URBAN TRAVEL TIME ESTIMATION USING REAL TIME BUS TRACKING DATA

By

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In this paper, the concept of using bus probes for urban street travel time estimation in the advanced traveler information system (ATIS) application is investigated through both a thorough literature review and a case study in downtown Chicago using the Chicago Transit Authority (CTA)'s buses. First, existing bus probes studies are reviewed and compared with respect to the research objectives, facility type, data source, modeling technique, and key research findings. The literature supports the concept of bus probes to ATIS applications. However, the past studies have focused on highways (freeways and principal arterials) and used what is called archived automatic vehicle location (AVL) bus data, which are not suitable for real time forecasting (online updating). The case study presented in the second part of the paper is the first of its kind that uses real-time bus tracking data for urban signalized street travel time estimation. Multivariate time series state-space modeling techniques are applied. The case study finds significant interrelation between bus and car speeds. In particular, stronger influence of car operations (in terms of speed) is found on bus operations in the traffic stream than buses on cars. These findings indicate that AVL buses are plausible probes for urban street ATIS. This conclusion, however, must be understood within the study limitations discussed at the end of the paper.

1 Introduction

Travel time is the most preferred information by travelers (Lappin, 2000). Many metropolitan areas in the United States are currently providing real-time travel time information on freeways and principle arterials. On the other hand, signalized urban streets are largely in void of real-time travel time information. One apparent explanation is the lack of appropriate traffic data on urban streets. The reason for it is the difficulties in reliable travel time and speed measurements on urban streets and thus travel time or speed prediction cannot be directly established (Vlahogianni et al., 2004).

On freeways and principal arterials, traffic information is typically measured with traffic sensors. There are inductive loop detectors, ultrasonic detectors, remote traffic microwave sensors (RTMS), and other fixed location detection devices. They are point traffic detection devices, typically measuring traffic volume and occupancy. Some also detect point speed (Coifman, 2002). The traffic information is used for the purposes of both advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). For example, majority of the urban travel time forecasting efforts are based on loop detector[1] information (Sisiopiku, 1994; Anderson and Bell, 1997; Palacharla and Nelson, 1999; Jiang and Zhang, 2001; Li, 2002; Stathopoulos and Karlaftis, 2003; Lucas et al., 2004; Robinson and Polak, 2005; Guo and Jin, 2006).

Although popular, the disadvantages of loop detectors in ATIS application, especially on signalized urban streets, are noteworthy. First, travel time and speed are the preferred traveler information in ATIS (Vlahogianni et al., 2004), whereas loop detectors

[1]Loop detector hereafter broadly refers to the aforementioned fixed location traffic detection devices.

measure traffic volume and occupancy. Travel time and sometimes travel speed are derived measures upon such assumptions as vehicle length and traffic speed-density-volume relationships (Petty et al., 1998; Dailey, 1999). In the case of dual loop detectors where traffic speed can be directly measured, travel time must still be carefully derived (Coifman, 2002). Uncertainties and errors in travel time calculation are deemed unavoidable. Second, loop detectors at signalized intersections are designed primarily for traffic signal control purposes and may not be suitable for providing travel time and speed information. For example, when vehicle queues persist over the detector location, travel time prediction is practically impossible (Sisiopiku, 1994). Sen et al. (1996) concluded that there existed considerable informational gaps in estimating travel times using loop detectors on arterial links unless there was sufficient coverage of detectors on all lanes, all links for all movements (especially turning movements), which could be cost prohibitive. Third, in predicting real-time travel times, not only are real-time traffic measurements necessary but real-time traffic signal timing information is often demanded. However, these requirements become insurmountable obstacles where traffic signal controls are not integrated or do not have the online reporting function.

In comparison, probe vehicles can directly measure speed and travel time between two interested locations and are considered one of the most promising data sources for arterial travel time estimation (Sen et al., 1996). In theory, any vehicle can be a probe as long as the vehicle can be tracked continuously or at least recognized at the starting and ending points of a route. Examples are personal vehicles instrumented with automatic identification tags (Chien and Kuchipudi, 2003; Dion and Rakha, 2006), identifiable by video cameras (MacCarley, 1998; Innamaa, 2001), traceable by cellular phone signals (Bar-Gera, 2007; Fontaine and Smith, 2007), or equipped with global positioning satellite (GPS) devices (Quiroga and Bullock, 1998; Taylor et al., 2000) or radio communication systems (Sen et al., 1999). Other probe vehicles can be pickup-delivery trucks (Ando and Taniquchi, 2006), taxis (Zhang et al., 2007), or transit buses equipped with automatic vehicle locators (AVL) (Cathey and Dailey, 2002). In reality, large-scale deployment of probe vehicles on urban streets is quite limited because the sample size requirement is not easy to meet, producing unreliable travel time/speed predictions. Cell phone probes may eliminate the sample size problem, but additional design refinements are needed before the first-generation wireless location technology (WLT)–based monitoring system can work reliably across a broad spectrum of roadway conditions (Fontaine and Smith, 2007). In addition, noise in cellular phone data, coming from multiple sources, can be enormous, which presents a major technical hurdle to overcome in obtaining accurate travel time and speed measurements (Bar-Gera, 2007). Other issues with cell phone probe data include privacy concerns, ineffective sensor in congested traffic conditions, and incompatibility between different cell phone networks (Wunnave et al., 2006).

Transit buses do not have those limitations. Transit buses travel alongside automobiles and even share lanes on urban streets. Quite often both experience similar intersection signal controls, traffic congestions and even traffic incidents. The interrelation between bus and car traffic seems inevitable and indeed has been found in several studies (Koshy and Arasan, 2005; Fernandez and Tyler, 2005). This interrelation provides the theoretical basis for using buses as probe vehicles. In addition, the already system-wide deployment of bus AVL technologies makes bus probes technically feasible and financially attractive. According to the U.S. Department of Transportation, two thirds of the 19 largest American transit agencies had their fleet fully equipped with AVL technology by 2004 and in particular the Chicago Transit Authority (CTA) is among those 100% AVL equipped agencies (U.S. Department of Transportation, 2007).

Even with AVL technologies being available, bus probe data may still be a concern for ATIS purposes. Application of AVL data thus far has mostly been with the so-called archived AVL data (Furth et al., 2003, 2006). That is, AVL data is recorded on an on-board computer in real time and only uploaded to a central server at the end of the daily bus operation. This feature has limited the application to historical travel time estimation (e.g., historical trend analysis). Real-time travel time broadcasting and forecasting (or sometimes referred to as "online updating") are not possible with archived AVL data. In fact, all of the existing urban street bus probe studies used archived data, either automatically or manually collected (Bertini and Tantiyanugulchai, 2004; Bae, 1995; Chakroborty and Kikuchi, 2004). More discussion is followed in next section.

Using AVL bus probes for urban (signalized) street travel time (speed) forecasting must overcome the following technical obstacles: (1) the sample size requirement, (2) data type as discussed above and (3) methodological challenges, to be discussed later. The sample size requirement includes (a) link sample size or reporting frequencies from probe vehicles on each link and (b) area sample size or link coverage (proportion of links to be sampled) during the measurement period. Past Studies have different recommendations of the minimum sample size requirement (Srinivasan and Jovanis, 1996; Sen et al., 1997;

Hellinga and Fu, 1999; Cheu et al., 2002). For example, Sen et al. (1997) suggest that at least five probe reports per link per measurement period needed for reliable estimation. Cetin et al. (2005), using traffic simulation techniques, find that fewer probe reports (less than five or even one) are possible to provide good travel time predictions. Li and McDonald (2002) demonstrate that using a single probe vehicle could produce reasonable update of historical (or "static") link travel time except under congested traffic conditions. Such inconsistency in the literature only points to the complexity of the problem in using bus probes for urban street travel time prediction.

The complex nature of urban traffic imposes challenges on real-time travel time prediction. Unlike freeway traffic, urban traffic is interrupted by traffic signals and is composed of both through and turning movements. A good proportion of travel time on urban streets is attributed to intersection delays. Local specification of signal timing and phasing makes the prediction even more difficult and model transferability less likely.

In this paper, the concept of using AVL bus probes for urban street travel time prediction in ATIS[2] is investigated through both a thorough literature review and a case study in downtown Chicago using the Chicago Transit Authority (CTA)'s buses equipped with AVL devices. As one of its kind, this study is the first to investigate the feasibility of using real-time bus tracking data (as opposed to archived AVL data) collected from urban signalized streets for travel time prediction by employing multivariate time series state-space modeling techniques, which treat intersection delays endogenously and are easily

[2]It is worth mentioning that there are real applications of transit buses as probes monitored by Traffic Signal Control for the purpose of determining arterial speeds or travel times in ATMS, in six major U.S. metropolitan areas. See http://www.itsdeployment.its.dot.gov/SurveyOutline1.asp?SID=tm. On the other hand, using AVL bus probes for urban street ATIS is very limited.

adaptable to different urban environments and online updating where quick predictions are desired.

The rest of the paper is organized as follows. Section 2 presents a thorough literature review on the state-of-the-art bus probe research in travel time (or speed) prediction. The review is focused on the research objectives, facility type, data source, modeling techniques, and key research findings. An extended discussion drawn from the literature review is included at the end of the section. Section 3 describes the design of the case study, including the study objectives, modeling techniques, study segment, and data preparation. This is followed by analysis results in Section 4 and concluding remarks in Section 5.

2 State-of-the-Art Research in Bus Probe Travel Time Prediction

Compared with the rich body of literature in travel time prediction based on loop detectors and video cameras, the literature of bus probes is very limited. To the authors' best knowledge, only six case studies are in existence in the U.S. thus far. Bae's dissertation research completed in May 1995 was among the first of this kind (Bae, 1995). In late 1995, a transit probe project intended to measure roadway congestion was kicked off in Orange County, California (Hall and Vyas, 2000). This project ended in failure at the end of the 1990s, but nonetheless provided valuable lessons to later studies. In the late 1990s and the early 2000s, Dailey and his colleagues used AVL buses as speed sensors to estimate real-time traffic conditions in King County, WA (Dailey and Elango, 1999; Elango and Dailey, 2000; Dailey and Cathey, 2002, 2003, 2005; Cathey and Dailey, 2002, 2003). This is by far the only real application of bus probes[3]. Two other studies were conducted almost at the same time in the early 2000's. One was the Tri-County Metropolitan Transit District (TriMet) in Portland, Oregon (Bertini and Tantiyanugulchai, 2004), and the other was supported by the Delaware Department of Transportation (Chakroborty and Kikuchi, 2004). The most recent bus probe study was by Coifman and Kim (2006) on a freeway segment in Central Ohio. Table 1 summarizes the key features of the six studies with respect to study objective, data source, facility type, modeling approach, and key findings, each of which is discussed in detail next.

Table 1. Summary of bus probe studies

Study	Objective	Facility type	Bus Data	Car Data	Model	Conclusion
Bae (1995)	Travel time and speed probe	Urban streets	Manually recorded	Test vehicle	Simple linear regression, ANN	Buses can be probes
King County, WA (Dailey *et al.* 1999-2005)	Speed probe	Freeways and principle arterials	Real-time AVL	Loop detector	Kalman filter, Speed mapping	Buses are used as speed probes in reality
Orange County, CA (Hall and Vyas, 2000)	Congestion detection	Urban streets	Generated by their own AVL tracking system	GPS floating car	Simple linear regression	Buses are imperfect probes
Delaware DOT (Chakroborty and Kikuchi, 2004)	Travel time probe	Urban arterials	Manually recorded	Test vehicle	Simple linear regression	Bus probe is promising
TriMet (Bertini and Tantiyanugulchai, 2004)	Travel time and speed probe	Urban arterials	On-vehicle archived AVL	GPS floating car	Simple linear reverse regression	Buses can be probes
Central Ohio (Coifman and Kim, 2006)	Travel time and speed probe	Freeways	Real-time AVL	Loop detector	Filtering	Bus speeds are consistent with car speeds

[3]The bus probe predicted traffic information is currently accessible through the Washington Department of Transportation web page: http://www.wsdot.wa.gov/traffic/seattle/

2.1 Research Objective and Facility Type

The research objectives of the six bus probe studies are noticeably different. The King county study used buses as supplemental speed sensors to loop detectors on highways. The ultimate goal was to create speed mapping over space and time for point-to-point travel time estimation. The Central Ohio study used AVL buses to measure travel time and average speeds and thereby traffic conditions on a freeway segment. The other four studies were carried out on urban arterials. The Orange County study was intended for congestion detection on urban streets by comparing the estimated bus speed to a nominal free-flow speed. The TriMet study investigated the extent to which the travel times and speeds of buses and cars on urban arterials are interrelated. The Delaware study and Bae's dissertation concentrated on building the relationships between bus and car travel times on urban arterials.

2.2 Data Source

Two types of data are required in bus probe studies: bus AVL data and vehicle traffic data. Four of the six studies acquired the bus AVL data and the other two (Bae's study and the Delaware study) manually collected the bus data as if the bus AVL systems had been in place. In the four urban arterial bus probe studies, the vehicle traffic data was collected manually by the research teams using test vehicles (with or without GPS). Constrained by limited manpower and budget, the general traffic data may suffer from the small sample size problem.

2.3 Modeling

In the travel time estimation/prediction literature, many modeling techniques have been explored, such as artificial neural networks (ANN) (Anderson and Bell, 1997; Palacharla and Nelson, 1999; Jiang and Zhang, 2001; Li, 2002; Liu et al., 2006a), multivariate state space models (Stathopoulos and Karlaftis, 2003), platoon recognition (Lucas et al., 2004), statistic mean and variation (Liu et al., 2005), k-nearest neighbors (Robinson and Polak, 2005), cross-correlation (Guo and Jin, 2006), traffic simulation (Liu et al., 2006b), the Bureau of Public Roads (BPR)'s link performance function and the Highway Capacity Manual (HCM) intersection delay function (Tsekeris and Skabardonis, 2004).

In modeling the relationships between bus and general vehicle travel time/speed, linear regression is the most commonly used technique. For example, Bae (1995) fitted the following simple linear model for travel time and speed:

$$CTT = a_1 + b_1 * BTT \tag{1}$$

$$CTS = a_2 + b_2 * BTS \tag{2}$$

where *CTT* is the car travel time, *BTT* is the bus travel time after excluding the dwell time at bus stops, *CTS* is the segment average car travel speed and *BTS* is the segment average bus travel speed.

The Delaware study (Chakroborty and Kikuchi, 2004) used a similar approach and further classified roads into less frequently and more frequently congested categories:

$$CTT = \begin{cases} \dfrac{length\ of\ \ section}{free\ speed\ of\ \ section} + 0.14(BTT - TST),\ \ for\ less\ \ frequently\ \ congested\ roads \\ \dfrac{length\ of\ \ section}{free\ speed\ of\ \ section} + 0.18(BTT - TST),\ \ for\ more\ \ frequently\ \ congested\ roads \end{cases} \tag{3}$$

where *TST* is the total bus stopping time at bus stops.

The TriMet study (Bertini and Tantiyanugulchai, 2004) applied a reverse regression and found the following relationship existed:

$$CTS = 0.72*MIBS + \varepsilon \tag{4}$$

where *MIBS* is the maximum instantaneous bus speed between two adjacent stops and ε is the random error.

In the Orange County study (Hall and Vyas, 2000), the link car speed was estimated with the following equation:

$$CTS= (N_1 * segment\ length) / (BTT – TST – N_2) \tag{5}$$

where N_1 and N_2 are empirical adjustment factors to account for performance differential between cars and buses.

In the King County study where AVL buses were primarily used as supplemental speed sensors, efforts were concentrated in obtaining smoothed instantaneous bus speeds using Kalman filter (Dailey and Cathey, 2002, 2003, 2005). The bus speeds were then mapped in space and time:

$$v = dx/dt = f(x, t) \tag{6}$$

where v is the instantaneous bus speed, x is the distance into block, and t is the minute after midnight. Point-to-point travel time could be derived from solving the above ordinary differential equation.

In the Central Ohio study (Coifman and Kim, 2006), travel time and distance (after adjusted for roadway curvature and lane changing) were directly measured, so the segment travel speed was the quotient of the travel distance and time. The travel time was the difference in the time stamps between the first and last AVL bus polling points on the study segment.

Artificial neural network (ANN) was used in Bae (1995) to associate bus speeds with ten static inputs (e.g. link length, number of lanes, number of intersections, parking availability) and six dynamic inputs (bus travel time, number of stops made, passenger boarding and alighting, number of incidents and weather condition). It was found ANN produced reasonably satisfactory speed mapping. On the other hand, ANN models could be difficult to interpret.

2.4 Key Research Findings

All except the Orange County study[4] have concluded AVL transit buses can be used as vehicle probes in detecting general traffic conditions. For example, Bae (1995) found that the conversion factor (i.e., regression coefficient) from bus to car speeds – link-based

[4] The Orange County Transportation Authority bus probe project started in late 1995 and ended in failure in May 1998. The study concluded "buses are imperfect as traffic probes". However, it appears that the failure was largely caused by the poor research design and thus the conclusion should be taken in perspective. The study developed a bus tracking system of its own that failed to attract any users at the transit agency. The burdens with respect to the operation, data maintenance and system interfaces exceeded the original expectations. As a result, the poorly performing AVL system generated very limited data for analyses - only 25 valid probe trajectories were obtained from three bus lines in the study period, which produced questionable statistics and exacerbated the performance of the intended congestion detection system.

average speeds – ranged between 0.66 (with an intercept of 11.88, which implies car speed is higher than bus speed when bus speed is below 55 km/h or 34mph) and 1.18 (with an intercept of 2.99, i.e., average car speed is always greater than average bus speed).

Buses generally travel at a lower speed than cars, such as those observed in the King County study and Bae's. For example, the data from the King County study revealed that bus speeds were on average 12.8 km/h (8 mph) lower than car speeds on freeways and 1.6 km/h (1 mph) lower on principal arterials. On the other hand, the data collected from a Central Ohio freeway showed the average link travel speeds of transit buses were generally consistent with those estimated based on the loop detector data.

The Orange County study, although ended in disappointment, identified challenges that are valuable for bus probe research. Most noticeably, buses operate according to schedules and bus drivers adjust their driving when running ahead of or behind the schedule. Such changes in travel speeds (or travel times) are irrelevant to the actual traffic conditions, and the causes, whether they are schedule related or traffic-related, cannot be identified from the AVL data alone. The other delicate issue concerns the sample coverage both spatially and temporally. Factors like large bus headway (e.g. 30 minutes) and the extent of the route coverage must be taken into consideration. A third issue has to do with the AVL data reliability related to missing observations and inaccurate or false location reporting, etc., all of which must be handled carefully during data processing.

2.5 Discussion

Thus far it has been shown that the literature generally proves the concept of utilizing buses as probes to obtain highway and arterial travel time information. It is worthwhile herein to distinguish travel time estimation and forecasting, which refer to different modeling procedures in the literature (van Lint, 2004). Travel time estimation is referred to as producing current and past estimates of travel time based on historical data; forecasting extrapolates historical and current trends to a future time interval. While this distinction may not be of concern when the interest is in finding the relationship between travel time and affecting factors, it becomes necessary in online updating applications especially when short-term future travel time is desired and when a non-recurring event is occurring (e.g., a sports event, road construction, an extreme weather condition). In the ADVANCE project, Sen and his colleagues (Sen and Thakuriah, 1995; Sen et al., 1998) proposed a travel time prediction framework that included a base model ("static model") describing the historical (normal) traffic patterns and an updating model to account for the impacts of special events such as the ones mentioned above on travel. Updating is only necessary when traffic variations are not due to randomness. This framework is appealing in real-time applications where quick predictions are desirable.

The distinction is also necessary because different types of AVL data are required. As mentioned earlier, the current AVL systems can be categorized into two types by their ability to transmit AVL data in real time, i.e., archived AVL data and real-time bus tracking data. Most of the AVL bus fleets in the country collect archived AVL data. In recent years, real-time bus tracking systems have been adopted in transit agencies (e.g., Bus Tracker at the Chicago Transit Authority) that transmit bus location information in real time. The former data type provides rich historical information about bus travel and the latter makes online updating possible. It is worth noting that, in the previous six bus probe studies, only the King County and Central Ohio studies, which focused primarily on highways, utilized real-time bus tracking data. The feasibility of using real-time AVL bus probes for urban street ATIS is yet to be demonstrated. This is what the following case study is intended for.

3 Case study Design

To be able to use buses as probes to derive traffic information one must assume bus speeds (or travel time) are dynamically interrelated to car speeds (or travel time) in the traffic stream. In other words, if buses and cars are traveling independently in the traffic stream, one cannot be inferred by the other. The objective of this case study is to identify to what extent bus and car speeds are interrelated to one another on urban signalized streets. Specifically, this paper concentrates on building the base model between bus and car speeds using real-time bus tracking data. The base model is the basis for real-time online updating (through an incremental or updating model) (Liu and Sen, 1994), which is outside the scope of this paper.

Bus and car speeds rather than travel times were used in the analysis for the following three reasons. First, in the CTA bus tracking data provided, bus speeds are directly measured while bus travel time must be derived. For different bus trips, the polling interval may be identical (e.g., every 40 seconds) but the polling locations are not fixed. This adds difficulty to the data processing when the travel time of a specified link is desired. Second, bus travel time includes bus stop dwell time and acceleration/deceleration delays when pulling in and out bus stops. These delays are unique to buses and cannot be determined without additional information, e.g., passenger activities at bus stops and bus stop configuration. Third, as demonstrated later, using speed over travel time models intersection and bus stop delays endogenously and thus the modeling complexity is reduced.

After initial screening, a multivariate state space model was chosen as the appropriate modeling tool for jointly modeling two dynamically related time series, bus speeds and car speeds. Linear regression models assume linear relationship between bus and car speeds (or travel times) and are cross-sectional models, which do not deal with the dynamical and autocorrelated nature of the data. State space models, in comparison, are nonlinear, time series models that predict the state of one time series at time t based on the observations of another time series at current and previous time points. Recent application of state space models in traffic studies is seen in Wang et al. (2007), Yang (2006), Wang and Papageorgiou (2005), and Stathopoulos and Karlaftis (2003).

The following state space model specification based on Akaike (1976) was adopted for the analysis. Equation (7) represents the state transition equation and equation (8) is the measurement equation (also known as the observation equation):

$$\mathbf{z}_{t+1} = \mathbf{F}\,\mathbf{z}_t + \mathbf{G}\,\mathbf{e}_{t+1} \tag{7}$$

$$\mathbf{x}_t = [\mathbf{I}_r\,\mathbf{0}]\mathbf{z}_t \tag{8}$$

where $\mathbf{x}_t$ is an observation vector of r elements; $\mathbf{z}_t$ is a state vector of s elements, in which the first r ($r < s$) elements are the same as in $\mathbf{x}_t$ and the last (s-r) elements are pre-specified state measures; $\mathbf{F}$ is an $s \times s$ transition matrix; $\mathbf{G}$ is an $s \times r$ input matrix, with the identity matrix $\mathbf{I}_r$ in the first $r \times r$ rows and columns; $\mathbf{e}_t$ is a vector of r independently normally distributed random errors with zero means and a covariance matrix $\mathbf{\Sigma_{ee}}$. In the following state space modeling, time step *t* is in fact the distance into the block from the starting location of the study street segment; the observation vector $\mathbf{x}_t$ always consists of the observed current bus and car speeds; and the specification of the state vector $\mathbf{z}_t$ is discussed later in the paper.

3.1 Study street segment

The Chicago Transit Authority (CTA) currently operates one real-time bus tracking system on Route #20. This system is similar to the King County's and Central Ohio's AVL systems, reporting real-time bus speed, location and heading when the bus is polled. The time interval between two successive polls is roughly forty seconds.

Route #20 is an east-west bus route running mostly on Madison Street that connects the west suburb and downtown Chicago. Two study segments were selected: eastbound Madison Street from Leavitt Street bus stop to Peoria Street bus stop with a length of 2.643 kilometers (1.643 miles), and westbound Madison Street from Morgan Street bus stop to Oakley Street bus stop with a length of 2.650 kilometers (1.647 miles) (Figure 1). There are nine signalized intersections and fifteen bus stops along the eastbound segment, and ten signalized intersections and fourteen bus stops along the westbound segment. Both segments are two-lane urban streets and the right lane is a parking lane. Buses pull into the parking lane at bus stops. The neighborhood is a mix of commercial, residential, and recreational[5] land use.

Field observations on regular vehicle speeds and travel times were conducted during a late morning normal traffic hour (10:30 a.m. – 11:30 a.m.) and an evening rush hour (5:30 p.m. – 6:30 p.m.) for five weekdays (September 4th ~ 7th and 10th, 2007). A GPS equipped passenger car was used as the test vehicle. The GPS device recorded the test vehicle's speeds, acceleration and deceleration rates, positions and other information at every 0.1 seconds. The driver was told to keep a normal speed during the survey to represent the average car driving condition as closely as possible. In the end, 20 test vehicle runs were made on each segment (eastbound and westbound) for each study period (AM and PM).

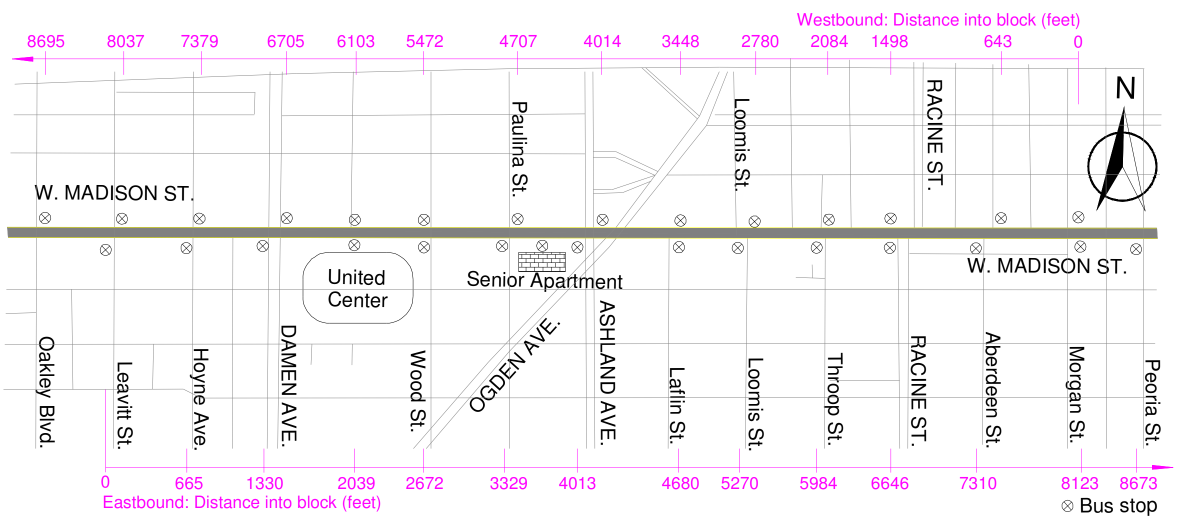


Figure 1. Study street segment

[5]United Center is home of the Chicago Bulls and Blackhawks. There were no scheduled matches during the study period.

Table 2 summarizes the study segments' statistics. The average segment travel time was around 290 to 300 seconds. Westbound PM was the busiest. The relatively small standard deviations of travel time indicate the traffic condition was quite consistent during the survey period and the test vehicle driving represented the general vehicle driving reasonably well, assuming the samples were independent and random (Hellinga and Fu, 1999). The real-time bus tracking AVL data were acquired from CTA and Clever Devices Ltd. for the same segments and study periods. There were 42, 24, 14, and 42 bus trips, respectively, during eastbound AM and PM, and westbound AM and PM. There were more eastbound bus trips in the morning than in the afternoon, and more westbound bus trips in the afternoon than the morning, because higher demand on eastbound bus trips to the City's central business district (CBD) in the morning and vice versa.

Table 2. Study segment and data

Study segment	Length (kilometers)	Number of signalized intersections	Number of bus stops	Study period	Number of bus trips	Number of test vehicle runs	Average test vehicle travel time (seconds)	Standard deviation of test vehicle travel time (seconds)
Eastbound Madison St.	2.643	9	15	AM(10:30-11:30)	42	20	291	19
				PM(5:30-6:30)	24	20	293	26
Westbound Madison St.	2.650	10	14	AM(10:30-11:30)	14	20	291	24
				PM(5:30-6:30)	42	20	303	46

3.2 Data preparation

The bus trips and test vehicle runs were separately pooled together to form four composite time series each, namely, eastbound morning (EBAM), eastbound evening rush hour (EBPM), westbound morning (WBAM), and westbound evening rush hour (WBPM). The composite speed series were constructed in the following steps:

Step 1: the study street segment was equally divided into 3.048-meter (10-feet) snippets;

Step 2: outliers within each snippets were removed. An outlier was defined by the interval [Q1 – (1.5)IQR, Q3 + (1.5)IQR], where Q1 is the lower quartile (25%), Q3 is the upper quartile (75%), and IQR is the interquartile range (IQR = Q3 –Q1);

Step 3: speed at a distance step (end point of a snippet) was the average speed of that snippet.

Step 4: where there was missing data, the missing values were linearly interpolated at distance steps where no speed observations were available.

This procedure produced the composite bus and car speed series equally spaced in distance. In addition, because the speed series were not stationary, differencing was applied to all series before the state space models were fitted. Bus speeds of WBPM were differenced in the second order to achieve convergence. All other speed series were transformed with the first order differencing.

4 Results

Four state space models were fitted for EBAM, EBPM, WBAM, and WBPM. As mentioned before, the observation vector $\mathbf{x}_t$ was the observed (composite), differenced bus and car speeds. The state vector ($\mathbf{z}_{t+1}$) was specified differently for each of the four scenarios to achieve the best model fit[6]: (1) $\mathbf{z}_{t+1} = \left(S^c_{t+1}, S^b_{t+1}, S^b_{t+2}\right)^T$ in EBAM, where *S* stands for speed (after differencing) and superscripts *c* and *b* stand for car and bus

[6] Goodness of fit of a state space model is measured with the minimum Akaike Information Criterion (AIC) value achieved.

respectively, (2) $\mathbf{z}_{t+1} = \left(S_{t+1}^c, S_{t+1}^b, S_{t+2}^c\right)^T$ in EBPM, (3) $\mathbf{z}_{t+1} = \left(S_{t+1}^c, S_{t+1}^b, S_{t+2}^c, S_{t+2}^b\right)^T$ in WBAM, and (4) $\mathbf{z}_{t+1} = \left(S_{t+1}^c, S_{t+1}^b, S_{t+2}^c, S_{t+2}^b, S_{t+3}^b\right)^T$ in WBPM.

The model estimation results are shown in Table 3. If the bus and car speeds are interrelated as hypothesized, the corresponding elements in the transition matrix (**F**) are expected to be statistically significant. For example, in the first scenario (EBAM), parameter F(1,2) represents the dependency of car speed (S_{t+1}^c) on bus speed (S_t^b) and F(3,1) the dependency of bus speed (S_{t+2}^b) on car speed (S_t^c). The t-statistic value of $t_{F(1,2)}$ (=0.96) indicates that car speed (S_{t+1}^c) is not significantly related to bus speed (S_t^b). On the other hand, the t-statistic value of $t_{F(3,1)}$ (=2.18) indicates that bus speed (S_{t+2}^b) is significantly related to car speed (S_t^c).

In both EBAM and EBPM, bus speeds are significantly related to car speeds and bus speeds, but the opposite is not found. In the westbound direction, where traffic is usually heavier than the opposing direction, bus and car speeds are found interrelated in both AM and PM scenarios. Moreover, when the transition parameters are significant, bus speeds are found much more highly dependent on car speeds than car speeds on bus speeds. For example, in WBAM, the transition parameter from bus speed (S_{t+1}^b) to car speed (S_{t+2}^c) is 0.14 (t-stat = 1.99), compared to 3.39 (t-stat = 3.41) from car speed (S_{t+1}^c) to bus speed (S_{t+2}^b). These findings confirm that there exists interrelation between bus and car operations in the traffic stream. They are also consistent with our expectation that stronger interaction (and interrelation) exists when traffic is heavier and that bus operations are likely to be more affected by general traffic than the other way around. On a given urban street segment, delays account for a non-trivial, even major, proportion of the total travel time. In light traffic, the dominant sources of delay for buses and cars are quite different. When traffic is heavier, buses and cars experience similar and increasing traffic related delays and their operations in the traffic stream are much more alike.

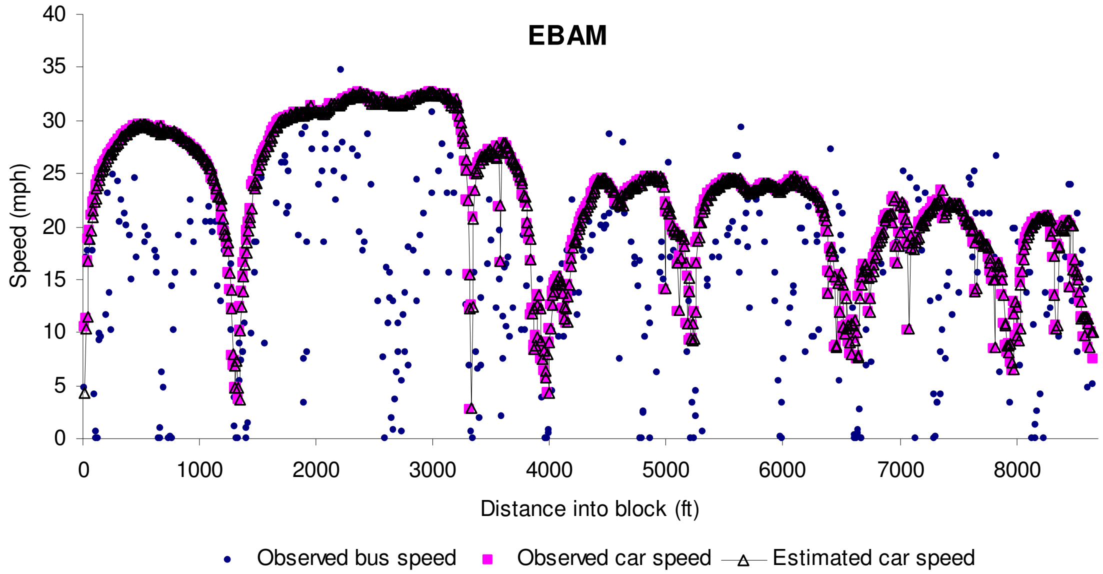
The small standard deviations of the car speed estimates indicate that the state space models produce very good estimations of the car speeds. This is also confirmed visually by the EBAM and WBPM plots of the observed bus and car speeds and the estimated car speeds in Figure 2. In general, the car speeds are found to be higher than the bus speeds. The first 1,200 meters (4,000 feet) of the eastbound segment (or the last 1,200 meters of the westbound segment) has higher bus and car speeds due to less off-street commercial activities, lower traffic volume and wider road surface. Bus stops and major signalized intersections are clearly identified.

The travel time to traverse the study segment was also estimated based on the estimated car travel speeds from the state space models. It was assumed that car traveled at a constant speed on each snippet. The estimation results are shown in Table 4. They are in very good agreement with the observed travel times. This suggests a base model built on state space modeling techniques, real-time bus tracking data, and a priori car speed input is plausible. Such a base model provides a good basis for online updating with the continuous incoming bus tracking data in real time.

Table 3. Model estimation results

Scenario	Model specification and parameter estimation	t-value[1]	Std. dev. of car speed estimation[2]
EBAM	$\begin{pmatrix} S^c_{t+1} \\ S^b_{t+1} \\ S^b_{t+2} \end{pmatrix} = \begin{pmatrix} -.02 & .01 & 0 \\ 0 & 0 & 1 \\ .19 & -.11 & .47 \end{pmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^b_{t+1} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ .11 & -.16 \end{pmatrix} \begin{pmatrix} e^c_{t+1} \\ e^b_{t+1} \end{pmatrix}$ $\begin{pmatrix} S^c_t \\ S^b_t \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^b_{t+1} \end{pmatrix}$	$t_{F(1,1)} = -.48$ $t_{F(1,2)} = .96$ **$t_{F(3,1)} = 2.18$** **$t_{F(3,2)} = -2.66$** **$t_{F(3,3)} = 5.17$** $t_{G(3,1)} = 1.40$ $t_{G(3,2)} = -4.59$	2.54km/h (1.58mph)
EBPM	$\begin{pmatrix} S^c_{t+1} \\ S^b_{t+1} \\ S^c_{t+2} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 1 \\ .25 & .07 & 1.62 \\ -.13 & .00 & -.04 \end{pmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^c_{t+1} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ -.08 & -.01 \end{pmatrix} \begin{pmatrix} e^c_{t+1} \\ e^b_{t+1} \end{pmatrix}$ $\begin{pmatrix} S^c_t \\ S^b_t \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^c_{t+1} \end{pmatrix}$	**$t_{F(2,1)} = 2.98$** $t_{F(2,2)} = 1.70$ **$t_{F(2,3)} = 5.38$** **$t_{F(3,1)} = -4.03$** $t_{F(3,2)} = .15$ $t_{F(3,3)} = -.20$ $t_{G(3,1)} = -2.43$ $t_{G(3,2)} = -.31$	2.35km/h (1.46mph)
WBAM	$\begin{pmatrix} S^c_{t+1} \\ S^b_{t+1} \\ S^c_{t+2} \\ S^b_{t+2} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -.03 & .01 & -.70 & .14 \\ .50 & -.16 & 3.39 & .60 \end{pmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^c_{t+1} \\ S^b_{t+1} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ -.06 & .02 \\ -.14 & -.05 \end{pmatrix} \begin{pmatrix} e^c_{t+1} \\ e^b_{t+1} \end{pmatrix}$ $\begin{pmatrix} S^c_t \\ S^b_t \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^c_{t+1} \\ S^b_{t+1} \end{pmatrix}$	$t_{F(3,1)} = -.80$ $t_{F(3,2)} = .68$ **$t_{F(3,3)} = -2.97$** **$t_{F(3,4)} = 1.99$** **$t_{F(4,1)} = 3.63$** **$t_{F(4,2)} = -2.78$** **$t_{F(4,3)} = 3.41$** **$t_{F(4,4)} = 2.98$** $t_{G(3,1)} = -1.92$ $t_{G(3,2)} = 1.74$ $t_{G(4,1)} = -1.77$ $t_{G(4,2)} = -1.37$	2.29km/h (1.42mph)
WBPM	$\begin{pmatrix} S^c_{t+1} \\ S^b_{t+1} \\ S^c_{t+2} \\ S^b_{t+2} \\ S^b_{t+3} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ -.07 & -.02 & .53 & .05 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ -.04 & .06 & -.83 & .15 & .81 \end{pmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^c_{t+1} \\ S^b_{t+1} \\ S^b_{t+2} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ -.09 & -.01 \\ -.02 & .63 \\ -.03 & -.28 \end{pmatrix} \begin{pmatrix} e^c_{t+1} \\ e^b_{t+1} \end{pmatrix}$ $\begin{pmatrix} S^c_t \\ S^b_t \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} S^c_t \\ S^b_t \\ S^c_{t+1} \\ S^b_{t+1} \\ S^b_{t+2} \end{pmatrix}$	**$t_{F(3,1)} = -1.98$** **$t_{F(3,2)} = -2.11$** **$t_{F(3,3)} = 4.62$** **$t_{F(3,4)} = 2.50$** $t_{F(5,1)} = -.47$ $t_{F(5,2)} = 1.78$ **$t_{F(5,3)} = -2.49$** **$t_{F(5,4)} = 2.80$** **$t_{F(5,5)} = 17.44$** $t_{G(3,1)} = -2.96$ $t_{G(3,2)} = -.44$ $t_{G(4,1)} = -.21$ $t_{G(4,2)} = 19.71$ $t_{G(5,1)} = -.48$ $t_{G(5,2)} = -8.86$	2.85km/h (1.77mph)

[1]Those that are statistically significant are highlighted in bold.
[2]These are the standard deviations of the estimated car speeds, not the estimated differenced values.



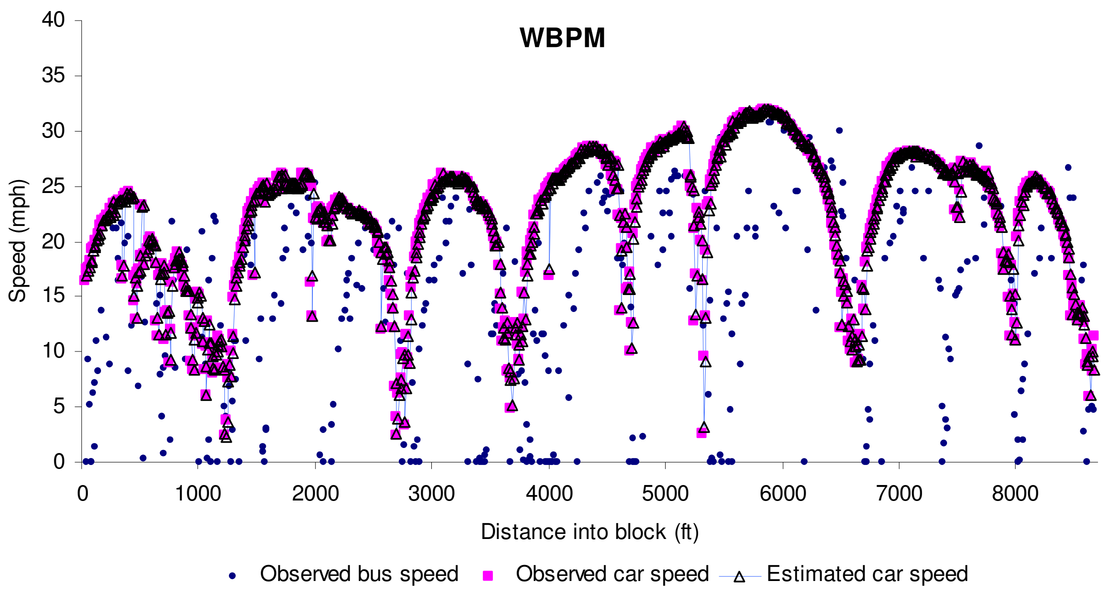


Figure 2. Model estimation results

Table 4. Travel time estimation results

Scenario	Observed average test vehicle travel time (seconds)	Estimated average test vehicle travel time (seconds)
EBAM	291	296
EBPM	293	289
WBAM	291	292
WBPM	303	303

5 Conclusions

This paper has demonstrated the plausible concept of using bus probes for ATIS urban street travel time prediction through both a thorough literature review and a case study in downtown Chicago using real time bus tracking data. The literature review finds that buses can be used as probes to infer travel information. However, the real application of AVL bus probes for ATIS applications on urban signalized streets is very limited. In addition to the complex nature of the problem, data availability has been a hindrance. Although most major metropolitan areas have AVL buses running on streets, the archived AVL data is not suitable for real time travel time prediction or online updating.

This study is the first in demonstrating the use of real-time AVL bus tracking data to predict car speeds on a two-lane urban signalized street. The case study finds stronger influence of car operations (in terms of speed) on bus operations in the traffic stream than bus on car. In particular, car speeds are found to be unaffected by bus speeds in light traffic even though significant influence is found in reverse, probably due to the prevalent presence of cars in the traffic stream. Therefore, the case study concludes that buses can be probes for travel information on signalized urban streets, especially under medium to heavy traffic conditions.

Multivariate state space modeling proves to be a plausible modeling tool compared to linear regression modeling. State space modeling is consistent with the time series nature of the bus and car speed (or travel time) data, that is, bus (or car) speed depends on its own preceding profile (i.e., autocorrelation). State space models are also able to quantify the interrelation between bus and car speeds with or without lags. Regular linear regression does not model the dynamic evolution of the series as state space models do.

Using speed rather than travel time in the models is an appealing idea because many factors causing travel delays on urban streets are now modeled endogenously, which facilitates the idea of transferring the model framework from one urban street to another. On the other hand, this approach becomes disadvantageous when the effects of those factors are wished to be explored explicitly.

Limitations of the study are noteworthy. The study street segment has relatively simple physical and geometrical configurations. It has a straight horizontal alignment and a flat vertical alignment throughout. There are no significant changes in geometry. Although the study segment has two lanes each direction, the right lane is a parking lane so traffic is practically running on one lane. On a street where there is more than one lane of traffic in the same direction, buses tend to stay on the right most lane. In such cases, the adequacy of using buses as probes to infer traffic conditions on other lanes remains to be seen. Another limitation has to do with the almost perfect grid layout of the streets in downtown Chicago. Most of the CTA buses are operating either north-south or east-west. So bus probes may prove to be ineffective for turning traffic. There is no readily available answer to those hard questions. More research is needed. As the CTA is rapidly expanding real-time bus trackers to the entire bus system, more data will be available and some of those research questions can be addressed.

Ultimately, the real value of real-time bus tracking data is in being utilized for real-time travel time forecasting through online updating of the static traffic pattern, estimated by a base model, upon continuously received bus operation information. Issues related to sample size and robustness of the updating are ongoing research efforts.

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