Using Bus Travel Time Data to Estimate Travel Times on Urban Corridors

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Obtaining near real-time information of travel times is a critical element of most applications of intelligent transportation systems. The use of transit vehicles as probe vehicles for collecting travel time data for automobiles on urban corridors was examined. Because transit vehicles are increasingly equipped with an automated vehicle locator (AVL) for reporting the current location of the vehicle, it may be possible to use the AVL data for travel time purposes. In anticipation of such an application of AVL, the relationship between travel times of a transit vehicle and of an automobile is examined for stability of data and adjustment needs. Travel times of transit vehicles and automobiles were measured simultaneously along the same sections on major corridors in Delaware. The difference in travel times was relatively stable, and, hence, appropriate formulas for predicting the travel time of automobiles were developed. The model coefficients were found to be reasonable and stable for various traffic conditions. The study suggests that the AVL-equipped transit vehicle can be used as a probe vehicle to collect travel time data at regular intervals with minimum cost.

Applications of transportation demand management (TDM) and intelligent transportation systems (ITS) have become the central strategy for mitigating congestion in many cities. An important element of such schemes is a system that collects, predicts, and disseminates traffic information to drivers in real time (*1, 2*).

Perhaps the most critical information required by the traveler and managers of ITS is the travel time on the links of the network. The problem, however, is how to collect the data, predict travel time for the immediate future, and disseminate the information continuously. Much research is being conducted into each of these aspects, including the device and mechanism with which to collect and transmit travel times. Figure 1 is a schematic of the state of the art in travel time prediction, and the figure identifies where the topic of this paper fits into the scheme of travel time prediction.

This study examines the possibility of using transit vehicles (buses) as probe vehicles for collecting data for predicting automobile travel time. This idea is motivated by the introduction by a large number of transit agencies of the automated vehicle locator (AVL) on their buses. AVL uses a Global Positioning System (GPS) to report the current location of the bus as it travels. The original purpose of AVL was to provide arrival time information to passengers and to report the current location to transit management. However, the information collected by AVL could also become the basis for calculating the travel time of automobiles. As discussed here, the use of buses as an information source has several benefits.

Despite the utility of buses as a possible data source on travel time, little or no work has been done to investigate the validity and usability of this source and how to convert the data to predict the average travel time of automobiles. This study determines whether buses can be used as probe vehicles in an urban traffic stream by analyzing the nature of the information collected by the buses and developing formulas to convert the travel time of a bus to that of the automobile. For this study, a large volume of data on bus and automobile travel times was collected and analyzed on various sections of arterials in the northern part of New Castle County, Delaware.

DESCRIPTION OF PROBLEM

The problem analyzed here is to develop a procedure that predicts the average travel time of the automobile, ATT, as based on the observed travel time of a bus, BTT, in the same traffic stream. The procedure should be simple yet accurate. The tasks involved are as follows:

- To measure the travel time of the bus and of the automobile for the same section at the same time;
- To analyze the characteristics of the components of BTT and their variability;
- To develop a model that converts the travel time of the bus to the average travel time of the automobile; and
- To verify the model by the data collected.

Consider the schematic presentation of the changes in travel time between two points over time shown in Figure 2. The solid line shows the average travel time of the automobile from Point A to Point B for the corresponding departure time on the *x*-axis; the line indicates that the vehicle that departs A at time *T* takes *Z* minutes to reach B on the average. The purpose of the travel time prediction models, in general, is to predict travel times that are close to this solid line. The figure also shows *x*, which indicate BTT over the same section for the corresponding departure times on the *x*-axis. These points are expected to be located above the solid line (which are ATTs).

The problem at hand is to produce the solid line from the observed BTT points (x). To do this, one would need to convert the observed BTT points x to points +, which are located close to the square dots on the solid line. Then, the + points are used to estimate the ATT that is expected before the next BTT data are updated. This is the model for predicting ATT in this study. Thus, the output of the model is the predicted travel times as shown by the dotted line. In this case, the predicted travel time is assumed to be equal to the estimate (represented as +) obtained from the last available BTT.

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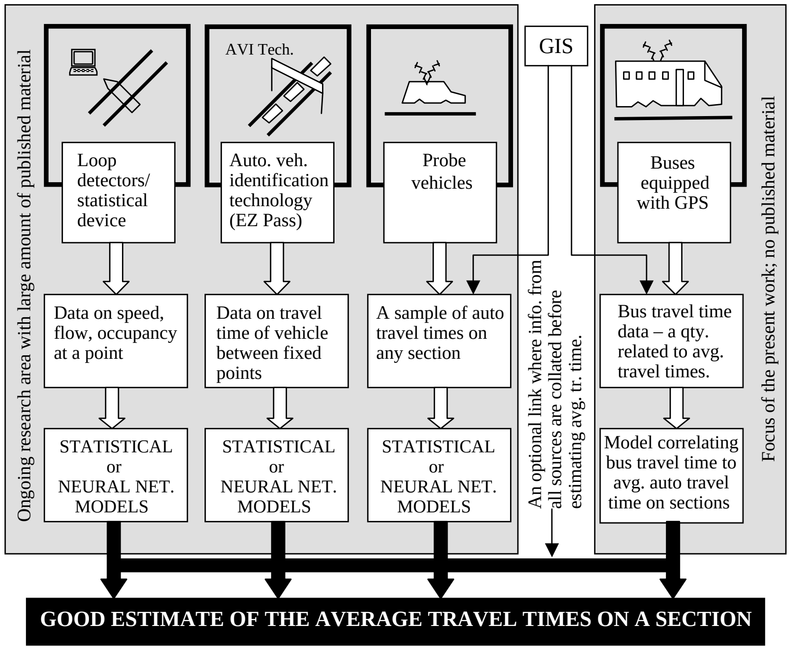

FIGURE 1 Architecture of travel time prediction (GIS = geographic information system).

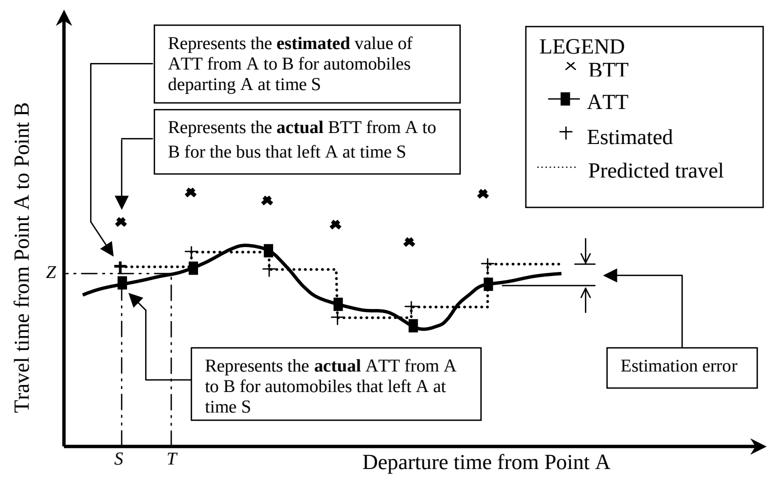

FIGURE 2 Problem of estimating average travel time from BTT.

Obviously, the prediction will be good if the points indicated by the + are close to the square dots. Further, if the + points are closely spaced, the predicted travel time should be closer to the actual travel time. The spacing of the x is solely dependent on the frequency of buses (or measurement intervals).

Thus, the success of the use of buses as probe vehicles is measured by how closely one can estimate ATTs from the corresponding BTTs (x). To measure the success, one must understand the allowable accuracy (error) and the practical distance for which the travel time is predicted.

Issues of Accuracy

Before proceeding with any estimation or prediction, a pertinent question is how accurate the predictions (ATT) should be. In the context of the potential application, this question translates to, By how much could the predicted travel time be off from the one experienced by the driver before these predictions become useless to the driver? No study so far has addressed this question. Because improved accuracy invariably complicates the measurement plans and the procedure of conversion (BTT to ATT), this question is addressed before the analysis is made.

A reference for answering this question can be how a typical automobile driver values the difference in travel time between what is predicted and what takes place. This has been investigated by researchers in transportation economics. Small presented a survey of estimates of the value of travel time (*3*). Calfee and Winston suggested that the value (in monetary terms) of travel time is between \$0.05 and \$0.12 per minute (*4*). From these studies, it can be concluded that 1 or 2 min of error (in predicted travel time) for a travel time of

10 to 15 min is tolerable by the average traveler considering traffic signals and the usual perturbations in traffic. That is, the tolerable error of the estimate may be about 10% to 15% of the actual travel time. In fact, this estimate of allowable error may well be a very conservative one. Similar observations on allowable error in travel time measurements were made by Toppen and Wunderlich (from their analysis of Los Angeles) (*5*). Figure 2 shows the definition of errors. As shown in the figure, the vertical distance between the point represented by + (denoting estimated ATT) and the corresponding point represented with a black square (denoting the corresponding actual value of ATT) is the error in estimation.

Issue of Distance

Another issue of interest concerns over what distances one should predict travel time. Some studies have considered sections as small as 0.14 km (about 0.1 mi) (*6*). It is thought that for travel time predictions to be useful, the distance over which travel time is predicted should be long enough so that predicted time is meaningful to the average driver. For example, if one assumes 55 km/h (about 35 mph) as the average speed on urban arterials, then the reasonable minimum length of sections (based on a travel time of at least 5 min) comes out to be about 4.6 km (about 3 mi). Similar calculations can easily yield a rough rule of thumb on the minimum length of sections over which travel time should be predicted on different types of arterials.

LITERATURE REVIEW AND MOTIVATION

The problem of predicting travel time on urban roads (or any road) has long been a topic of research. The initial motivation for developing these models was their use in traffic assignment and dial-a-ride problems, and that travel time is perhaps the most important performance measure of a transportation system. One of the first studies on this topic resulted in the Bureau of Public Roads equation that tried to relate travel time on a link to the volume on that link (*7*). Another of the early studies was by Sussman et al. (*8*), who tried to develop relations for predicting travel time between two points from the Cartesian distance between the two points. In recent years, the interest in predicting travel times has increased with the activities related to ITS. A large number of studies are being conducted. Some studies use loop or other static detector data (*9–13, 6*). Sisiopiku and Rouphail gave a good review of early work on use of loop detector data for travel time estimation (*14*). Others have studied the use of probe vehicles (vehicles equipped with GPS) to estimate travel time (*15, 16*). Yet others, like Park et al. (*17*), used data from automatic vehicle identification stations to estimate travel time. The methodologies used in these studies fall primarily into two classes for expressing the measured variables and the variables to be predicted: statistical estimation techniques, like regression analysis and cross-correlation, and artificial neural networks. Further, many of the existing works concentrate on predicting travel time on freeways and not on urban arterial roads. Zhang rightly pointed out that, “[T]he interrupted nature of traffic flow on arterial routes and numerous other factors . . . however, make the estimation of travel time on arterials a much more challenging task” (*13*). Similar observations were made by Sisiopiku and Rouphail (*14*).

Although researchers have looked at probe vehicles as possible sources of data, no one has considered buses as another kind of probe vehicle. A search of the literature yielded few papers that looked at buses as probe vehicles. Hall and Vyas used buses as probes for detecting incidents (*18*), and Elango and Dailey (*19*) and Cathey and Dailey (*20*) looked at use of buses as traffic probes for measuring spot speeds. However, these papers did not give any relation that can be used to predict average travel time (over a reasonable section of a road) based on BTT. Use of buses as probe vehicles adds little or no financial burden to a transit agency, because most buses are equipped with GPS for predicting bus arrival times. Further, a large number of buses run on the most used arterials (the ones that are of greater importance for average ATT prediction) and generally have higher frequencies during peak periods. These characteristics of bus routes and schedules make them ideal as probe vehicles. Even if bus-based prediction systems cannot be used as stand-alone systems for predicting travel times, buses certainly can augment travel time information available from various other sources. Although buses can be used as probe vehicles, they cannot be treated as ordinary probe vehicles because of various characteristics inherent to the travel pattern of the bus (which are discussed later). This study tries to analyze the issues involved in use of buses as probe vehicles and explores whether BTTs can be used effectively to predict average ATTs.

CHARACTERISTICS OF BTT DATA

When using bus travel as the source of information for predicting ATT, one needs to be cognizant of the unique aspect of BTT. It is important to recognize that the difference between ATT and BTT is a random variable even for the same section of a corridor because of the following reasons.

Buses stop at bus stops. They leave and join the traffic stream many times during their travel; therefore, they incur additional time for merging and diverging as well as deceleration and acceleration to and from a stop. Buses idle at bus stops to collect and discharge passengers for a certain amount of time. Because the number of times that a bus stops and the duration of stop vary randomly, the BTT’s difference from the average travel time of the stream is a random variable.

Typically, buses travel in the rightmost lane of an urban corridor. The average speeds differ among the lanes. That buses travel in the rightmost lane introduces a bias in the travel time of buses. In addition, often in suburban operations, buses may leave the urban corridor and enter large developments—a shopping center or employment center. In this case, obviously the measured BTT and ATT are significantly different.

Despite these sources of randomness and bias in the difference between ATT and BTT, buses are attractive candidates for probe vehicles because buses typically run on heavily traveled urban corridors, sites for which information on travel time is in high demand. Also, it is supposed, buses observe traffic rules and speed limits. Further, information on ATT is most needed during peak periods; it is during these periods that buses have a higher frequency and therefore a greater sampling rate. For example, on Fifth Avenue in New York City between 7:00 and 9:00 a.m., on average there is one bus every minute (*21*).

COLLECTION OF BTT AND ATT DATA

Data on BTT and ATT were collected on five arterial sections in northern New Castle County, Delaware. These sections correspond to the four classes of arterial identified in the 2000 *Highway Capacity*

Manual (HCM) (*22*). For the purposes of this study, the sites are designated Site I through Site V and are described in Table 1 with the corresponding lengths and general class. The data were collected at morning and evening peak periods and also during the off-peak period in the fall of 2002.

At each site, 28 to 30 measurements of BTT and ATT were conducted in the following manner. A vehicle and the bus departed the same location at the same time. One surveyor traveled on the bus and recorded the times at which the bus started and stopped for the entire section, including the stopping time of buses at the bus stops, and the number of times buses stopped at bus stops and the number of passengers that boarded and alighted. At the same time, another surveyor rode as a passenger (not as the driver) of an automobile and recorded the travel time for the same section, noting any incidents along the way. The driver of the vehicle was instructed to travel more or less with the traffic flow. For the sections studied, on average a team of three surveyors required about 4 to 5 h to obtain seven to eight measurements. The time required depended on many factors: section length, average travel speed, bus frequency, schedule adherence of buses, and road geometry.

ESTIMATING ATT FROM BTT

Determining the functional form that predicts ATT from BTT is the main analytical effort. In doing so, two general requirements were considered: the form should be as simple as possible and the predicted value of ATT (by the function) should be within 10% to 15% of the measured value of ATT (i.e., within an allowable error of 1 to 1.5 min for a 10-min travel time).

Functional Form of the Model

It is postulated that the difference between ATT and BTT arises primarily because of the following:

- The stopping time of the bus at the bus stops,
- The time lost by the bus because of repeated accelerations and decelerations from and to a stop (e.g., bus stops),
- The basic difference between the operating abilities of the bus and the automobile,
- Adherence (by the bus and the automobile) to the posted speed limits, and
- The tendency of the bus to use the right lane.

From these postulates and the requirement to develop a simple predictive equation, the following form is proposed initially:

$$\text{ATT}_p = \alpha + \beta(\text{BTT} - \text{TST} - \gamma\text{TBS}) \tag{1}$$

where

ATT_p = predicted ATT value,
TST = total time bus spends stopping at all bus stops, and
TBS = total number of times bus stops at bus stops.

(BTT – TST – γTBS) is treated as the independent variable because this variable represents the actual running time of the bus. Note that the parameter γ has the units of time and represents the time lost because of acceleration and deceleration from and to a stop.

Equation 1, however, requires the use of nonlinear regression analysis as the parameters β and γ, whose values are unknown, appear in the product form. Because the primary purpose of the model is prediction and not explanation, the following simplified form of Equation 1 is used next:

$$\text{ATT}_p = a + b(\text{BTT} - \text{TST}) + c\text{TBS} \tag{2}$$

Although this equation does not represent the physical interpretation of Equation 1, it still has all the variables present in Equation 1 and is now in a form in which linear regression can be used to estimate the parameters *a*, *b*, and *c*.

Initial analysis, however, showed that for the data collected the parameter *c* is not statistically significant. This is because given the overall average running speeds of buses (which include stopping times at intersections and bus stops), the effect of time loss due to acceleration and deceleration on ATT_p is not substantial. Therefore, in line with the idea of a simple expression, the following form of the equation is selected as the suggested model for predicting ATT from BTT. A discussion of the meanings of parameters *a* and *b* is provided later; for now, consider *a* and *b* as calibration constants.

$$\text{ATT}_p = a + b(\text{BTT} - \text{TST}) \tag{3}$$

Results

For Equation 3, the values of *a* and *b* were calibrated by using the linear regression approach with the data on BTT and ATT for the same section. The results show that for all the cases, at least 91% of the predicted values had errors less than 15%, and at least 77% had

TABLE 1 Data Collection Sites

Site	Approximate Location	Class	Length (km)
I	US Rt. 40 between State Rt. 896 and State Rt. 7 intersections	I	7.9 (4.9 miles)
II	Lancaster Pike (State Rt. 48) between Brackenville Rd. and State Rt. 100 intersections	I/II	8 (5.0 miles)
III	Concord Pike (US Rt. 202) between Broom St. and Silverside Rd. intersections	II	5.2 (3.2 miles)
IV	Kirkwood Hwy. (State Rt. 2) between Main St. and Duncan Rd. intersections	II	10.8 (6.7 miles)
V	Newport Pike (State Rt. 4) between State Rt. 7 and Broom St. intersections	III/IV	7.4 (4.6 miles)

TABLE 2 Values of Parameters and Effectiveness of Predictions with Equation 3

Site	*a*	*b*	% of points with less than 10% error	% of points with less than 15% error
I	6.85	0.12	91	91
II	3.09	0.55	100	100
III	6.00	0.00	100	100
IV	9.82	0.19	80	100
V	1.38	0.68	77	100

errors less than 10%. The error is the difference between the measured and the predicted ATT.

The values of coefficient for each of the sites and the percentage of points with less than 10% and 15% error (when compared to the observed ATT values) are shown in Table 2. Because the observed ATT values were to the nearest minute, the values are compared after rounding the predicted values to the nearest minute.

The results are also shown in Figures 3 through 5. Figure 3 shows Sites I and II, Figure 4 shows Sites III and IV, and Figure 5 shows Site V. The graphs for each site have three frames. The topmost shows the observed BTT and the observed ATT for each run at the site. The middle frame compares the predicted ATT values and the observed ATT values based on Equation 3. The bottom frame shows the regression function as well as the plots of the observed ATT values. This frame shows two lines. One line corresponds to the calibrated regression function of the form shown in Equation 3, and the other corresponds to a modified model to be presented next.

As can be seen from Table 2 and Figures 3 through 5, there is a reasonably good correlation between the ATT and the explanatory variable, (BTT − TST), and ATT can be predicted with fairly good accuracy from the information on BTT and TST. However, the obtained coefficients are values found to give the best fit for the given data but they fail to give any insight into the relation between the variations in the data of BTT and ATT. To look for better insight for this relation, a modified form of Equation 3 is hypothesized.

The constant *a* in Equation 3 can represent the average time an automobile will take to travel over the section when there is little or no traffic. In this case, the coefficient *b* represents the effect of traffic congestion (as measured by the running time of buses) on ATT. Further, to make the models as calibration free as possible, it was thought that constant *a* can be determined from the class of the arterial, the suggested free speed in the 2000 HCM (*22*), and the length of the section. Thus, the general modified model for ATT prediction is as shown in Equation 4. The specific models for the five sites are shown in Table 3.

$$\text{ATT}_p = \frac{\text{length of the section}}{\text{free flow speed}} + b(\text{BTT} - \text{TST}) \qquad (4)$$

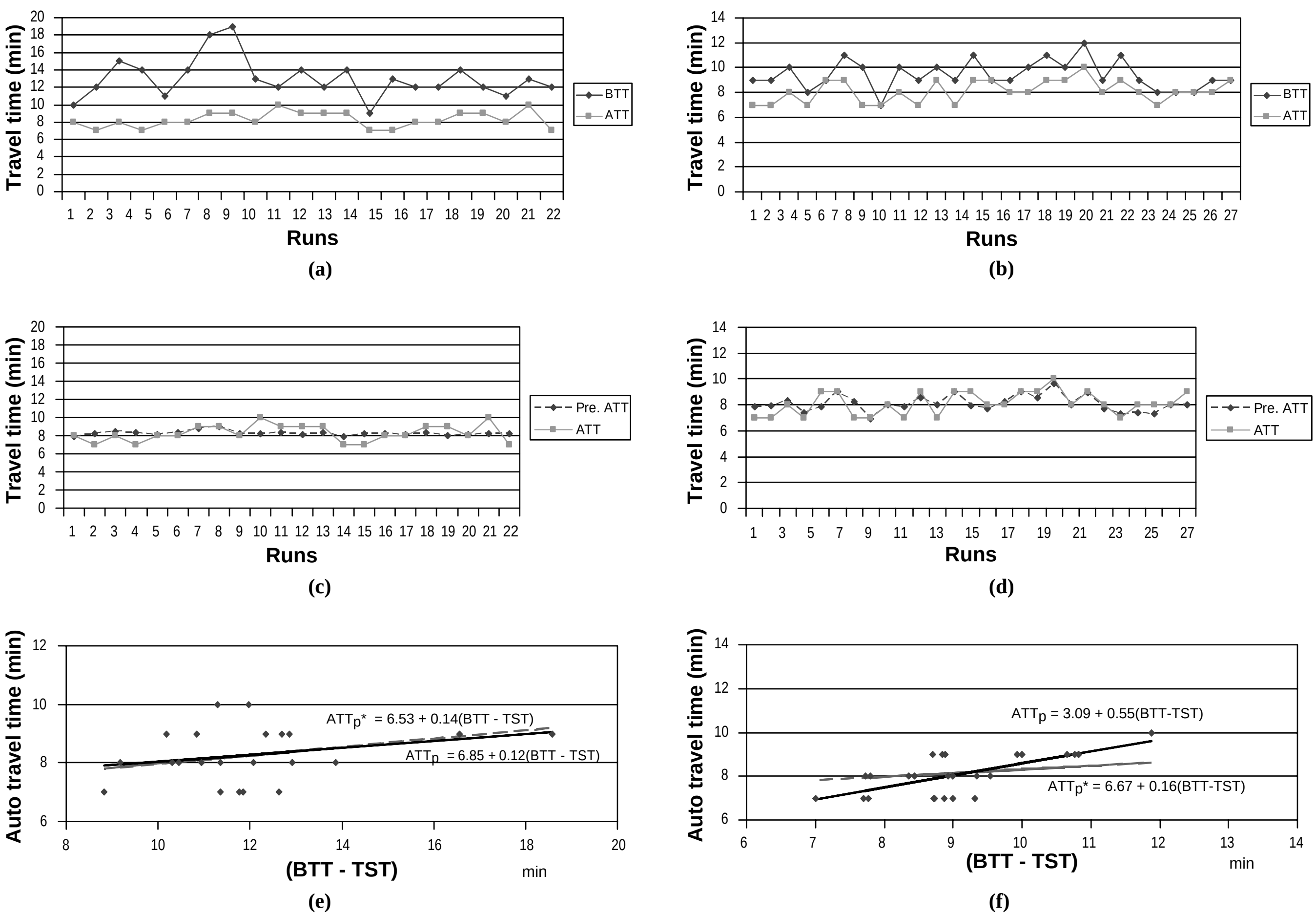

FIGURE 3 Collected data on (*a*) Site I (Route 40) and (*b*) Site II (Lancaster Pike). Predicted travel time and ATT for (*c*) Site I and (*d*) Site II. Relation between BTT and ATT for (*e*) Site I and (*f*) Site II. (ATT_p is predicted on basis of Equation 3. ATT_p* is predicted on basis of Equation 4.)

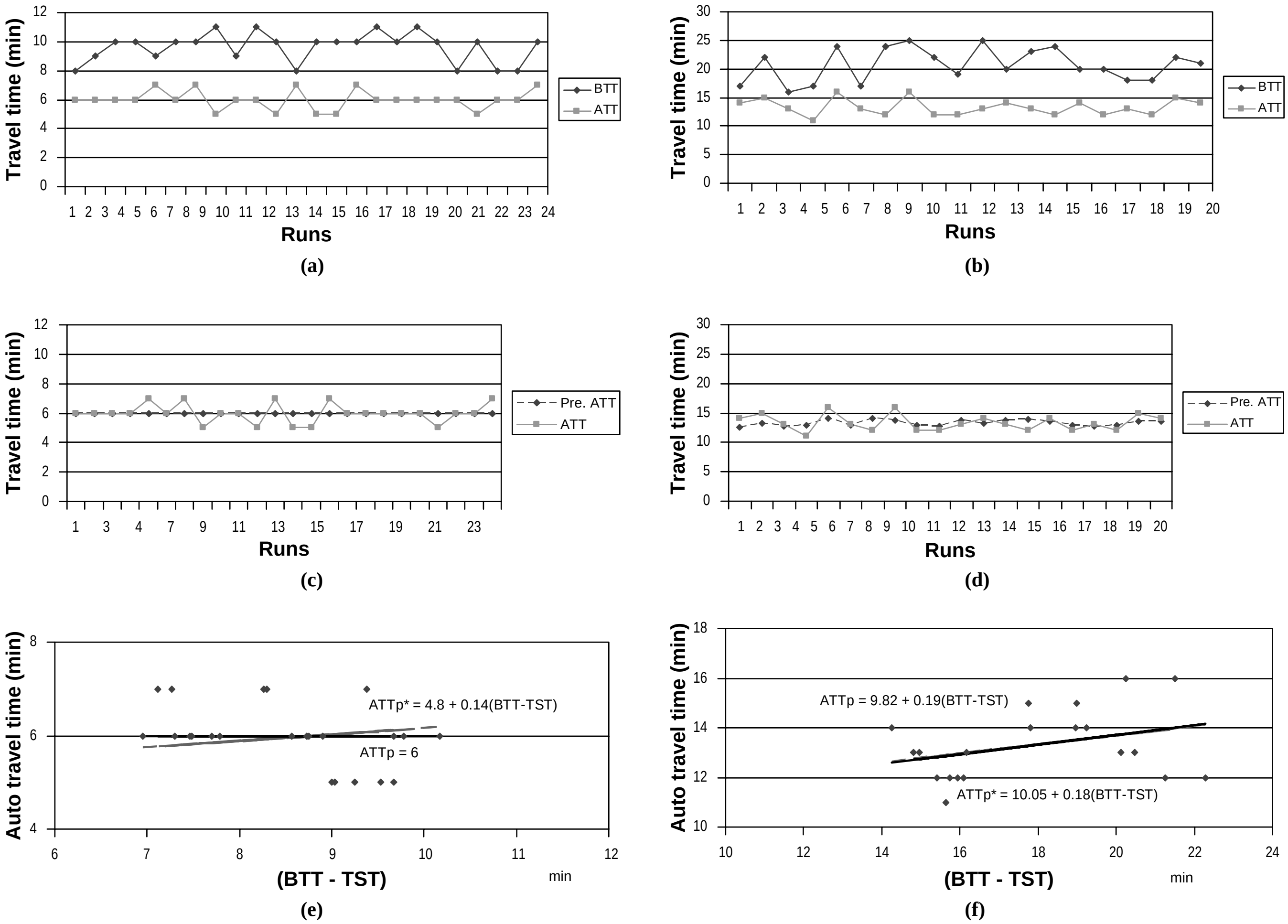

FIGURE 4 Collected data based on (*a*) Site III (Concord Pike) and (*b*) Site IV (Kirkwood Highway). Predicted travel time and ATT for (*c*) Site III and (*d*) Site IV. Relation between BTT and ATT for (*e*) Site III and (*f*) Site IV. (ATT_p is predicted on basis of Equation 3. ATT_p* is predicted on basis of Equation 4.)

The value b_i, which is specific to each site i, is determined by using linear regression. The values are shown in Table 4. The table also shows the percentage of time the predicted value is within 10% and 15% of the observed value (i.e., an error of 1 to 1.5 min for a 10-min travel time). Because the actual ATT values were to the nearest minute, the comparisons were done after rounding the predicted values to the nearest minute.

As seen in Table 4, for the modified models (as given in Table 3), the predicted values are close to the observed values. This can also be seen by observing the calibrated regression line corresponding to the modified models in the bottom frame of Figures 3, 4, and 5 (shown as ATT_{p*}).

What is perhaps more important is that the calibrated b_i values show some interesting features. First, all the values lie within a reasonably narrow range (0.14 to 0.19). Second, there appear to be two distinct groups, Sites I and III with $b_i = 0.14$ and Sites II, IV, and V with b_i in the narrow range of 0.17 to 0.19.

During the surveys, it was noted that although traffic volume varied on all the sites, its effect on travel quality was noticed more in Sites II, IV, and V than in Sites I and III. This could be because capacity conditions were reached on these three sites (II, IV, and V) more often than on the other two sites (I and III). That is, Sites II, IV, and V tended to become congested more frequently than the other two sites. Given this observation, the two groups of b_i take on special meaning because this hints that for roads that become congested less frequently, the appropriate value of $b_i \approx 0.14$, and for roads that get congested more frequently, the value of $b_i \approx 0.18$ is recommended in Equation 4.

Although five sites may not be considered sufficient for developing a rule of thumb, one can say that from the results, the following conclusions can be drawn:

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

The strength of the result lies in that with this, one can predict the average travel time of the automobile from the data on the BTT and the general characteristics of the road section. That is, unlike with

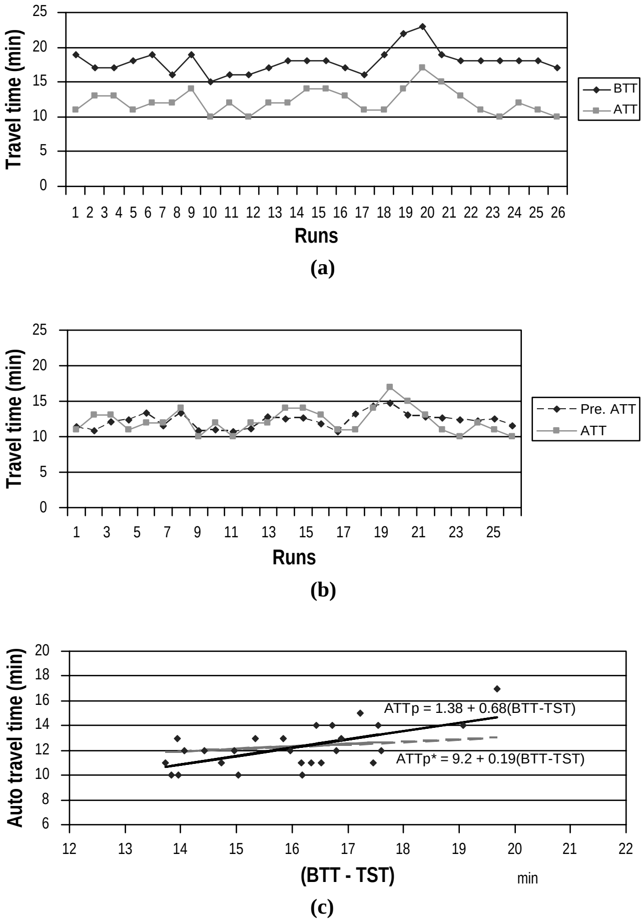

FIGURE 5 Site V (Newport Pike): (*a*) collected data, (*b*) predicted travel time and ATT, and (*c*) relation between BTT and ATT. (ATT_p is predicted based on Equation 3. ATT_p* is predicted on basis of Equation 4.)

the model given in Equation 3, one does not have to obtain the constants for each and every arterial section. If nothing else, the result demonstrates that there is a good chance that such a rule of thumb can be developed after study of many more arterial sections.

CONCLUSIONS

Predicting travel times on urban arterials is a difficult task, yet it is the crucial information in today's ITS applications. In the past, probe vehicles and loop detector data were used to obtain travel time estimates. Here, use of transit buses as probe vehicles is suggested, in addition to other approaches. This paper compared bus travel time to automobile travel time and suggested a functional form that predicts the automobile travel time as based on the travel time of the bus.

A relatively simple linear equation is suggested for the conversion. This equation has two parts. The first part considers the travel time under free flow, and the second part considers the bus travel time without stopping. This expression is found to be easy to explain, and the values of the parameters are stable; it depends only on the general roadway classification and the pattern of congestion in the area.

Use of AVL-equipped buses as the data source is promising, because the measurement function is already available by default and the task of prediction can be performed frequently with minimum manual intervention. However, more work on the following four issues needs to be done to realize the application of the model for specific situations: (*a*) updating of travel time formula by incorporating results of continuous measurement, (*b*) accuracy requirements, (*c*) effects of time of day and other local factors on travel time estimation, and (*d*) the appropriate distance of road section for which the model should be applied.

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TABLE 3 Values of *a* and Equation Forms

Site	Class	Length (km)	Free-flow speed from 2000 HCM	Value of *a* (in min.)	Equation form
I	I	7.9 (4.9 mi)	72.4 km/h (45 mph)	$\frac{4.9}{45}60 = 6.53$	$ATT_p = 6.53 + b_I(BTT - TST)$
II	I/II	8 (5.0 mi)	72.4 km/h (45 mph)	$\frac{4.9}{45}60 = 6.67$	$ATT_p = 6.67 + b_{II}(BTT - TST)$
III	II	5.1 (3.2 mi)	64.4 km/h (40 mph)	$\frac{3.2}{40}60 = 4.80$	$ATT_p = 4.80 + b_{III}(BTT - TST)$
IV	II	10.8 (6.7 mi)	64.4 km/h (40 mph)	$\frac{6.7}{40}60 = 10.05$	$ATT_p = 10.05 + b_{IV}(BTT - TST)$
V	III/IV	7.4 (4.6 mi)	48.3 km/h (30 mph)	$\frac{4.6}{30}60 = 9.2$	$ATT_p = 9.2 + b_V(BTT - TST)$

TABLE 4 Values of Parameters and Effectiveness of Predictions with Table 3 Model

Site, *i*	b_i	% of points with less than 10% error	% of points with less than 15% error
I	0.14	90.91	90.91
II	0.17	100.00	100.00
III	0.14	100.00	100.00
IV	0.18	80.00	100.00
V	0.19	65.38	96.00

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