate the resampling procedures a synthetic data set of buses running on Route 1 has been generated by using a microscopic simulator implementing the optimal velocity model as presented in Treiber and Kesting with a discrete time update of 1 s and a total simulation time of 10 h (*12*). Only one direction with no overtaking is simulated. The shape contains 33 bus stops. If a bus reaches a stop, a random integer is drawn simulating uncertain boarding and alighting processes. The stop duration is distributed in discretely uniform {0, 1, 2} seconds except for Stops 6, 21, and 31 where the range is 30 to 149 s and Stops 7 to 20, where the range is 5 to 19 s. On the route, 20 intersections with traffic signals are simulated. The signal timing is coordinated by using the maximum allowed speed with red and green time split evenly at 30 s each. During the red light periods of signal 2, 7, 12, 17, and 18, cars enter the road segment with intensity $t/36{,}000 * 0.75$ according to a Poisson arrival process. Other than that cars enter the road at the start of the shape at an arrival rate of 0.2. Every 3 min a bus is drawn. The stopping of a bus in a stop is not modeled in detail, but rather buses stop immediately when reaching the stop and leave after boarding and alighting is completed. In between cars pass the bus. The added complexity of deceleration into the stop is included in the random boarding and alighting; the reintegration into traffic follows the rule that cars need to stop for reentering buses.

One hundred ninety-five bus trajectories are generated at a sampling frequency of 1 s. Subsequently the trajectories are subsampled to a sampling frequency of 60 s by using a random starting time stamp. The two resampling strategies (simple linear as well as the procedure proposed above) are applied, and stopping times as well as travel times between bus stops are calculated with the two approaches. For the distribution-based resampling the 10 h are partitioned into three intervals. A sample of the output of the resampling procedure can be found in Figure 3. It can be seen that the resampling follows the true observations more closely than linear interpolation.

The results show that the more complicated resampling pays off, resulting in a smaller mean absolute deviation for stop duration of 8.8 s compared with 11.2 s for the simple linear interpolation–based resampling. Also the travel times between the stops are replicated with a higher accuracy (mean absolute deviation of 10.3 s compared with 12.0 s). In addition, the absolute performance is high in comparison with the sampling interval of 60 s, which is mainly the result of a better capturing of the long stops. For the three long stops 6, 21, and 31, the

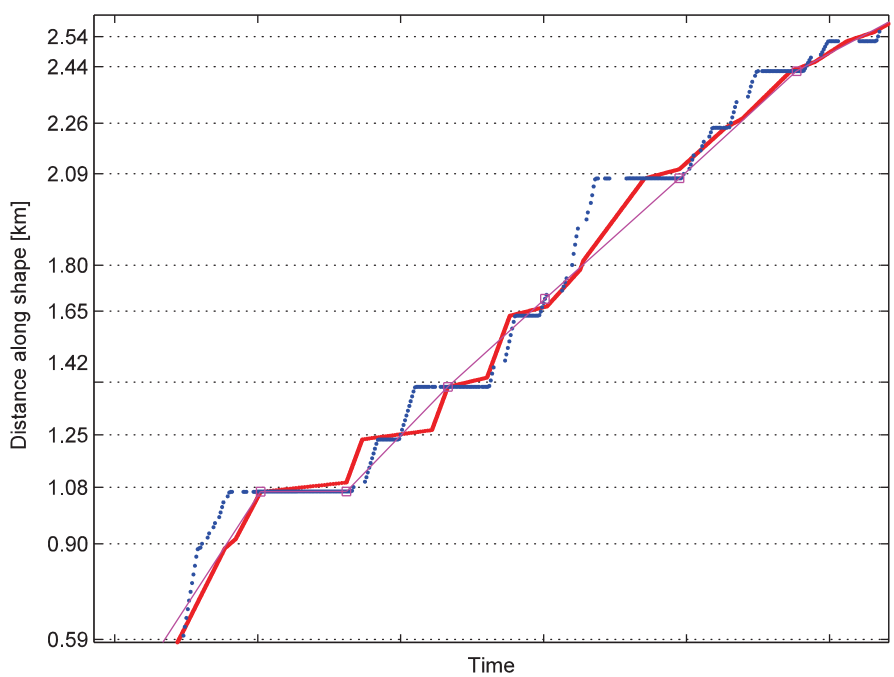


FIGURE 3 MBTA Route 1. Sample output of resampling scheme (dots = high-frequency observations; squares = observations with 60-s temporal resolution; thin lines = linear resampling; thick lines = proposed resampling).

mean absolute deviation of the resampling equals 21.4 s compared with 46.3 s for the simple method.

Validation with High-Frequency GPS Data

To validate the methodology, high-frequency GPS records with a sampling frequency of 1 s were collected on Bus Line 1 on 2 days—Thursday, February 23, and Saturday, February 25, 2012. A total of 15 trips provide data that are map matched and converted to sequences of (time stamp, distance along shape) pairs. The 1-s-interval GPS data provide ground truth against which the two sampling strategies are validated. For that purpose the trips are separated into different regimes according to weekend or weekday as well as five intervals during the day.

The two resampling schemes have been applied to subsampled (by using each 60th observation) copies of each of the 15 trips. To remove random effects due to the starting point all 60 subsampled versions are used.

The results are less pronounced than for the synthetic data, but still one can observe an advantage of the more complex resampling scheme compared with the simple method. The mean absolute deviation in stopping time over all stops in Direction 1 totals 4.83 s for the presented resampling method and 7.7 s for the simple interpolation. In Direction 0 the values of 6.5 for the method proposed in this paper compared with 7.7 for the simple method show the slight advantage of the proposed method.

In that respect the errors are comparable but smaller than in the synthetic data set. Thus, in the following the presented resampling method will be used.

ANALYSIS OF SERVICE QUALITY

The resampled data provide a great opportunity to evaluate bus service performance. The usual service quality measurements relate strongly to variations of headway, travel time, and variability of travel time. Transit operators are interested in optimizing indicators on the basis of these components, which include elements that are not under the influence of the transit operators, such as traffic conditions and demand fluctuations. In this section it is shown that the resampled data set can be used to extract useful information about these three components of service quality measurement.

Headway

Headway is defined as the time interval from the tip of one vehicle to the tip of the next one behind it arriving at a certain place (usually a stop). The expectation μ and the variance σ^2 of headway influence expected waiting times at stops according to the following formula [see Holroyd and Scraggs (*13*)]:

$$W = \mu * \frac{1 + \frac{\sigma^2}{\mu^2}}{2}$$

where W is the expected headway.

For MBTA Route 1, Figure 4, *a–c*, shows how the actual headways compare with the scheduled ones at the initial stop, the 15th stop, and the last stop on one of the workdays. The headway deviation is defined as the difference between the actual headway and the scheduled headway. Even at the initial stop the deviations are significant. The deviations at the initial stop are caused by operation issues: either there are buses available at the terminal but the operators fail to dispatch them in time, or there is not enough bus slack time at the terminal so that buses are not ready at their scheduled departure time.

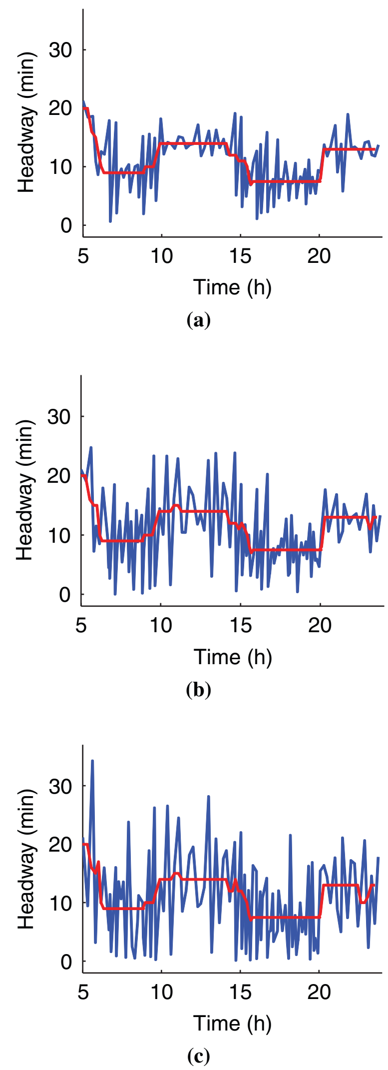


FIGURE 4 Actual versus scheduled headway at (*a*) initial stop, (*b*) 15th stop, and (*c*) last stop.

To explore how headway changes from the first to the last stop, consider the evening peak. The headway distribution at each stop is calculated, and various distributions, such as exponential, Erlang, gamma, and normal distribution, are fitted (*14, 15*). It is observed that the best statistical fit was obtained by the three-parameter gamma distribution, which is recommended by the traffic engineering handbook (*16*). The corresponding probability density function equals

$$f(x) = \frac{(x-\gamma)^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} \exp\left(-\frac{x-\gamma}{\beta}\right) \qquad x \geq \gamma,\ f(x) = 0,\ x < \gamma$$

Here $\alpha > 0$ is the continuous shape parameter. When $\alpha = 1$ the distribution becomes an exponential distribution, and when α equals

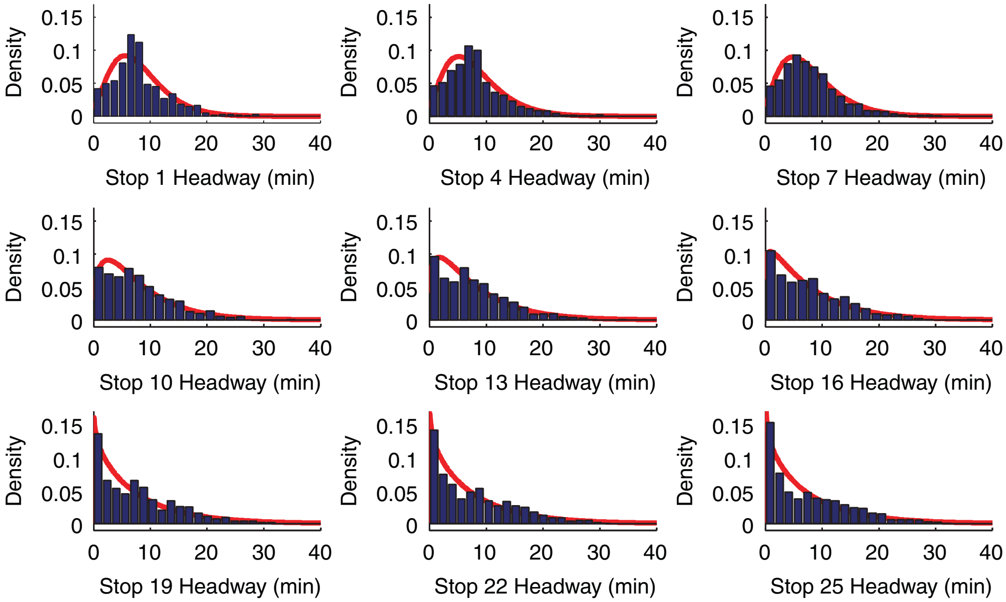


FIGURE 5 **Headway fitting results at stops with three-parameter gamma distribution.**

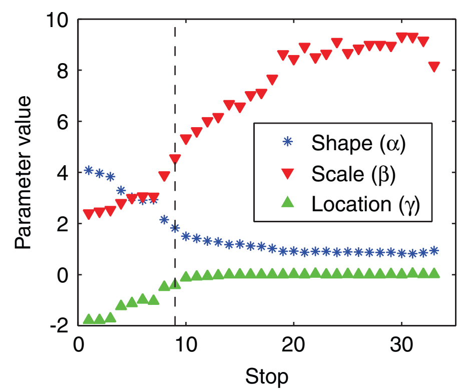
4 or 5 the shape is close to a normal distribution. $\beta > 0$ is the continuous scale parameter. The larger the scale parameter, the more spread out the distribution. γ is the continuous location parameter, which determines the center of the distribution. Γ is the gamma function.

The comparison of headway histograms and fitted distributions is shown in Figure 5. The three parameter-gamma distribution fits quite well from the initial stop to the last stop. Figure 6 shows how the three parameters change from the first to the last stop. At the initial stop, the shape parameter is close to 4, which shows that headway distribution is relatively close to a normal distribution. The shape parameter decreases quickly along the route. After Stop 9 it stabilizes at about 1, which indicates that headways are close to being exponentially distributed. The location parameter also stabilizes at about 0 after Stop 9, which means that after Stop 9 a large proportion of headways are close to 0, indicating that bus bunching is severe. After the shape and the location parameter stabilize, the scale parameter keeps increasing, which shows that the variance of headway keeps increasing.

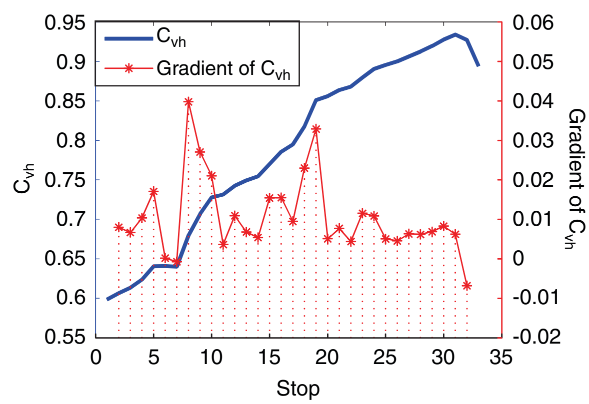
To understand further the headway variations, the headway coefficient of variation C_{vh}, a measurement proposed in the *Transit Capacity and Quality of Service Manual,* was calculated at different stops (*17*):

$$C_{vh} = \frac{\text{standard deviation of headway deviations}}{\text{mean scheduled headway}}$$

Figure 6*b* shows how the headway coefficient of variation at each stop changes along the route. The general trend is that the headway coefficient of variation keeps increasing, but the rate of increase varies from stop to stop. Between some stops it increases more quickly, which shows that in these segments travel times (between arriving at consecutive stops) are more unstable. To observe the change rate, the gradient of the headway coefficient of variation at each stop is shown in Figure 6*b*. At Stops 8 and 19 it increases the most. Inspection of the map shows that between Stops 8 and 9 the bus turns from a secondary road (Albany Street) to the main artery connecting



(a)



(b)

FIGURE 6 **Gamma distribution and headway coefficient of variation: (*a*) evolution of parameters of gamma distribution across bus route during evening peak and (*b*) headway coefficient of variation (left axis) and its gradient (right axis), showing bottlenecks with high headway variation increase at Stops 9 and 19.**

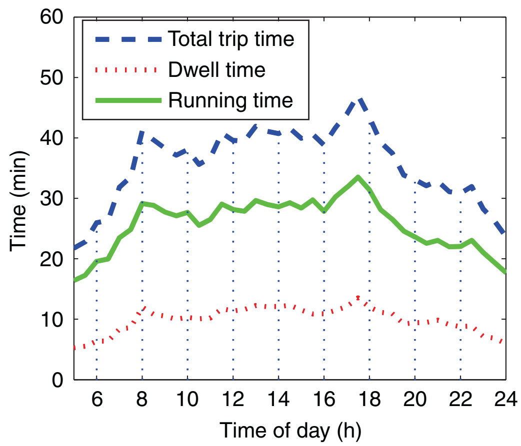
Boston and Cambridge (Massachusetts Avenue). The traffic signal waiting time at this intersection could vary greatly, which causes higher headway variance. Bus priority at this intersection therefore could greatly increase headway regularity. Between Stops 18 and 19 there are three closely spaced intersections. The Metro Green Line also transfers with Route 1 at Stop 18. Therefore the waiting times at intersections and the varying passenger flows make the headway unstable here. Two possible ways to improve the service quality are better bus priorities at these traffic lights and holding strategies to better synchronize buses and the metro line.

In-Vehicle Travel Time

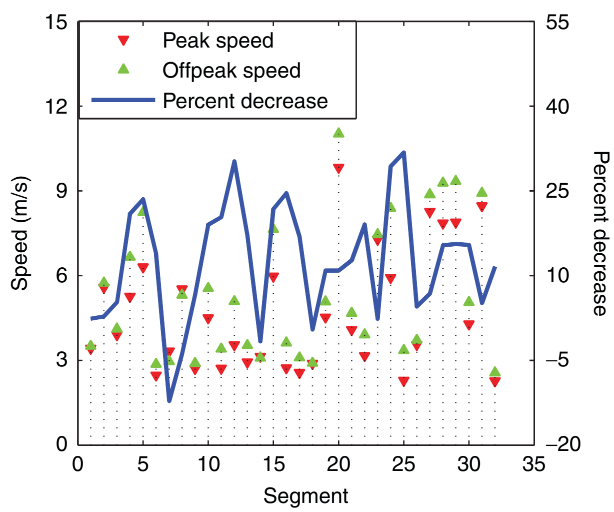
Another component of the total travel time is in-vehicle travel time, which is composed of two parts: travel time between stops and stop dwelling time. In-vehicle travel time is determined largely by traffic conditions and the road network structure. Figure 7*a* shows how the average total trip time, running time, and stop dwelling time change during different times of day. The total trip time has clear morning and evening peaks at 8 a.m. and 5:30 p.m., respectively. Running time and stop dwell time show identical peaks, which means that the increase in the total peak trip time is caused by increasing passenger volumes and slower travel speed. Running time has a larger influence on the increase in the total peak trip time.

Figure 7*b* compares the average travel speed (stop dwell time not included) and the percentage decrease from off-peak to peak hours at each segment. Segment *i* is the road between stop *i* and *i* + 1. At Segment 20, the average speed is always the highest because this segment is at Harvard Bridge and on the bridge there are no traffic lights or stops. The peak hour speed is generally lower than the off-peak hour speed. The highest percentage decreases are at Segments 12 and 25, which are respectively at the intersection of Massachusetts Avenue and Tremont Street and at Central Square, both crowded commercial areas in Boston and Cambridge, respectively.

The stops with the greatest percentage decrease in peak hour speed do not correspond to stops where the statistics of headway vary the most. The reason is that the headway coefficient of variation is a measurement of stability while the in-vehicle travel time is a measurement of the average speed performance.



(a)



(b)

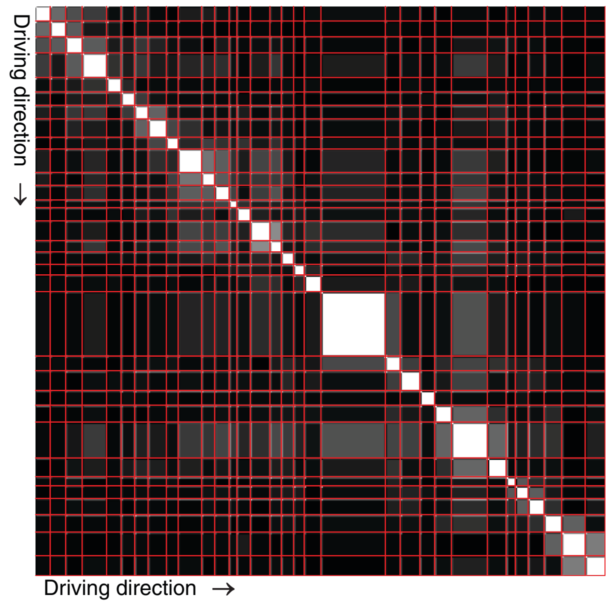
FIGURE 7 Trip time and peak and off-peak travel speed: (*a*) trip time composition (values represent sum over entire route) and (*b*) average speed during peak and off-peak periods (solid line = speed percentage decrease in peak hours).

Variability of Trip Travel Time

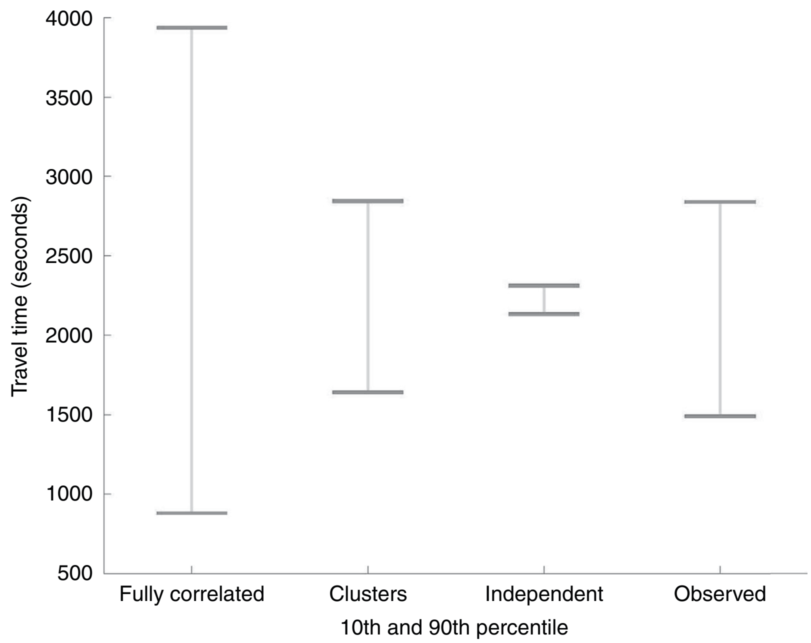
Another component of bus performance is constituted by travel time variability. High variability implies low predictability and therefore uncertain travel times. Thus alongside the expected travel time, travel time reliability is one of the most important factors when a route to a desired destination is selected. The expected travel time can be calculated easily by summing up the mean segment travel times along the route in the transportation network. However, to estimate variability, it is necessary to account for correlations between the individual segments composing the trip. Figure 8*a* shows the correlation matrix of the segment travel times along the bus route. The probability distribution of the trip travel time can be approximated by building clusters of highly correlated segments and assuming full correlation within each cluster and independence between segments in different clusters. The quantile function (i.e., the quasi inverse of the cumulative distribution function) of the sum of fully correlated segment travel times $\widehat{\mathrm{TT}}_s$, $s \in C$ in cluster C is computed as the sum of the quantile functions of the individual constituents, that is,

$$Q_{C(p)} = \sum_{s \in X} Q_{\widehat{\mathrm{TT}}_s}(p)$$

where $Q_{C(p)}$ denotes the *p*th quantile of the travel time for cluster *C*. The distribution of the sum of independent cluster travel times is approximated by Monte Carlo simulation, in which cluster travel times are drawn repeatedly and randomly according to the previously calculated probability distributions of the respective clusters. Figure 8*b* compares the resulting estimations with empirical travel time distributions for trips from the first to the last stop of MBTA Route 1. For comparison, also depicted are the results under the assumption that all segments are independent and assuming that every segment is fully correlated with every other. These results show that not accounting for dependencies leads to underestimation of travel time variability, while the proposed approximation yields good agreement with the observed distribution. Thus the low-frequency localization data can be used to infer route travel time reliability for



(a)



(b)

FIGURE 8 Correlation between segment travel times and comparison of estimated travel time with observed travel time under various assumptions: (*a*) correlation matrix of segment travel times on MBTA Route 1 (white = high correlation; black = low correlation; square grids = stop positions) and (*b*) (from left to right) spread between 10th and 90th percentile of estimated travel time distribution assuming (i) full correlation between all segments, (ii) full correlation within and independence between segment clusters, (iii) independence between all segments, and (iv) observed travel time distribution.

arbitrary routes along the line, providing another way to investigate bus performance.

APPLICATION: CALIBRATION OF A BUS MOVEMENT MODEL

Besides performing service quality analysis and bottleneck diagnosis, transit agencies may be interested in evaluating the effect of different measures to improve service quality. In this section it is shown that the headway and travel time statistics calculated in the previous section can be used to calibrate bus movement simulation models.

The bus movement is affected by traffic conditions, traffic signals, and the number of passengers boarding and alighting. The number of passengers is related to passenger arrival rates and the arrival time of the previous bus. In Daganzo, a convenient bus movement model is built incorporating the effect of the previous bus and the random noise caused by road conditions and traffic signals (*18*). This model can be calibrated by using the measured statistics of service performance.

The Model

Daganzo's bus movement model can be expressed as (*18*)

$$U_{n,s} = C_s + \beta_s (h_{n,s} - H) + v_{n,s+1}$$

Here $U_{n,s}$ is the nth run's segment travel time from stop s to $s + 1$. The dwell time at stop s is included; the dwell time at stop $s + 1$ is not. C_s is the scheduled travel time from s to $s + 1$. H denotes the scheduled headway, and $h_{n,s}$ is the actual headway for the nth run at stop s. β_s is a dimensionless parameter expressing the effect of the deviation from the scheduled headway on the dwell time. If a headway is longer than the scheduled value and the passenger arrival rate remains constant, there will be more passengers arriving than expected, which causes longer than expected stop dwell time. The inclusion of β_s makes two buses attract each other when their headway is shorter than H and repel each other when the headway is longer than H. In Daganzo, it is mentioned that β_s typically ranges from 10^{-2} to 1 (*18*). The noise term $v_{n,s+1}$ incorporates effects such as road conditions and traffic signals. It is assumed to have zero mean and variance σ^2_{s+1} and to be independent of $h_{n,s}$.

If $a_{n,s}$ is used to represent the arrival time of the nth run at stop s the above equation can be transformed as

$$a_{n,s+1} - a_{n,s} = C_s + \beta_s (a_{n,s} - a_{n-1,s} - H) + v_{n,s+1}$$

Model Calibration

As $a_{n,s+1}$, $a_{n,s}$, and $a_{n-1,s}$ can be acquired directly from the interpolated data, estimates of β_s can be obtained by using regression.

The regression results with error bars, provided in Figure 9, show the expected positive signs for 27 out of 32 segments. None of the negative coefficients are significant. These values all agree with the typical β_s values indicated in Daganzo (*18*). The low number of significant coefficients may be an indication of insufficient sample size and therefore small power of the tests.

With the interpolated AVL data all components needed for the movement simulation model are present. C_s and H can be acquired from the schedule. Headway distributions using the gamma family of densities have been fitted above; $v_{n,s+1}$ is approximated by using a lognormal distribution. Figure 10 provides a comparison between simulated and true segment travel time distributions. Kolmogorov–Smirnoff (KS) test statistics have been calculated to compare the accuracy of the simulations by using a lognormal distribution (solid lines) and a normal (dashed lines) distribution for the random noise term. It can be observed that for all segments except the first, the fit of the distribution for the lognormally distributed noise is acceptable at a confidence level of 95% in the KS test.

CONCLUSIONS AND OUTLOOK

A low-frequency AVL data analysis procedure that allows service performance evaluation and calibration of a bus movement model is proposed in this paper. It is demonstrated how low-frequency location-at-time AVL records, as provided, for example, by NextBus, can be used to obtain useful information on bus service performance. The main contributions of this study to the state-of-the-art research follow:

1. A more robust and accurate data preprocessing methodology that is demonstrated to be superior to the widely applied linear inter-

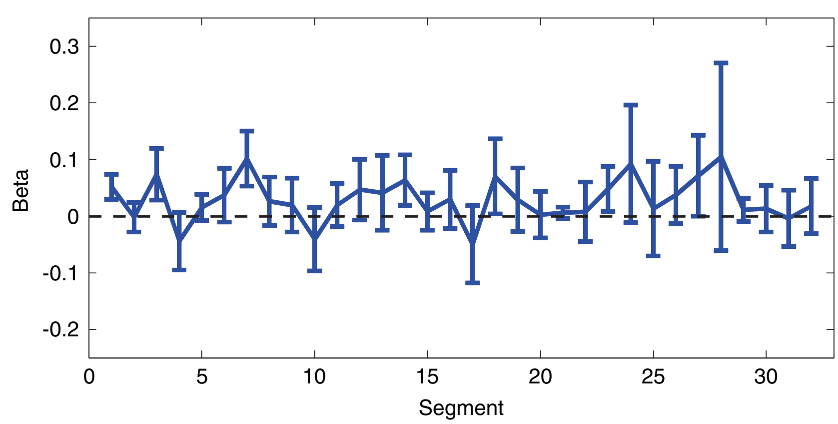


FIGURE 9 Regression result of β_s (see first equation in subsection on model) at each segment.

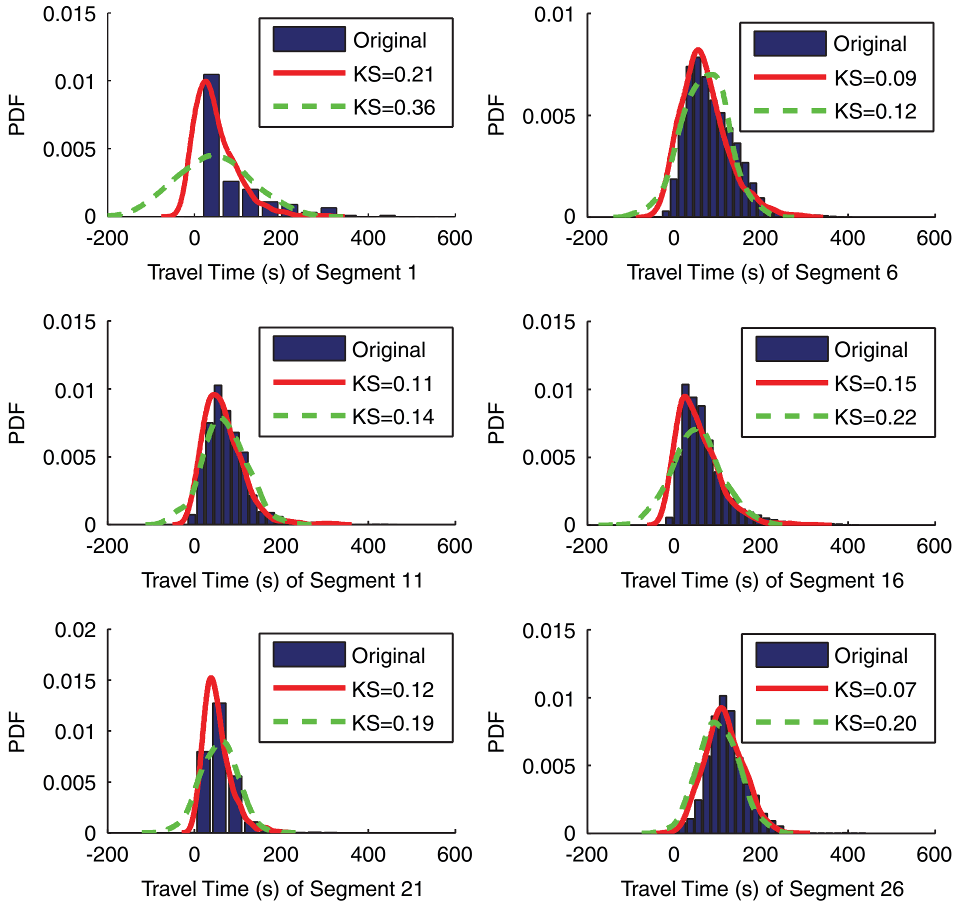


FIGURE 10 Comparison of bus travel time (U_s) at different segments of the route with original data and two simulated bus models (dashed line assuming normally distributed random noise term; solid line calibrated with statistical distributions observed in study; Kolmogorov–Smirnov test values in legends).

polation method is provided. More accurate stop arrival and departure time estimates are obtained by using a kernel density estimator of bus dwell time.

2. With this preprocessing method, headway distribution evolution along one bus route is studied in detail. It is demonstrated that the method can be used to detect bottlenecks caused by road layout and traffic conditions separately so that they can be treated differently to improve service quality.

3. Route travel time variability can be inferred from the clustering of segments on the basis of segment travel time correlations. The inference delivers hints on bus performance problems via increases in variability, thus providing a more complete view of the performance of the bus line.

4. These results can be used to calibrate bus simulation models, which in turn can be further applied to evaluate various bus control strategies.

Therefore the paper demonstrates the potential of widely available (and therefore low-cost) low-frequency AVL data to improve bus service and to provide valuable information for the passengers in regard to travel time predictions including travel time reliability. In particular it is shown that such data provide an alternative means for monitoring and controlling bus performance for transit authorities not willing to invest in more expensive solutions.

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