Real-Time Estimation of Urban Street Segment Travel Time Using Buses as Speed Probes

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Using transit buses as probes to detect general vehicle traffic conditions could be a real-time traffic monitoring mechanism in an urban advanced traveler information system. The feasibility of such an application depends primarily on the existence of quantifiable relationships between bus traffic and general vehicle traffic and infrequent bus travel observations (constrained by the scheduled bus headway and route configuration) that are sufficiently sensitive to infer real-time general vehicle traffic conditions. Considering that urban bus probe studies have focused only on the first criterion, this study is designed to examine real-time sensitivity between buses and cars. A generic framework of real-time urban travel time estimation is proposed, followed by a field study in which real-time bus travel information is available and a simulation study that examines the impact of passenger demand on performance of the proposed framework. The study findings provide insights into the feasibility of a real bus probe application in an urban traffic environment. Future studies are desired to explore bus probe performance in nonrecurrent traffic congestion.

Advanced traveler information systems play an increasingly important role in reliving traffic congestion and increasing level of service. Although real-time traffic information is available on freeways and suburban highways in most metropolitan areas in the United States, real-time traffic monitoring on urban arterials and streets remains limited. There are many challenges in developing urban advanced traveler information systems, with lack of real-time traffic detection being an important one. Using transit buses as probe vehicles has been recognized as a possible approach to traffic detection since the mid-1990s (*1–13*). To date, bus probes have received only limited attention.

Concerns about the feasibility of widespread bus probe implementation in an urban traffic environment include the usability of bus travel information for nontransit vehicles, the temporal–spatial coverage of bus service, and the reliability of bus operations (*14*). There are difficult challenges that have been recognized and important research questions that should be addressed. Another reason for the limited attention paid to bus probes may be that no real-time automatic vehicle location (AVL) bus probes have been explored for urban streets; a real-time AVL system is necessary for real-time traffic monitoring. AVL encompasses a variety of location and communication technologies. Archived AVL (or on-vehicle data recording) uses an onboard computer to record and store bus operation data and upload them to a data tank at a specific time (usually daily); real-time AVL (or off-vehicle data recording) sends bus travel and operation data to a central computer in real time (usually at a frequency of 30 s to 5 min) (*15, 16*). The data generated by the two types of AVL systems are very different in content and have different applications in bus probe studies. For more information about the difference, see Pu and Lin (*13*).

This paper focuses on the usability of bus travel information to infer general vehicle traffic conditions. The usability can be proven if two conditions are met: Condition 1, there are quantifiable relationships between bus travel and car travel; Condition 2, infrequent bus travel observations (constrained by the scheduled bus headway and AVL polling frequency) are sufficiently sensitive to infer real-time general vehicle traffic conditions (probably by means of the relationships identified in Condition 1). A large amount of historic data can be used to identify possible bus–car relationships, as in past bus probe studies (*1–3, 6*). Historic relationships, however, do not guarantee the real-time sensitivity of bus probes to traffic conditions, as bus observations could be too sparse to draw a reliable conclusion in a short time. Thus, Condition 2 needs to be satisfied.

Previously, Pu and Lin identified statistically significant relationships between bus and car speeds with historic real-time AVL bus data and test car data on a signalized urban street in Chicago (*17, 18*). This paper is designed to examine whether real-time AVL bus data can be used for real-time estimation of car speeds and travel times. The real-time AVL system considered in both studies polls buses about every 30 s and obtains bus speed, location, time stamp, and other identity information.

The study is structured as follows. A generic framework of real-time estimation is proposed, followed by a field study in which light and congested traffic conditions are observed and then a simulation study in which unexpected passenger demand surge is created. Conclusions are presented at the end of the paper.

PREVIOUS WORK

Previously, it was found that speed was a better traffic parameter than travel time to be directly used in modeling bus–car relationships (*17, 18*). This circumstance has to do with intrinsic measurement errors in measuring bus travel time in the interval-based real-time AVL polling scheme, and bus stop dwell time—the most significant noise to be filtered when relating bus travel time to car travel time (*1, 3, 6, 14*)—is not available. The intrinsic measurement error of bus travel time has

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to do with the way data were collected. In the real-time AVL system, the location where a bus reports its instantaneous point speed is not fixed along the route so the travel time for a predefined link or segment is not always available. This paper continues to use buses as direct speed probes (after converting instantaneous point speed to space mean speed, travel time and speed may be used interchangeably for modeling because one is simply the inverse of the other).

Pu and Lin found that bus–car speed relationships were location specific: at midblocks, buses and cars exhibit similar speed patterns with or without constant differences; at bus-stop-only locations (where no control is imposed on nontransit vehicles), bus and car speeds could differ greatly as buses have to respond to passengers' demands while cars can travel freely if not disturbed by buses; and at controlled intersections (with or without bus stops), buses and cars are subjected to the same control strategies (assuming no transit priority strategy presents) but buses tend to have slower start-up and slow-down times (i.e., longer acceleration and deceleration distances) than cars (*17, 18*). In this paper, the study segments are divided into smaller links of any one of those three types. The link length is defined by the length of cruising (in the case of midblock links) or the acceleration and deceleration length (in the cases of bus-stop-only and intersection links). After segmentation, the speed used in the latter analysis is average link speed.

FRAMEWORK

Overview

The generic framework of real-time estimation of bus speed and then car speed and travel time incorporates historic bus and car speeds and newly incoming AVL bus speeds received in the estimation interval, as shown in Figure 1. The framework applies to each link l after the segmentation and each predefined estimation–updating interval i (e.g., 15 min). For simplicity, subscripts l and i are not shown in Figure 1 or in later equations. The backbone of the framework is the historic bus–car speed relationships, which are jointly defined by historic bus and car speeds. In a real-time situation when car travel information is unavailable, the means of newly incoming bus speeds in an estimation interval $(\overline{b})$ are used to update the historic mean speed $(\overline{b^0})$ by comparing $\overline{b}$ with a confidence interval of $\overline{b^0}$; if $\overline{b}$ is within the confidence interval, no updating of $\overline{b^0}$ is necessary and the current $\overline{b^0}$ is used; otherwise, Bayesian updating is carried out to take into account the newly received information. If no new bus speeds are reported during the estimation interval, the historic mean speed $(\overline{b^0})$ is used by default. The latest average bus speed is then applied to the historic bus–car relationships to derive the concurrent car mean speed $(\overline{c})$ and mean travel time $(\overline{t_c})$ in the estimation interval. Link car travel times are finally summed to obtain total study segment travel time, which is compared with observed values in model evaluation.

Confidence Interval

A two-sided $100 \times (1 - \alpha)\%$ confidence interval of the historic bus mean speed $(\overline{b^0})$ of a given link and interval is constructed in Equation 1.

$$\overline{b^0} \pm z_{\left(1-\frac{\alpha}{2},n-1\right)} \frac{s}{\sqrt{n}} \tag{1}$$

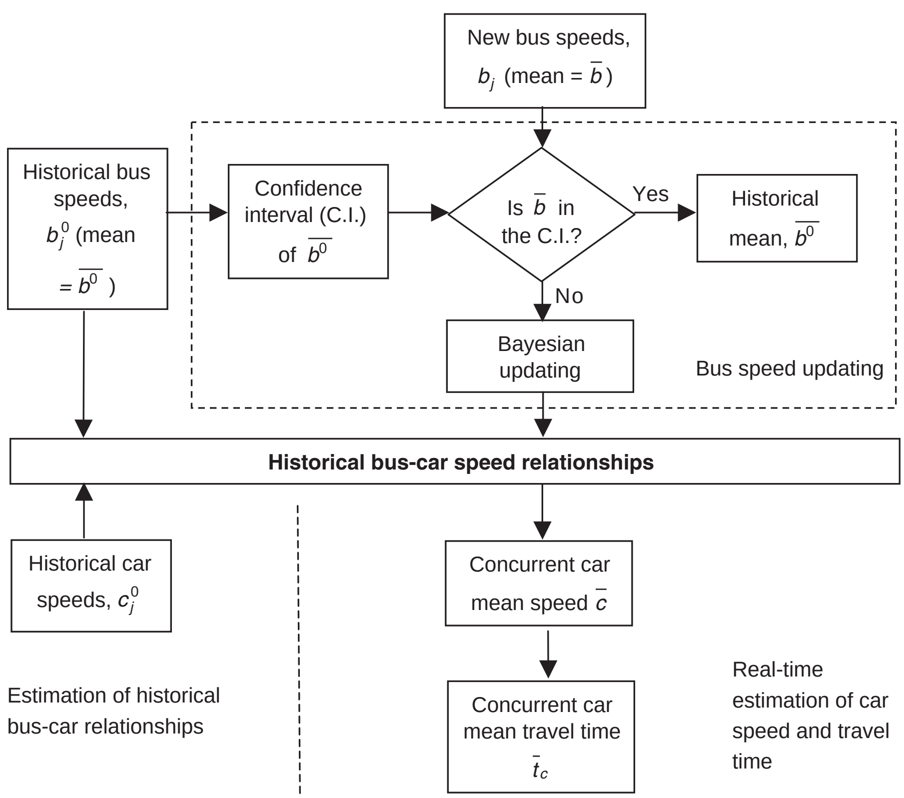

FIGURE 1 Generic framework of real-time estimation.

where s equals the sample standard deviation,

$$\sqrt{\frac{1}{n-1}\Sigma\left(b_j-\bar{b}\right)^2}$$

and

$$z_{\left(1-\frac{\alpha}{2},\,n-1\right)}=\left(1-\frac{\alpha}{2}\right)$$

the critical value of the z-statistic with $n-1$ degrees of freedom.

If the sample size used in calculating the historic mean speed is reasonably large (the rule-of-thumb value is 30), no assumption about distribution of the sampled population is needed because the central limit theorem guarantees that the sample mean is approximately normal. The value of α determines the acceptable confidence level of the estimated historic mean speed. A past study concluded that a traveler's tolerable error of an estimated travel time may be 10% to 15% of the actual value (*6*). This tolerable error range can be used to find an appropriate α value as described in the field study.

Bayesian Updating

When significant changes are observed in newly incoming speeds (whose mean is outside the confidence interval of the historic mean), a speed updating algorithm is implemented. A Bayesian method provides a good mechanism to combine an initial estimate with some new data to come up with a better estimate, so it is used in the framework. A particularly convenient form of Bayesian updating can be adopted if normality of the historic mean ($\overline{b^0}$) and mean of the newly observed bus speeds ($\bar{b}$) can be assumed (*19*). That is, let σ_0^2 be the variance of the historic mean speed $\overline{b^0}$ and let $\sigma_{\bar{b}}^2$ be the variance of new mean speed $\bar{b}$, then the updated (posterior) distribution of mean speed $\overline{b^u}$ is normal with mean

$$\overline{b^u}=\frac{\frac{\overline{b^0}}{\sigma_0^2}+\frac{\bar{b}}{\sigma_{\bar{b}}^2}}{\frac{1}{\sigma_0^2}+\frac{1}{\sigma_{\bar{b}}^2}} \tag{2}$$

and variance

$$\sigma_u^2=\frac{1}{\frac{1}{\sigma_0^2}+\frac{1}{\sigma_{\bar{b}}^2}} \tag{3}$$

This updating procedure in fact uses the inverse of the variance as the weight in combining the initial estimate and the estimate from the new samples. Before updating, the normality of relevant parameters needs to be checked. According to the central limit theorem, the normality of the initial mean speed $\overline{b^0}$ should be easily satisfied as long as the historic AVL bus data archive a large number of speed observations. However, normality of the mean speed $\bar{b}$ for a given link during an interval is difficult to test directly, because the observations are typically sparse. Sen et al. reasoned that "since the attempt is to construct a mean-like estimate, it is not unreasonable to assume normality as long as the estimate is reasonably mean-like" (*20*). Wilmot and Stopher noted that the Bayesian updating procedure is particularly useful when the new samples are too small to provide reliable values on their own (*21*). Therefore, normality of $\bar{b}$ is assumed and the preceding formulations are adopted.

The calculation using Equations 2 and 3 is straightforward. If only one new observation is received in a given interval, the Bayesian updating procedure is not used even if the observation is out of the confidence interval, because the variance $\sigma_{\bar{b}}^2$ is unavailable. In this case, the historic mean speed is the default updated mean speed. If the number of observations is greater than one but all are of an equal value, the new mean speed is directly used as the updated mean speed because the new mean speed has infinity weight in the Bayesian equations.

FIELD STUDY

Study Segments and Data

Two study segments were selected along West Madison Street in the west of the central area of Chicago, Illinois, for the field study: eastbound Madison Street from the Leavitt Street bus stop to the Peoria Street bus stop with a length of 1.643 mi (2.643 km), and westbound Madison Street from the Morgan Street bus stop to the Oakley Street bus stop with a length of 1.647 mi (2.650 km).

Figure 2 shows the street layout of the study segments, with "distance into block" measuring the distance from the origin bus stop to the successive stops in the direction of traveling. There are nine signalized intersections and 15 bus stops along the eastbound segment and 10 signalized intersections and 14 bus stops along the westbound segment. The speed limit is 30 mph. East of Ashland Avenue, the outside lane in each direction is usually occupied by on-street parking, so the segments in both directions were treated as one-lane segments; buses pull into the parking lane at a bus stop, making it operate like a bus bay. The neighborhood is a mix of residential and commercial land use. West of Ashland Avenue, the street surface in both directions is wide enough to accommodate two vehicles traveling side by side and on-street parking is rarely present, so the segments were considered as two-lane segments. The neighborhood is a mix of residential and recreational land use. (United Center is home of the Chicago Bulls and Blackhawks. There were no scheduled matches during the study period.)

The AVL bus data contain bus point speed, location, and time stamp at an approximate resolution of every 30 s. The Chicago Transit Authority control center, supported by a vendor, is able to archive a real-time data stream and make it available for later analysis. This study acquired a data set that covered the period June 1 to September 19, 2007.

Regular vehicle traffic data were collected by using a repeated measures experimental design (*22*), which means taking observations repeatedly on the same experimental unit(s). The experimental unit here was the study segment and the traffic condition along it was of interest. A passenger car equipped with a Global Positioning System (GPS) was used to measure the traffic condition. The driver of the test vehicle was trained to drive like other vehicles in the traffic flow to obtain an "average" representation of field traffic conditions. The GPS device recorded the vehicle's speed, position, acceleration–deceleration rate, time stamp, and other information every 0.1 s and stored them in a secure digital card. Test vehicle data were collected for nine weekdays from September 4 to 14, 2007, one morning hour (10:30 to 11:30 a.m.) and one afternoon hour (5:30 to 6:30 p.m.) each day. During the morning hour, both study segments carried uncongested traffic. During the afternoon hour, the westbound segment carried congested traffic, as many after-work trips coming from downtown Chicago were going home, dining out, or shopping.

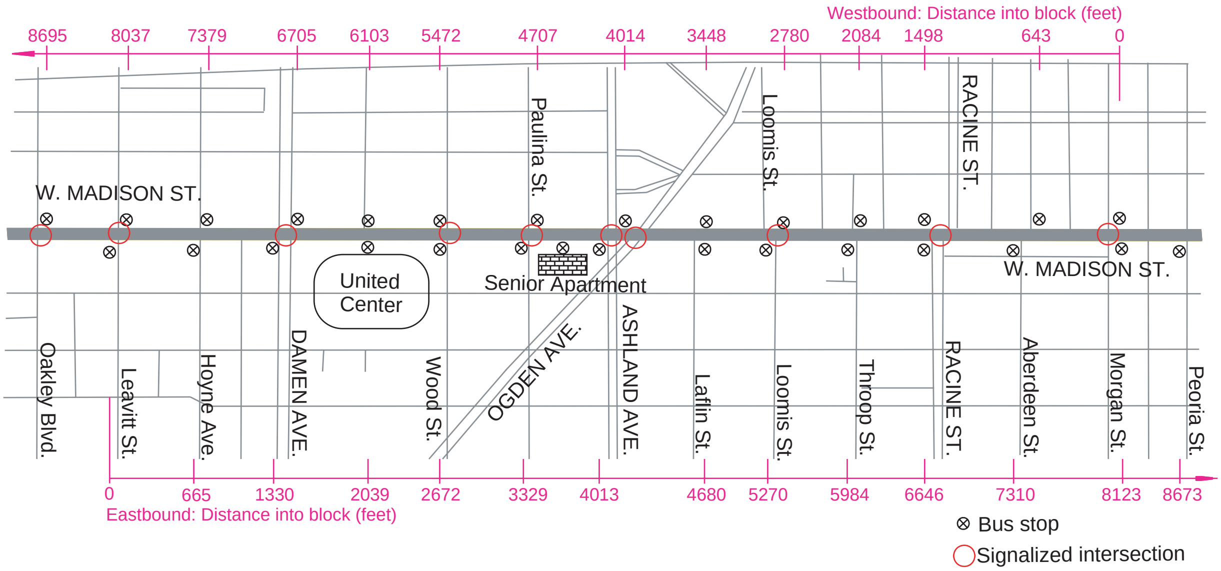

FIGURE 2 Field study segments.

A floating car was driven back and forth on the study segment and produced one measurement of total travel time at a 15-min interval for each direction every day during the 9-day period. Thus, a total of nine travel-time measurements were accumulated for the same 15-min interval in each direction at the end of the field work. The mean and standard deviation of the nine travel-time observations, with the required sample size m for a reliable travel-time measurement for the same 15-min interval during the 9 days are shown in Table 1. The required sample size was calculated as follows:

$$m = \left(\frac{t_{\alpha/2,n-1} \cdot s}{e} \right)^2 \tag{4}$$

where

s = standard deviation of the nine travel times,

$t_{\alpha/2,n-1} = \left(1 - \frac{\alpha}{2}\right)$ critical value of the t-statistic with $n - 1$ degrees of freedom, and

e = tolerable error.

The m values in the table were calculated with $\alpha = 0.10$ and $e = 15\% \times$ mean travel time. Travel time on the study segments was generally steady within the same 15-min interval on weekdays. As a result, one or two observations were sufficient to obtain reliable travel-time measurement in most cases. It was assumed that one travel-time observation in a given 15-min interval on a weekday was statistically representative of the traffic condition in that 15-min because of the small variation observed over the 9 days of study.

Historic Bus–Car Speed Relationships

On the basis of the available car data (nine weekdays, 2 h/day), concurrent bus data were extracted from the original 4-month data set. The obtained nine-weekday data set was then divided into two subdata sets: data from the first five weekdays (September 4 to 10) were used to build the historic relationships between bus traffic and general vehicle traffic, and data from the last four weekdays (September 11–14) were used for model validation.

The length of the estimation–updating interval was decided to be 15 min (i.e., estimated car speed and travel time were updated every

TABLE 1 Required Sample Size

	Eastbound			Westbound		
	Mean (s)	SD (s)	Required Sample Size (m)	Mean (s)	SD (s)	Required Sample Size (m)
10:30–10:45 a.m.	263	25	1.4	250	23	1.3
10:45–11:00 a.m.	272	29	1.8	260	26	1.5
11:00–11:15 a.m.	255	13	0.4	256	26	1.6
11:30–11:45 a.m.	254	27	1.8	270	14	0.4
5:30–5:45 p.m.	264	20	0.8	260	31	2.2
5:45–6:00 p.m.	267	23	1.1	284	55	5.8
6:00–6:15 p.m.	254	22	1.1	251	26	1.6
6:15–6:30 p.m.	256	28	1.8	272	32	2.1

NOTE: SD = standard deviation.

15 min). This value was a compromise between the interval length and the usability of information. On the one hand, a longer interval is desired because more bus trips and therefore more bus speed observations can be received. The scheduled headways of the bus services on the study street range from 5 to 9 min during morning and evening peak hours, from 9 to 15 min during other normal service hours, and up to 30 min during the owl service hours (actual headways are also affected by traffic and operation conditions). Hence, a 15-min interval could include up to three trips during peak hours and at least one trip at other times except early morning and late night.

On the other hand, the usability of information to travelers decreases as the length of the updating interval increases. If updating is carried out every half hour, every hour, or even longer, the information about the latest traffic conditions will become less useful to travelers.

Historic bus–car speed relationships were quantified by classic multiple linear regressions, in which the dependent variable is the difference between bus mean speed and car mean speed of a link (car speed minus bus speed) and the final independent variables are two locational dummies: BusStopOnly and Signal. BusStopOnly (=1) indicates a short link (about 200 ft) that includes only a posted bus stop, and general vehicles can travel freely if not disturbed by buses. Signal (=1) indicates that a signalized intersection exists. Other explanatory variables such as number of lanes and bus stop type (curbside or bus bay) were initially included but turned out to be insignificant, so they were removed in the final models. This result could be site specific and should not be generalized without further investigation.

Table 2 presents the estimation results of the historic bus–car speed relationships in each 15-min interval during the morning and afternoon hours. Each equation includes 58 links from eastbound and westbound segments. The intercept ranges from 3.6 to 6.5 mph, meaning that car speed on average is much faster than bus speed across all types of locations on the study segments. The speed difference is increased by 8.7 to 13.8 and 4.6 to 8.2 mph at bus-stop-only locations and signalized intersections, respectively. BusStopOnly and Signal cannot equal 1 simultaneously because of the way they are defined.

Bus Speed Updating

The data used to construct the confidence interval of historic bus mean speed covered all weekdays between June 1 and September 10, 2007 (data from September 11 to 14 were left for real-time estimation). This large sample size ensures normality of the historic mean speed. Concerning the value of α, this study carried out a trial-and-error calculation and found that $\alpha = 0.05$ is enough to ensure the error of the estimation of total segment car travel time is within 10% to 15% of the ground truth. Thus, the 95% confidence interval of bus mean speed for each link and each 15-min interval is constructed. The mean of the newly incoming bus speeds is compared with the confidence interval, and the Bayesian updating (Equations 2 and 3) is carried out if the new mean speed falls outside the interval.

Figure 3 shows an example of bus speed updating for the eastbound segment between 10:45 and 11:00 a.m. on September 11, 2007. According to the updating strategy, the historic mean speeds of Links, 4, 8, 9, 12, 13, 15, 16, 17, 19, 21, 23, 25, 27, and 28 are updated by the newly incoming bus speeds. An odd number on the horizontal axis in Figure 3 represents an intersection–bus stop link and an even number represents a midblock link. Figure 3 shows that an intersection–bus stop link has lower average speed than a midblock link.

Concurrent Car Speed and Travel Time

The results from bus speed updating applied in the historic bus–car speed relationships to derive the concurrent car mean speeds. The estimated link car mean travel time $\overline{t_c}$ was the quotient of link length L and car mean speed $\overline{c}$—that is, $\overline{t_c} = L/\overline{c}$. Car mean travel time on the entire study segment T was the sum of $\overline{t_c}$, $T = \sum_l \overline{t_c}$. Intersection delay was not modeled explicitly in calculating total travel time but was accounted for implicitly in deriving link car mean speed $\overline{c}$. If a major delay occurred at an intersection, the updating algorithm would correct (i.e., lower) the bus mean speed on the intersection link to reflect that. Consequently, low link car speed and long link car travel time would result because of the linear relationships between bus and car speeds shown in Table 2. This situation is arguably viewed as a major advantage for three reasons: (*a*) it greatly simplifies the modeling process without having to collect signal timing, queue length, and other information that is not readily available in real time; (*b*) these algorithms are easy to implement, especially in the real-time environment; and (*c*) the models should be easily transferable to other arterial streets.

TABLE 2 Historic Bus–Car Speed Relationships

				Parameter Estimates					
				Intercept		BusStopOnly		Signal	
15-min Interval	N[a]	RMSE[b] (mph)	Adj. R^2[c]	Estimate (mph)	*p*-Value	Estimate (mph)	*p*-Value	Estimate (mph)	*p*-Value
10:30–10:45 a.m.	58	7.85	.1608	6.50	<.0001	8.72	.0020	6.09	.0139
10:45–11:00 a.m.	58	6.11	.3436	5.87	<.0001	11.73	<.0001	4.77	.0135
11:00–11:15 a.m.	58	5.01	.5484	3.97	<.0001	13.87	<.0001	7.65	<.0001
11:30–11:45 a.m.	58	7.81	.2236	3.62	.0155	10.78	.0002	6.53	.0083
5:30–5:45 p.m.	58	5.85	.3911	6.36	<.0001	12.43	<.0001	4.65	.0119
5:45–6:00 p.m.	58	6.04	.3879	4.48	.0002	12.33	<.0001	6.49	.0009
6:00–6:15 p.m.	58	6.01	.3064	4.82	<.0001	9.94	<.0001	6.35	.0011
6:15–6:30 p.m.	58	6.51	.3042	4.21	.0010	9.67	.0002	8.20	.0001

[a]Number of observations of the data used in regression.
[b]Root-mean-square error.
[c]Adjusted R^2.

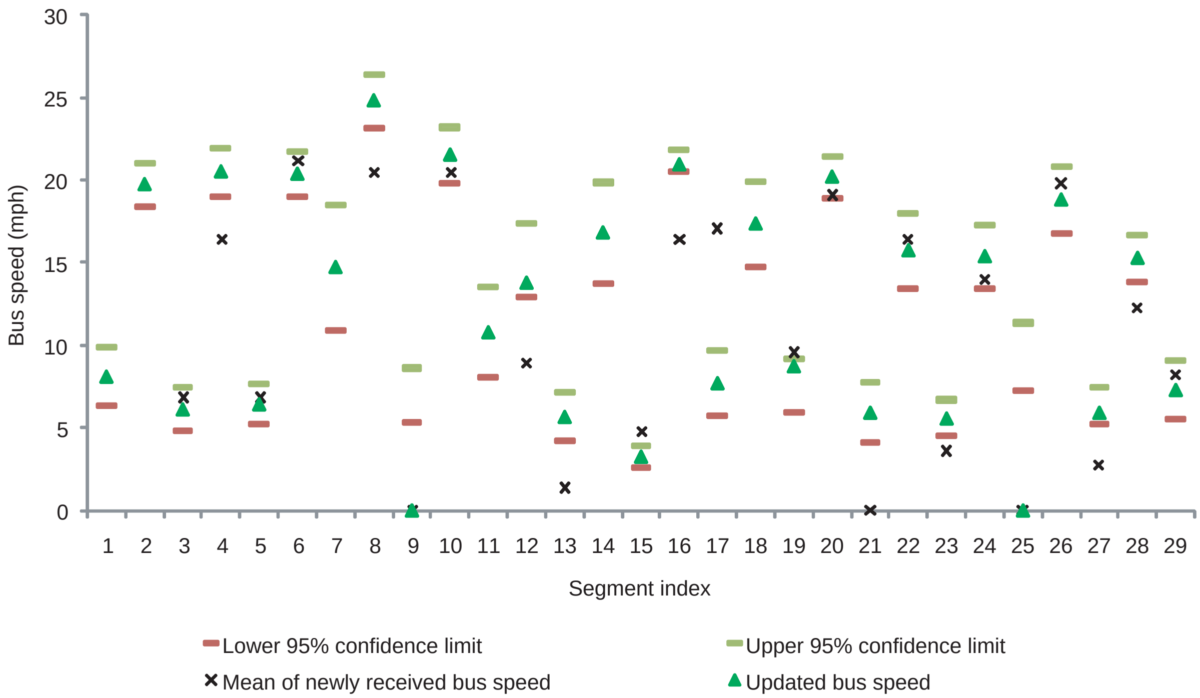

FIGURE 3 Example of bus speed updating.

Table 3 lists the estimated total segment car travel times and compares them with observed values. In most cases, the estimated car travel times are within 15% of the observed times. There are only five exceptions (in 64 cases) with errors larger than 15% of the observed travel time, indicating the proposed method works well.

SIMULATION STUDY

A major concern in using transit buses as traffic probes is the impact of bus-specific operations (e.g., loading–unloading passengers) on performance of bus probes. Neither bus stop dwelling time nor boarding–alighting passenger count at bus stops is available from the real-time AVL system, so the proposed real-time estimation framework and algorithms should be smart enough to filter out or reduce automatically the noise caused by passenger activities. To investigate the impacts of passenger demand on bus probe performance, a simulation study was carried out by using a microscopic traffic simulation package, VISSIM.

Test Bed

The simulation test bed replicated a 1-mi urban arterial section on West Roosevelt Road between Ashland Avenue and Halsted Avenue in the southwest of Chicago's central area (Figure 4). The 1-mi length satisfied the *Highway Capacity Manual*'s requirement about minimum length (1 mi) of the study segment when evaluating the performance of an urban street (*23*). The selected section of Roosevelt Road included seven signalized intersections and 10 posted bus stops with annual average daily traffic ranging from 20,300 to 28,100 (*24*). Both eastbound and westbound segments were considered, each of which has two through lanes and a third parking lane, if present.

The reason for choosing a street other than the field study street as the simulation test bed is twofold. Roosevelt Road is a major urban arterial in Chicago and carries much higher traffic volume than Madison Street. Practically, a field study could not be carried out on Roosevelt Road because the bus routes serving it were not yet implemented with the real-time AVL system and the Madison Street bus (Route 20) was the only route equipped with the real-time AVL system at the time the study was carried out.

Simulation was performed in VISSIM, which has the capability of simulating transit operations and capturing microscopic interactions between vehicles, including cars and buses through its car-flowing and lane-changing models. It also generates high-resolution (up to 0.1 s) vehicle speed, location, and time stamp information (*25*). The simulation was calibrated extensively with respect to total segment bus and car travel times, subsegment car speeds, traffic flow rate, signal timing, bus passenger volume, acceleration, deceleration, and desired speed distribution. The final calibrated simulation represented average traffic conditions from 4:30 to 6:30 p.m. on weekdays. Ten simulation runs with different random speeds were conducted. For each run, the overall simulation period was 5,400 s (1.5 h), including 15 min (0 to 900 s) of warm-up time to fill the network and 75 min (900 to 5,400 s) of data recording time. The generated bus data were sampled with a frequency of 30 s, which replicated the polling mechanism of the real-time AVL system. A large sample of car travel times was recorded continuously every 15 min, the mean of which would be used as the ground truth to compare the estimated values.

Baseline Bus–Car Speed Relationships

A similar segmentation treatment also applied to the study segment. The heuristic engineering segmentation resulted in 19 location-specific links eastbound and 15 westbound. The final linear relationships of the difference between bus and car speeds (car speed minus bus speed) and locational explanatory variables are provided in Table 4.

TABLE 3 Total Segment Car Travel Time

		Car Travel Time (s)					
		Eastbound			Westbound		
Day (Sept.)	15-min Interval	Observed	Estimated	Error[a] (%)	Observed	Estimated	Error[a] (%)
11	10:30–10:45 a.m.	259	268	3.42	249	260	4.19
	10:45–11:00 a.m.	341	280	–18.03	275	279	1.45
	11:00–11:15 a.m.	295	279	–5.58	272	282	3.44
	11:30–11:45 a.m.	309	294	–4.72	294	296	0.63
12	10:30–10:45 a.m.	340	261	–23.45	262	259	–1.22
	10:45–11:00 a.m.	293	297	1.29	297	276	–7.10
	11:00–11:15 a.m.	251	292	16.38	291	282	–2.93
	11:30–11:45 a.m.	294	301	2.49	286	300	4.82
13	10:30–10:45 a.m.	282	262	–7.07	288	259	–10.30
	10:45–11:00 a.m.	294	272	–7.44	273	279	2.32
	11:00–11:15 a.m.	298	285	–4.08	288	287	–0.42
	11:30–11:45 a.m.	292	294	0.82	280	391	39.48
14	10:30–10:45 a.m.	289	262	–9.39	266	276	3.89
	10:45–11:00 a.m.	263	271	3.09	310	291	–6.22
	11:00–11:15 a.m.	254	279	9.71	295	291	–1.40
	11:30–11:45 a.m.	267	294	10.23	295	293	–0.84
11	5:30–5:45 p.m.	288	274	–4.73	266	276	3.95
	5:45–6:00 p.m.	286	288	0.67	283	282	–0.25
	6:00–6:15 p.m.	301	276	–8.17	245	288	17.36
	6:15–6:30 p.m.	282	270	–4.24	269	289	7.53
12	5:30–5:45 p.m.	330	282	–14.71	257	274	6.56
	5:45–6:00 p.m.	300	281	–6.11	312	282	–9.58
	6:00–6:15 p.m.	287	284	–1.07	322	279	–13.49
	6:15–6:30 p.m.	294	267	–9.10	303	292	–3.73
13	5:30–5:45 p.m.	289	269	–6.86	295	271	–8.07
	5:45–6:00 p.m.	279	289	3.57	280	287	2.50
	6:00–6:15 p.m.	253	280	10.53	292	285	–2.43
	6:15–6:30 p.m.	281	271	–3.55	286	290	1.24
14	5:30–5:45 p.m.	268	276	2.75	307	277	–9.77
	5:45–6:00 p.m.	294	281	–4.40	291	284	–2.43
	6:00–6:15 p.m.	264	278	5.26	317	283	–10.65
	6:15–6:30 p.m.	257	266	3.62	305	285	–6.64

[a]Error = 100% ∗ (estimated—observed)/observed.

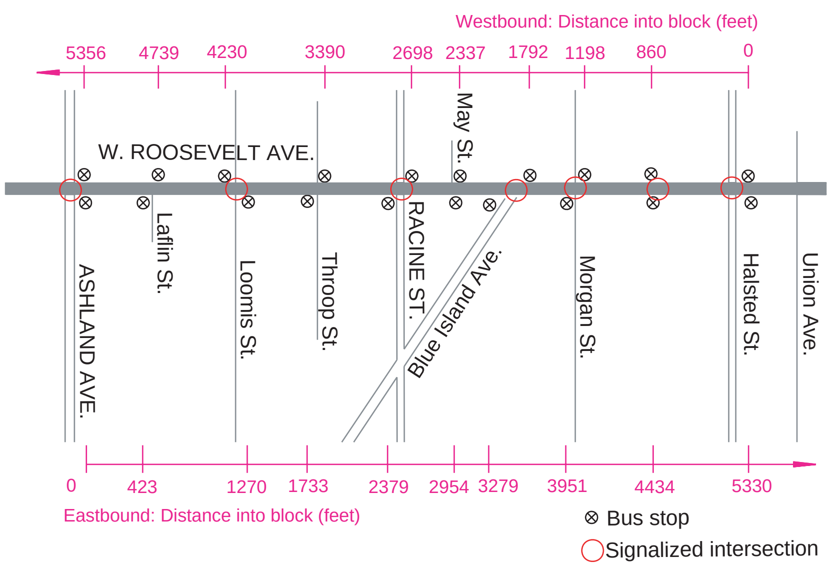

FIGURE 4 Simulation test bed.

TABLE 4 Baseline Bus–Car Speed Relationships

				Parameter Estimates			
				Pr > | t |			
Direction	N[a]	RMSE	Adjusted R^2	Intercept	BusStopOnly	Signal	BusBay
Eastbound	19	2.70059	.5997	5.07399 <.0001	8.03635 <.0001	NE[b] NE	NE NE
Westbound	15	7.68916	.3362	10.99136 0.0019	NE NE	–8.92132 0.0569	13.13285 0.0177

NOTE: Pr > designates the t-value of a parameter estimate (i.e., the top value in a cell is the parameter estimate and the bottom volume is the t-value of the estimate).
[a]Number of observations of the data used in regression.
[b]No estimate for that parameter because it is not significant in the regression model.

Both eastbound and westbound models identify a significant linear relationship between bus and car speeds. For the eastbound segment, only BusStopOnly is significant (the coefficient is about 8.04) and explains 60% of the model variation (adjusted $R^2 \approx .60$). For the westbound segment, both Signal and BusBay are significant. The coefficient of Signal is –8.92, the coefficient of BusBay is 13.13, and the adjusted R^2 is about .34. The reason for a lower goodness-of-fit of the westbound model may lie in the less congested traffic conditions (greater variation in car travel speed) during the afternoon peak period on the westbound segment.

Bus Probe Performance in Passenger Demand Surge

The scenario of surge in passenger demand was created by increasing the original passenger volumes at all stops, which were mostly less than 10 persons per hour, to 20 persons per hour—an increase of >100%.

Upon receiving bus speeds from the simulated scenario, the tasks of estimating car travel time were to update the baseline average bus speeds with the newly received bus speeds and to apply the baseline bus–car speed relationships identified in Table 4 to derive the concurrent car speeds and travel times. The same updating and estimation techniques in the field study also applied here. Ten simulation runs with different random seeds were carried out. Figure 5 shows the estimated total segment car travel times in two of those simulation runs; the other eight runs generated similar results. The solid lines in Figure 5 represent the actual total segment car travel times in the five 15-min intervals (75 simulating minutes) from the simulation and the dashed lines are the estimated total segment car travel times from the regression model.

The estimated travel times closely follow the simulated values. On average, the root-mean-square error is 32 s and accounts for 15% of the average of simulated values, representing only a modest impact of a large surge in bus ridership on estimated travel time. This situation can be attributed to the proposed real-time estimation framework and link speed-based algorithms. These algorithms are based not on any bus stop dwell time information but simply on speed. The baseline average bus speed on a bus-stop-only link is generally already low over a relatively short distance, so when passenger activities increase at bus stops the marginal effect of decreased speed on travel time is small. In other words, the proposed travel-time estimation framework is relatively robust to passenger demand, which is a desirable feature. With the proposed link speed-based algorithms, the noise caused by bus passenger activities can be filtered out.

CONCLUSIONS

This paper has proposed a generic real-time estimation framework and presented two case studies in examining the real-time sensitivity of bus probes to nontransit vehicle traffic conditions on signalized urban street segments. The findings suggest that the framework

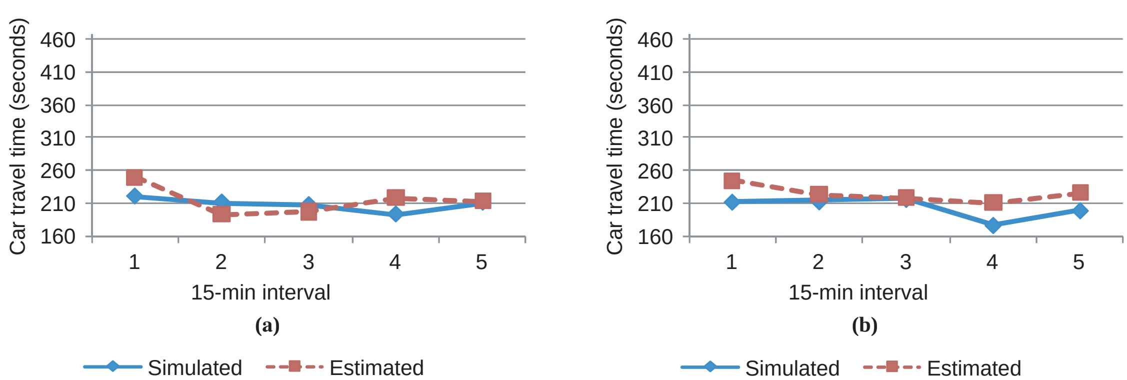

FIGURE 5 Estimation of car travel time under abnormal passenger demand surge: (*a*) Run 1 and (*b*) Run 2.

represents a possible logical solution of implementing real-time bus probes by using both historic bus–car speed relationships and real-time bus travel information.

The field study of real-time estimation of urban arterial segment travel time using real-time AVL bus tracking information has given promise to the bus-probe concept and the proposed framework in a real application. On the other hand, the findings should not be generalized without careful examination of specific local settings.

The simulation study of bus passenger demand surge has shown that the proposed link speed-based algorithms can produce robust travel-time estimation in spite of large passenger activities. This situation is desirable and enhances the feasibility of real bus probe applications because no bus stop dwelling time is available from the real-time AVL system.

Future research is necessary. Further investigation in bus probe performance under other types of traffic changes, such as unexpected surge in traffic demand and incidents, is desirable. More efforts are needed to address issues that may arise in practice on a larger-scale network, such as the influence of day of the week and weather. In addition, computerized processes are needed to automate all algorithms and data-processing work online. This process will require software engineering and a considerable programming effort.

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