Travel Time Estimation in Urban Networks Using Buses as Probes

Mohamed El Esawey, Research Assistant, University of British Columbia
Tarek Sayed, Professor, University of British Columbia

Paper prepared for presentation at the "**Traffic Control Measures that Encourage a Shift in Travel Modes"** Session of the 2010 Annual Conference of the
Transportation Association of Canada
Halifax, Nova Scotia

ABSTRACT

Using transit vehicles as probes offers a number of advantages as they cover a large portion of urban networks and the equipment required for data collection is usually already installed by transit operators. Despite the fact that transit vehicles and automobiles have different running behaviours, a relationship can be developed to estimate auto travel times using transit data. Travel time estimation using buses as probes is usually limited to their travel routes. This research investigates the potential of using bus travel time data to estimate general link travel times of neighbour (nearby) links. The main research hypothesis is that travel times of nearby links have strong correlation as these links are subject to similar traffic conditions. A general methodology is presented for travel time estimation using historical travel time data of the link itself and real-time bus data from neighbour links. A case study was undertaken using a VISSIM microsimulation model of downtown Vancouver. The model was calibrated and validated using real-life traffic volumes and travel time data. Travel time estimation accuracy was assessed using the Mean Absolute Percentage Error (MAPE), the value of which was 17.6%. The method was proven to be useful to estimate travel time on links that do not have real-time travel time data while having strong travel time correlation with neighbouring links.

INTRODUCTION

Faced with the rapid increase in the number of motorized trips, along with the availability of limited road infrastructure, polices are being implemented to support multimodal sustainable transportation. These polices aim at either encouraging the use of sustainable modes of travel, or discouraging the use of private cars. Dedicating HOV lanes for transit operations during the peak period is one example of the policies that attract travellers to use public transit. Policies that encourage using non-motorized modes of travel include building cycling lanes, widening sidewalks, etc. Various policies can be deployed to reduce the use of single-occupancy private vehicles such as increasing gas taxes, and/or parking and vehicle registration fees. Promoting the use of carpooling and park-and-ride programs is also another option to reduce the number of single-occupancy vehicle trips.

Together, with the implementation of these policies, providing travellers with real-time traffic information can play a dominant role in changing their choices of modes of travel. Among different indicators of traffic condition, travel time is considered one of the most important measures that can be easily perceived and understood by the public. In the utility maximization theory of discrete choice analysis, travel time is always considered a main cost component that influence people's choices of routes/modes of travel. To enable individuals take better travel decisions, information about other modes/routes of travel has to be provided via a multimodal information system. Examples of such information include: updated bus schedules, maps of cycling paths, shortest route travel time by mode of travel, etc. To illustrate, a trip maker who is knowledgeable of the traffic status through access to real-time information can easily evaluate the utility of using each mode of travel, and, accordingly can shift to more sustainable modes if faced with severe network congestion. The shift can be more significant if coupled with the implementation of policies that support the use of public transit and non-motorized travel modes.

Delivering reliable real-time travel time information to the road network users can be achieved through the implementation of Advanced Traveller Information Systems (ATIS). ATIS require the availability of several measurement sensors that are capable of collecting raw travel time data. The cost of data collection can be high, especially if the covered network is vast. One cost-efficient approach to collect travel time data is to use probe vehicles. Probe vehicles can be commercial fleet vehicles, taxis, buses or any other type of vehicles that are not primarily used for traffic data collection. Rather, they move on a road network to serve a particular purpose and hence can be tracked in real-time to collect traffic information.

Using transit vehicles as probes offers a number of advantages as they cover a large portion of urban networks and the equipment required for data collection is usually already installed by transit operators (*1*). A transit vehicle experiences more delay than an automobile due to more acceleration/deceleration running, stoppage at bus stops to pick up passengers (dwelling time), and the relatively low speed they run in. Despite the fact that transit vehicles and automobile vehicles have different running behaviours, a relationship can be developed to estimate auto travel times using transit data. Transit vehicles run along predefined routes in the network, and therefore travel time estimation using buses as probes is usually limited to these routes. In this research, a new method is proposed to estimate travel times on segments without travel time information using bus travel time data of nearby (neighbour) links. Unlike other probe vehicles such as taxis, the routes and the schedules of transit vehicles are known. This enables the identification of link neighbourhood apriori. As well, the number of transit vehicles that traverse each segment within a measurement interval can be estimated with reasonable accuracy from fleet schedule (unlike the randomness in using passenger probe vehicles).

LITERATURE REVIEW

Many researchers have investigated the potential use of transit vehicles as probes. In the next paragraphs, a review of some recent research efforts that studied using transit vehicles as probes is presented.

Hall et al. (*2*) conducted a field operational test for the Orange County Transit Authority (OCTA) Transit Probe Project. GPS-equipped buses were tracked in real-time for a number of purposes that included investigating schedule adherence, fleet management, and transit information dissemination to travellers. Moreover, the potential of using bus data to estimate automobile speeds and travel times was studied. The authors suggested that bus tracking provided many potential benefits such as drivers adherence to schedules, dispatchers respond to problems, schedulers allocation of suitable time between schedule checkpoints, and travellers having real-time information on bus arrivals. A number of problems were associated with this research that included: missing data from failed units, incomplete coverage on routes, and the inability to immediately update data at schedule changes. The authors concluded that the reliability expectations for an actual deployment of a transit probe system were not met. In addition, they found little correlation between transit speeds and automobile speeds in normal traffic conditions. Nevertheless, strong correlation existed between bus delays and automobile delays when major incidents occurred. The authors suggested that car probes could be used for predicting transit delays. The analytical model that was used to estimate average link speed was:

$$\text{Estimated Average Speed} = (N_l \times SL)/(ST - SDT - N_2)$$

Where:

SL = Physical length of segment
ST = Measured time to traverse the segment
SDT = Station dwell time
N_1,N_2 = Empirical coefficients to compensate for performance differences between autos and buses

Cathey and Dailey (*3*) developed a system that used transit vehicles as probes to collect travel time and speed data. AVL data from the King County Metro Transit system were used in their analysis. The developed system was composed of a tracking module with a Kalman Filter to smooth position and speed estimates, and a speed estimation algorithm. The authors developed a system of virtual probe sensors based on the information obtained from the tracking and speed estimation modules. Raw data were found to have large variability and therefore a simple exponential smoothing equation was used to smooth their estimates. The authors showed that the smoothed speed estimates were similar to those obtained from loop detectors in terms of variability along the day. Cathey and Dailey (*4*) extended their previous research by developing an approach to estimate corridor travel time and speed. A comparison of corridor speed profiles estimated from probes and inductive loop detectors showed some similarity, with transit probes speed estimates providing lower (more conservative) speeds.

In both of the previous two papers, the authors used transit vehicles to obtain the speed of the general traffic and compared it to the data obtained from inductive loop detectors. This work implicitly assumed that transit vehicles are representative of the traffic stream. As transit vehicles and automobile vehicles have different running behaviours, the assumption is not completely correct. Most of the results presented in these two papers showed that the speed variability in time and space using data from transit vehicles was similar to the speeds obtained from loop detectors. The word "similar" means that the trends were similar but with different values. For example, in Cathey and Dailey (*3*), the median speed profile from detectors data was shifted upwards by 8 mph from the median speed profile of transit probes. Better results could have been reached if a robust procedure was adopted to carefully isolate the impact of different factors that cause the behaviour to be different.

Tantiyanugulchai and Bertini (*5*) compared speeds and travel times of probe buses to those obtained from GPS-instrumented vehicles. Bus trajectories were graphically plotted and used to estimate bus mean travel time and speed. Two imaginary scenarios were presented of what the authors called "the hypothetical bus" and "the pseudo bus". A hypothetical bus, as defined by the authors, is a bus that does not stop to serve passengers. Hypothetical bus travel time was calculated as the running time minus the total stopping time at all stops. A pseudo bus was assumed to run between each two stops with the maximum recorded instantaneous speed between this pair of stops. Comparing test vehicle mean speed to the real bus, the pseudo bus, and the hypothetical bus mean speeds, the results showed that average test vehicle speed was equal to 1.66 of real bus speeds, 0.79 of the pseudo bus speed, and 1.03 of the hypothetical bus speed.

Tantiyanugulchai and Bertini (*6*) extended their previous research by collecting bus data in a different day. The findings of this research were very similar to the previous one. The ratios between the test vehicle speed and the actual bus speed, the pseudo bus speed, and the hypothetical bus speed were 1.63, 0.84, and 1.35, respectively. Bertini and Tantiyanugulchai (*7*) introduced another hypothetical bus that was referred as to the "modified pseudo bus". The concept of that imaginary bus is that it runs with the maximum instantaneous speed recorded between each two stops while the dwelling time is added to its running time. The test vehicle travel time was equal to about 1.36 of the travel time of the modified pseudo bus. It was also shown that the test vehicle speed was about 72% of the maximum instantaneous speed of buses.

Bertini and El-Geneidy (*8*) used an analytical regression model to compute the total transit travel time on a freeway route. As the developed model was for a freeway route, no terms were added to the model to account for delays caused by control devices and mid-blocks congestions.

Chakroborty and Kikuchi (*1*) explored the use of buses as probes to estimate automobile travel times. Data were collected for bus travel times (BTT) and average automobile travel times (ATT) for five arterial segments during the AM peak, PM peak, and the off-peak period. A linear regression model was developed to relate the BTT and the ATT. This model had the general form:

$$ATT = A + b\ (BTT - TST)$$

Where:

TST = total stopping time at all bus stops

Another modification for this general model was applied such that:

$$ATT = \frac{Length\ of\ Travel\ Section}{Free\ Flow\ Speed} + \ b(BTT - TST)$$

The percentage of data points with an error of less than 10% increased when using the new model which indicated better fit to the data. The authors noticed that the coefficient b had a narrow range and hence they suggested using two general formulae for less frequently and more frequently congested roads. One shortcoming of this research is that the same dataset was used for both the development and the validation of the linear regression models. As the coefficients of linear regression models are estimated by the least square method that minimizes the sum of squared residuals, it is always expected to have small estimation errors.

Pu et al. (*9*) used historical data to develop linear regression models that relate bus and auto space mean speeds. Bus speed mean and variance were calculated for each measurement interval and consequently confidence intervals of the mean bus speeds were obtained. Upon receiving real-time bus speeds, the mean real-time speed during a measurement interval is compared against the historical mean boundaries. If the real-time mean speed lies within the historical boundaries, it is discarded and the historical mean speed is used along with regression models to estimate average automobile speed of the link. When the real-time mean bus speed is outside the boundaries of the historical mean, it is used to update the historical mean using the variances of the historical mean and the real-time mean. The regression models developed in this research did not include the dwelling time or the acceleration/deceleration time. The estimation errors varied between 39% to -18% for the two segments and two peak periods tested.

Uno et al. (*10*) used bus probes data to study travel time variability on urban corridors. Acceleration, deceleration, and stopping times were estimated and eliminated from bus travel time to estimate automobile travel times. The authors did not mention whether the speed profiles of buses and autos were similar and how they accounted for any variability.

In summary, previous research has focused on using transit as probes to estimate general traffic speed/travel time of the link itself. Most of the previous studies used regression models to estimate automobile travel times using bus travel times. In this research, transit vehicles travel times are used not only for travel time estimation of the link itself, but also for neighbouring links travel time estimation. Additionally, several data fusion methods are proposed and compared to combine estimates from neighbour links transit data and link historical average data.

NEIGHBOUR LINKS TRAVEL TIME ESTIMATION METHODOLOGY

The concept of travel time neighbourhood was introduced by El Esawey and Sayed (*11,12*). In simple terms, the authors advocated the potential use of travel times of some links to estimate travel times on nearby links. The motivation behind the idea is the strong travel time correlation that has been theoretically and empirically proven in many previous studies (*13,14,15,16,17,18,19,20*). In general, strong positive travel time correlation between nearby links can be attributed to: (a) correlation in traffic demand, (b) similarity in traffic control and (c) queue spillback. The potential of using travel time correlation for travel time estimation on segments with no data in urban networks has received little interest. A methodology was presented using simulation data (*11*) to define link neighbours and estimate travel times on links with no data using data of other links. The method was further validated using real-life data in (*12*).

The choice of link neighbours is dependent on many factors that include 1) area type and location, 2) road class, 3) traffic control level, and 4) travel time correlation. Appropriate choice of the boundaries of the study area is essential to ensure that all links are subject to similar traffic conditions. Further segments that are not affected by demand changes within a specific area should be excluded. Similarity in the road class classification is important to ensure consistency in the speed profiles. A major arterial segment cannot, in most cases, be chosen as a neighbour of a local street for example. Traffic control level is also a major determinant in defining link neighbours. Travel times of segments with signalized intersections will definitely be different from segments with stops signs. Finally, strong travel time correlation between nearby links of the same class and operational characteristics facilitates developing accurate estimation models.

The approach proposed to estimate travel times on links that do not have travel time records using data of neighbour links follows El Esawey and Sayed (*11,12*). Two clues are combined for travel time estimation; historical travel time data and probes data from neighbour links. Let:

x_{hl} = Historical average travel time on link l during a measurement period t
x_{rl} = Real-time average travel time on link l during t
x_{rn} = Estimated real-time average travel time on link l using data of neighbour links n during t
$\hat{x}$ = The best estimate of real-time average travel time on link l during t

To estimate real-time travel time for link l , the following cases can take place:

1. There is a sufficient sample of probe vehicles on link l during t, then $\hat{x} = x_{rl}$
2. No probe vehicles are available on link l during t, then $\hat{x} = f(x_{hl}, x_{rn})$
3. No probe vehicles are available on link l or on its neighbours n during t, then $\hat{x} = x_{hl}$

The focus of this research is on case (2) as cases (1) and (3) are straightforward. In case (2), $\hat{x}$ can be calculated using a simple weighting formula such that:

$$\hat{x} = \alpha . x_{rn} + (1 - \alpha). x_{hl} \tag{1}$$

Where α , (1- α) are weights for x_{rn} and x_{hl}, respectively, $0 \leq \alpha \leq 1$, and $\alpha = 1$ if an incident is detected on link l during t.

The question of interest now is how to compute x_{rn} and the weight α. In our previous research, x_{rn} was estimated using a sample of probes vehicles that existed on neighbouring links. In this research, bus travel times of neighbour links are used instead of a sample of passenger vehicle probes. Firstly, bus travel times of neighbouring links are used to estimate average automobile travel times on these neighbours. Subsequently, the estimated neighbour travel times are used to compute x_{rn}.

An Empirical Bayes (EB) method was proposed in El Esawey and Sayed (*11,12*) to compute α based on the variance of the neighbour links models. In this method, α can be calculated as:

$$\alpha = 1/[1 + \frac{Var(x_{rn})}{E(x_{rn})}] \tag{2}$$

In this research, two more fusion methods are proposed and compared to the EB method. In the first method, historical records are used only to compensate for missing neighbour bus travel times during some time intervals. Nevertheless, historical records are not used when neighbour links transit data are available. This method herein and after will be referred as to "Historical". It can be expressed by the following rule:

$$\text{IF } x_{rn} = zero \text{ THEN } \hat{x} = x_{hl} \text{ OTHERWISE } \hat{x} = x_{rn} \tag{3}$$

In the second method, the weight α is computed using the variance of the historical data and the variance of neighbour link models. This method will be referred as to "Variance Weighting" and can be mathematically expressed as:

$$\alpha = \frac{\frac{1}{Var(x_{rn})}}{\frac{1}{Var(x_{rn})} + \frac{1}{Var(x_{hl})}} = \frac{Var(x_{hl})}{Var(x_{hl}) + Var(x_{rn})} \tag{4}$$

A similar fusion scheme to equation (4) is found in Pu et al. (*9*).

Where:

$Var(x_{rn})$ = Variance of the estimated real-time average travel time on link *l* using data of neighbour links *n* during *t*
$Var(x_{hl})$ = Variance of the historical average travel time on link *l* during *t*
$E(x_{rn})$ = Expectation of the estimated real-time average travel time on link *l* using data of neighbour links *n* during *t*

To estimate the weight α in equations (2) and (4), the expectation and the variance of real-time average travel time on link l using data of neighbour links n during t denoted by $E(x_{rn})$ and $Var(x_{rn})$ need to be calculated. The method of statistical differentials is used to obtain $E(x_{rn})$ and $Var(x_{rn})$ as follows:

$$x_{rn} = \sum_{i=1}^{n} w_i . x_{ri} \tag{5}$$

$$E(x_{rn}) = x_{rn} + \frac{\left[\sum_{i=1}^{n} \frac{\partial^2 x_{rn}}{\partial x_{ri}{}^2} . Var(x_{ri})\right]}{2} \tag{6}$$

$$Var(x_{rn}) = \sum_{i=1}^{n} \left(\frac{\partial x_{rn}}{\partial x_{ri}}\right)^2 \cdot Var(x_{ri}) \tag{7}$$

x_{ri} = Estimated travel time on link *l* using data of neighbour *i* during *t*, where $i \in n$
w_i = Assigned weight to the estimated travel time on link *l* from neighbour *i* during *t*
$Var\ (x_{ri})$ = Variance of the estimated travel time on link *l* from neighbour *i* during *t*

Which leads to:

$$E(x_{rn}) = x_{rn} \tag{8}$$

$$Var(x_{rn}) = \sum_{i=1}^{n} (w_i)^2 \cdot Var(x_{ri}) \tag{9}$$

In order to be able to compute x_{rn} , link neighbours have first to be defined. Consequently, models that relate link travel time to travel times of its neighbours are developed. In the next sections, a case study is presented using data generated from a microsimulation model of downtown Vancouver.

CASE STUDY: DOWNTOWN VANCOUVER

The Study Area

Downtown Vancouver is a typical urban environment with traffic signals interrupting the traffic operation. It suffers considerable congestion during the AM and the PM peaks which elapse between 6 AM and 9 AM and 3 PM to 6 PM, respectively. The study area covers almost half of downtown area as shown in Figure 1. The network is a grid network composed of 23 streets, of which, 12 are in the east-west direction, and 11 are in the north-south direction. The 23 streets comprise 115 intersections, of which 108 are signalized. The average segment length of east-west streets in downtown Vancouver is between 70-80 m, while for the north-south streets is between 160-190 m.

The choice of this condensed network for the current analysis was carried out so as to include spatially nearby links with similar characteristics. For example, all segments are classified as urban, located in CBD, have approximately the same length, signalized from both ends, and have similar cross section elements as per the number of lanes. This ensures that any strong positive travel time correlation is not accidently found but rather is attributed to the fact that all these links are subject to similar traffic conditions.

The Microsimulation Model

A VISSIM microsimulation model for downtown Vancouver was early developed at the University of British Columbia in 2005 for the AM peak period. Several revisions and updates were applied to improve the earlier simulation model including the geometric elements of the model, movement restrictions, new transit routes and schedules, and HOV lanes.

One shortcoming of the earlier developed simulation model is that it involved using static assignment (routing decision) based on traffic counts and turning volumes of downtown intersections. This approach is not appropriate for large networks where many routes between each OD pair exist. Therefore, it was necessary to turn the earlier static simulation model into a dynamic assignment model. In Dynamic Assignment (DA), traffic demand is modeled by means of origin-destination (OD) matrices rather than static routing decisions. Each cell in an OD matrix includes the number of trips between an OD pair during a given time period. First, all origins and destinations in the network were identified. The simulation model has 36 zones. A simple approach was employed using the microsimulation model itself to obtain a seed OD matrix. Travel time detectors were placed at the start of each origin link and at the end of each destination link for all OD pairs to estimate OD travel times and traffic volumes. At this point, travel times were neglected and traffic volumes between each OD pair were used to build a seed (i.e. initial) OD matrix. The obtained trip matrix was then linked to the pre-defined traffic composition of downtown (2% trucks). Consequently, all vehicular static routing decisions were deleted except those of pedestrians and transit. Having obtained the seed OD matrix, the static simulation model was turned into a dynamic one by adding the necessary modelling elements such as zonal parking lots and nodes.

Model Calibration and Validation

The application of microsimulation models to derive a critical decision depends on their accuracy and reliability. In the absence of proper calibration and validation of the model, its accuracy will always be questionable. The calibration of large scale microsimulation models involves OD matrix calibration, route choice parameters calibration, and driver behaviour parameters calibration. A sequential procedure was used to calibrate the model. In this procedure, the modeller does not proceed to the following calibration stage unless needed. First, the OD matrix was calibrated and the assigned traffic volumes of the model were compared to observed real-life volumes. TFlow-Fuzzy module of VISUM was used to update the seed OD matrix using recent traffic counts obtained from the engineering department of the City of Vancouver. Route choice calibration was carried out by adding link surcharges to change the assignment results to match the observed traffic volumes. Four rounds of local calibration were needed to reach an acceptable calibration. A subset of VISSIM driver behaviour parameters were fine tuned so that the model output matches field observed corridor travel time data. Details of the model calibration and validation procedures are given in El Esawey and Sayed (*21*).

Dynamic Assignment Control

The DA process in VISSIM is based on iterated simulations. Hence, a modeled network is simulated repetitively and drivers choose their routes based on some route choice criteria they have experienced during the preceding simulations. This behaviour is rational as it represents driver's growing experience of the network when driving repetitively on different days (*22*). In this study, the utility function, which describes the individual's personal utility of each route, was based only on route travel time. In VISSIM's DA module, a number of paths are defined for each OD pair. The travel times on these paths are updated every small time interval called the evaluation interval. The evaluation interval was selected to be 15 minutes, as VISSIM's User Manual suggests this period to be between 5 to 30 minutes (*22*). To decrease convergence time and reduce the number of possible paths between each OD pair, paths with total costs of more than 50% higher than the best path were rejected from the route search. Several iterations are required to achieve convergence or dynamic assignment user equilibrium. The criterion selected to achieve convergence was travel time on paths, and the tolerance value was set to 10%. The Method of Successive Averages (MSA) was used to compute path travel times of the past four iterations and compare it to path travel times of current iteration. Convergence is achieved if the difference in travel times on every path between the average of the previous four consecutive iterations and the current iteration for all evaluation intervals is less than 10%.

Transit Routes in Downtown Vancouver

The simulation model included 44 transit lines that were updated according to recent routes and schedules. Translink website was used to obtain the route information of each transit line that runs through downtown, along with all corresponding bus stops. Many of the transit lines end at midblock locations. In VISSIM, if the end of a transit route is left as it is in real life, the transit vehicle will float on random routes till the end of the simulation period (*22*). To handle this problem, dummy links were created and linked to the end point of the bus route to remove the buses from the network just after the destination station. Figure 2 illustrates the idea.

In general, the bus frequency in downtown Vancouver is 8-10 minutes. Most of the transit routes in downtown Vancouver run on four major streets: Richards, Howe, Seymour, and Burrard streets (Figure 1). Seymour, and Burrard streets have HOV lanes dedicated only for bus operation during the AM peak. The travel behaviour, and consequently bus travel time on HOV segments is not indicative to that of the general traffic. Therefore, these segments were excluded from the analysis. Furthermore, only two segments on Howe street did not have HOV lanes and were included in the analysis. In total, eight transit sections were analyzed, of which, four segments had bus stops (group 1) while the other four did not have any (group 2). Table 1 shows summary statistics of the analyzed transit segments. Figure 1 shows the section ID for each transit travel time section.

Data Generation

The network updated OD matrix was scaled by different factors starting from 60% and up to 100% with 10% increments to reflect different demand levels. The dynamic assignment model was run for each volume level until convergence. The simulation period was one hour. Average link travel times were measured on five major corridors in downtown Vancouver in the North-South direction. The five corridors are composed of 35 travel time sections, including the eight transit travel time sections. Link travel times were measured using virtual detectors placed just after the stop line of each link to incorporate the delay at the downstream signal. For each link, the generated information included average automobile travel time and average bus travel time, if any. The data aggregation interval used in this analysis is 10 minutes. The length of the data aggregation interval was selected to ensure that at least one bus existed on the travel time section during each measurement period. As well, choosing a longer measurement interval will not enable capturing the dynamic and rapid changes of the traffic in the study area. Furthermore, Srinivasan and Jovanis (*23*) suggested using a measurement interval of 10 minutes for probe vehicles applications. Noteworthy is that in real life the aggregation interval could be pre-defined by a Transportation Management Centre (TMC) and cannot be changed.

For a measurement period of 10 minutes and 5 volume levels, every link had 30 observations. These synthetic data hypothetically represented the historical dataset and they served several purposes. Firstly, they were used to investigate the travel time correlation between the 35 travel time sections. Secondly, the dataset was used to develop models that relate average bus travel time to average automobile travel time of the same link. Finally, this dataset was used to define link neighbours and develop statistical models that relate automobile travel times of each link to its neighbours.

To generate the dataset that represent real-time data, the network volume OD matrix was again scaled by 75%, 85%, and 95%. The same travel time virtual detectors were used to obtain the travel times of both transit vehicles and automobiles for the new demand levels. The average automobile travel time for each section was used as the true (i.e. validation) travel time, while average bus travel times were used as the online travel times. For the three volume levels, one hour of simulation, and a measurement interval of 10 minutes, the number of validation records was 18 observations.

RESULTS

Correlation of Bus and Automobile Average Travel Time

The strength of the relationship between average bus and automobile travel times of the same link was assessed using Pearson correlation. The p-value was used to test the null hypothesis of correlation, H_0: r = zero. If $p < 0.05$, then the probability of having a positive correlation is >

97.5%. As the correlation coefficient is not normally distributed and its variance is not constant, Fisher transformation was used to normalize the distribution and stabilize the variance. As well, it was used to construct confidence intervals for correlation coefficients.

For links with no bus stops (group 2), the correlation was estimated directly between the average bus and automobile travel times. For other links with one or more bus stops (group 1), the correlation was obtained between average automobile travel time and the bus travel time after subtraction of the average dwelling time multiplied by the number of bus stops on the segment. It was hypothesized that subtracting the total dwelling time from the travel time will result in a better relationship. A similar approach was used in Chakroborty and Kikuchi (*1*). Table 2 shows Pearson correlation for the two transit segment groups along with correlation Upper Limit (UL), Lower Limit (LL), and p-values. As shown in Table 2, the correlation of average bus and automobile travel times for both groups is high and statistically significant. This indicates strong relationship between the average travel times of buses and autos and facilitates developing auto-transit travel time models.

Models Development

Similar to previous studies (*1,8,9*), linear regression models that relate average bus travel time to average automobile travel time of the same link were developed. Two models were developed for the two different transit segment groups. For group 1, segments with bus stops, the model has the form:

$$Auto\ TT = a + b(Bus\ TT - Average\ Stop\ Dwelling\ time \times Number\ of\ Stops) \quad (10)$$

The constant a should account for all variables that were not included in the model such as acceleration/deceleration times.

As buses of group 2 do not experience any delays caused by acceleration, deceleration, or dwelling time, it was hypothesized that average bus travel time of these segments is a ratio of the average auto travel time. For group 2, segments without bus stops, the intercept was forced to be zero and the model had the form:

$$Auto\ TT = c.Bus\ TT \quad (11)$$

Results of models' development and goodness of fit are presented in Table 3. As shown in the table, all coefficient have logical meanings, and significant parameters. The R^2 value for the second model is higher than that of the first model which indicates, as institutively expected, a stronger relationship between auto travel times and bus travel times on segments with no stops. Interestingly, the value of the coefficient of bus travel time in the second model is very close to the ratio between the bus mean speed, 40 km/hr. and the auto mean speed 50 km./hr (i.e. ratio of 0.8).

Models Validation

In order to use bus travel times of one link to estimate automobile travel times of neighbouring links, it is important first to ensure that the developed models can accurately estimate the average automobile travel time of the link itself. The validation dataset was used to assess the accuracy of the developed models. For each of the transit segments, bus travel times were used along with the developed linear regression models to estimate automobile average link travel times. The estimated automobile travel times were combined with link historical average automobile travel times using equations similar to (2), (3), and (4). The only one difference is that instead of using neighbour links travel times x_{rn}, estimates of link automobile travel times as obtained from the linear regression models were used. The new estimates of average link travel times were compared against the true link average travel times measured directly from the microsimulation. Examples of the estimated travel times and the true travel times of some links during the 18 intervals are presented in Figure 3. To quantify the estimation accuracy of the three proposed methods of combining link historical data and bus real-time data (Equations 2, 3, and 4), the Mean Absolute Percent Error *(MAPE)*, was calculated for the eight segments and the 18 evaluation intervals. The MAPE is calculated as:

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{x_{True} - \hat{x}}{x_{True}} \right| \qquad (12)$$

The results are presented in Figure 4 and they show an MAPE of 9%-13%. This indicates an acceptable accuracy level for the three fusion methods with Variance Weighting being slightly better than the other two methods.

Having accurately estimated average automobile travel time of the transit segments, a next step is to estimate automobile travel times of neighbour links using travel times of transit sections.

Identification of Link Neighbours

Pearson Correlation Coefficient (r) was used to define neighbour links. The *p*-value was used to test the null hypothesis of correlation, H_0: r = zero. If $p < 0.05$, then the probability of having a positive correlation is > 97.5%. An arbitrary correlation threshold of 0.3 was used to define link neighbours for each transit segment. This threshold was presumed to achieve a reasonable trade-off between the estimation accuracy and the number of neighbours. Relaxing this value will increase the number of defined neighbours, however it might impact the estimation accuracy and vice versa. Table 5 shows the defined neighbours for transit travel time sections. Sections 10, 26, and 27 did not have any neighbour that satisfies the neighbourhood criteria. For all other neighbour pairs, the null hypothesis of zero correlation was rejected with $p < 0.05$.

Neighbour Links Travel Time Estimation Models

Four travel time segments were selected from the remaining 27 travel time sections (after the exclusion of the eight bus sections) as an example of links with unknown travel times. The section numbers of the four selected segments are 14, 19, 23, and 28. As shown in Table 5, each of these sections has at least one neighbour link with bus data. Similar to El Esawey and Sayed (*11*), models that relate target link travel time to travel times of neighbour links were developed.

Each model incorporated only one dependant and one explanatory variables. This can be beneficial when very few travel time data are available so that travel times of one neighbour link only can be used. As well, it solves the problem of inter-collinearity between explanatory variables (i.e. neighbours' travel times correlation). El Esawey and Sayed (*11*), also found that the exponential model form showed better fit to the data than the linear and the power model forms in terms of goodness of fit criteria. Regression models were developed using the least square method. Five exponential models were developed according to the number of neighbours defined for the four segments as in Table 5. Automobile travel time estimates of each individual neighbourhood model represent the variable denoted earlier as x_{ri}.

Developing link to link models can solve the problems of inter-collinearity and lack of data on some neighbours. Nevertheless, in many cases travel time data might exist on more than one link and therefore more than one model can be used. For example, average travel time of segment 28 can be estimated using data of two neighbours: 11 and 13. This raises the issue of how to combine the estimates of different models to obtain a robust single estimate of the unknown travel time (i.e. x_{rn}). More specifically, how to give weights to each model estimate. In this research, a simple weighting scheme was applied to combine estimates of different neighbour models. The chosen scheme assigned weights inversely proportional to model's variance ($\sigma_i{}^2$). The weighting scheme is expressed mathematically as:

$$w_i = \frac{1/\sigma_i{}^2}{\sum_{i=1}^{n} 1/\sigma_i{}^2} \qquad (13)$$

$$\sigma_i = \sqrt{\frac{SSE_i}{df}} \qquad (14)$$

Where:

SSE $_i$ = sum of squared errors of model relating unknown link travel time to neighbour *i*, and
df = degree of freedom = 30 - number of parameters to be estimated = 30-2 = 28

Applying Weighting Schemes to the Developed Models

To this point, historical data were used to develop bus-auto travel times relationships of the same link, as well as auto-auto travel time relationship between neighbour links. Estimates as obtained from bus-auto travel times relationships were used to represent data of neighbour links. Neighbourhood models were used to estimate travel times of segments 14, 19, 23, and 28.

For each measurement interval that did not have neighbours travel time records, the estimation of neighbour link model was replaced by "zero" indicating that no data were available for the neighbour during this measurement interval. In real-life, an outlier travel time record might be found on one of the neighbours for an unusual event. To remove these outliers, a filtering scheme was applied to the estimates as follows:

$$x_{ri_{Filtered}} = x_{ri_{Model}} \qquad If \qquad x_{ri_{Model}} \leq \mu + 2\sigma$$

$$x_{ri_{Filtered}} = N/A \qquad if \qquad x_{ri_{Model}} > \mu + 2\sigma$$

Where:

$x_{ri_{Model}}$ = Model estimate of average travel time on link l using data of neighbour i during t

$x_{ri_{Filtered}}$ = Filtered model estimate of average travel time on link l using data of neighbour i during t

μ = Mean historical travel time on link l during t

σ = Standard deviation of the mean historical travel time on link l during t

In this filter, if the model estimation exceeds the $\mu + 2\sigma$ value at a specific measurement interval, the link data are excluded from the set of neighbours during the interval. In real-life, the filter threshold value can be set as the maximum historical recorded travel time on the link during the same measurement time. The $\mu + 2\sigma$ value theoretically corresponds to a 95% confidence level of the mean travel time for normally distributed travel times. After refining single model's estimates, the weighting scheme using model variance as in equations (13) and (14) was applied to combine estimates of all neighbours.

The three data fusion methods were used to add historical data to neighbour links travel time estimates. The true auto travel times as obtained from the simulation runs for the three validation scenarios were compared against models' estimates using the MAPE. The MAPE was calculated as the average for the 18 intervals (i.e. 3 demand levels and 1 hour divided to 6 intervals), and the four segments. The average MAPE for the three methods is illustrated in Figure 4.

As shown in the figure, the estimation accuracy of neighbour links travel times is relatively high with the MAPE less than 20% for the EB and Variance Weighting methods. This indicates that bus travel times can be used not only to estimate auto travel times of their travel links but also for neighbouring links. The accuracy deteriorates when using bus data to estimate neighbour links travel times compared to using bus data to estimate auto travel times of the same link. However, it is still within the acceptable limits. Figure 5 shows plots of the estimated travel times using the Variance Weighting method versus true travel times as obtained from the validation simulation runs. The graphs show similarity between the estimated travel times and the true travel time. Indeed, the estimation accuracy is not perfect. Some intervals might have higher errors than others. As well, the accuracy varies from one link to another due to the natural variations in the link characteristics. The overall average MAPE was about 17.6% for all links and intervals. This accuracy level was considered acceptable considering the high travel time fluctuations in the study area and the complex traffic pattern that includes pedestrians, signalized intersections, etc.

CONCLUSIONS

The potential of using transit vehicles as probes to estimate auto (i.e. general) link travel time has been extensively investigated. However, using buses as probes for neighbour links travel time estimation has not been yet considered. Neighbour links are nearby links that have similar characteristics and are subject to similar traffic conditions. Strong travel time correlation exists between neighbour links for various reasons. This correlation can be useful in developing travel time relationships between neighbour links. These relationships, in turn, can be used to estimate travel times on links with no data if the data are available for their neighbours. This research proposes a general framework to integrate historical link travel time data and sparse bus travel time data for urban travel time estimation. The methodology was applied to a case study in downtown Vancouver. First, regression models were developed to relate bus travel times to general link travel times. Consequently, the estimated link travel times were used to estimate travel times of neighbouring links. Three different methods of data fusion were introduced to combine average historical travel times of the link itself with estimates of neighbouring links models. It was shown that assigning weights to historical data and neighbour links data based on their variances slightly outperforms the other two methods. In general, the travel time estimation accuracy was below 10% when using buses to estimate auto travel times of the same link, while it was about 17.6% when using buses for neighbour links travel time estimation. This accuracy level was considered acceptable considering the high travel time fluctuations in the study area and the complex traffic pattern that includes pedestrians, shared lanes, signalized intersections, etc. Hence, it can be concluded transit vehicles can be used as a useful source of travel time information for the links they are running on, as well as nearby links that have similar traffic characteristics.

REFERENCES

1. Chakroborty, P., and Kikuchi, S. Estimating Travel Times On Urban Corridors Using Bus Travel Time Data. CD-ROM. Transportation Research Board the 83rd Annual Meeting, Washington, D.C., 2004.
2. Hall, R., Vyas, N., Shyani, C., Sabnani, V., and Khetani, S. Evaluation of the OCTA Transit Probe System. PATH Research Report, UCB-ITS-PRR-99-39, November 1999.
3. Cathey, F.W., and Dailey, D.J. Transit Vehicles as Traffic Probe Sensors. CD-ROM. Transportation Research Board the 81st Annual Meeting, Washington, D.C., 2002.
4. Cathey, F.W., and Dailey, D.J. Estimating Corridor Travel Time by Using Transit Vehicles as Probes. Transportation Research Record, 1855, pp 60-65, 2003.
5. Tantiyanugulchai, S. and Bertini, R.L. Arterial Performance Measurement Using Transit Buses as Probe Vehicles. In IEEE Intelligent Transportation System Conference, Shanghai China, 2003a.
6. Tantiyanugulchai, S. and Bertini, R.L. Analysis of a Transit Bus as a Probe Vehicle for Arterial Performance Measurement. Presented at the ITE Annual Meeting and Exhibit, Seattle, WA, USA, 2003b.
7. Bertini, R.L. and Tantiyanugulchai, S. Transit Buses as Traffic Probes: Empirical Evaluation Using Geo-Location Data. Transportation Research Record 1870, pp 35-45, 2003.
8. Bertini R. L. and El-Geneidy A. M. Modelling Transit Trip Time Using Archived Bus Dispatch System Data. Journal of Transportation Engineering, ASCE, pp. 56-67, 2004.
9. Pu, W., Lin, J. and Long, L. Real-Time Estimation of Urban Street Segment Travel Time Using Buses as Speed Probes. CD-ROM. Transportation Research Board the 88th Annual Meeting, Washington, D.C., 2009.
10. Uno, N., Kurauchi, F., Tamura, H. and Iida, Y. Using Bus Probe Data for Analysis of Travel Time Variability. Journal of Intelligent Transportation Systems, 13: 1, pp. 2-15, 2009.
11. El Esawey, M. and Sayed, T. Travel Time Estimation in an Urban Network Using Sparse Probe Vehicle Data and Historical Travel Time Relationships. CD-ROM. Transportation Research Board the 88th Annual Meeting, Washington, D.C., 2009.
12. El Esawey, M., and Sayed, T. Travel Time Estimation in Urban Networks Using Neighbour Links Travel Time Data. CD-ROM. Transportation Research Board the 89th Annual Meeting, Washington, D.C., 2010a.
13. Hall, R. The Fastest Path Through a Network with Random Time-Dependent Travel Time. Transportation Science, Vol. 20, No. 3., pp. 182-188, 1986.
14. Sen, A., Thakuriah, P., Zhu, X., and Karr, A. Frequency of probe reports and variance of travel time estimates. Journal of Transportation Engineering, ASCE, 123(4), pp. 290-297, 1997.
15. Fu, L. and Rilett, L.R. Expected Shortest Paths in Dynamic and Stochastic Traffic Networks. Transportation Research B, Volume 32, Number 7, pp. 499-516, 1998.

16. Rilett, L.R., Park, D. Direct Forecasting of Freeway Corridor Travel Times Using Spectral Basis Neural Networks. CD-ROM. Transportation Research Board the 78th Annual Meeting, Washington, D.C., 1999.

17. Chen, M., Chien, S. Dynamic Freeway Travel-Time Prediction with Probe Vehicle Data: Link Based Versus Path Based. Transportation Research Record 1768, pp. 157-161, 2001.

18. Eisele, W.L. and Rilett L.R. Estimating Corridor Travel Time Mean, Variance, Covariance with Intelligent Transportation Systems Link Travel Time Data. CD-ROM. Transportation Research Board the 81st Annual Meeting, Washington, D.C., 2002.

19. He, R. R., Liu, H. X., Kornhauser, A. L., and Ran B. Temporal and Spatial Variability of Travel Time. Paper UCI-ITS-TS-02-1. Center for Traffic Simulation Studies, 2002.

20. Gajewski, B.J., and Rilett, L.R. Estimating Link Travel Time Correlation: An Application of Bayesian Smoothing Splines. CD-ROM. Transportation Research Board the 82nd Annual Meeting, Washington, D.C., 2003.

21. El Esawey, M. and Sayed, T. Calibration and Validation of Downtown Vancouver VISSIM Model. Submitted for publication in the Advances in Transportation Studies- An International Journal., 2010b.

22. VISSIM Version 5.1 Manual. PTV Planug Transport Verkehr AG, Innovative Transportation Concepts, Inc., July, 2008.

23. Srinivasan, K.K. and P.P. Jovanis. Determination of Number of Probe Vehicles Required for Reliable Travel Time Measurement in Urban Network Transportation Research Record 1537, pp. 15-22, 1996.

LIST OF FIGURES

LIST OF TABLES

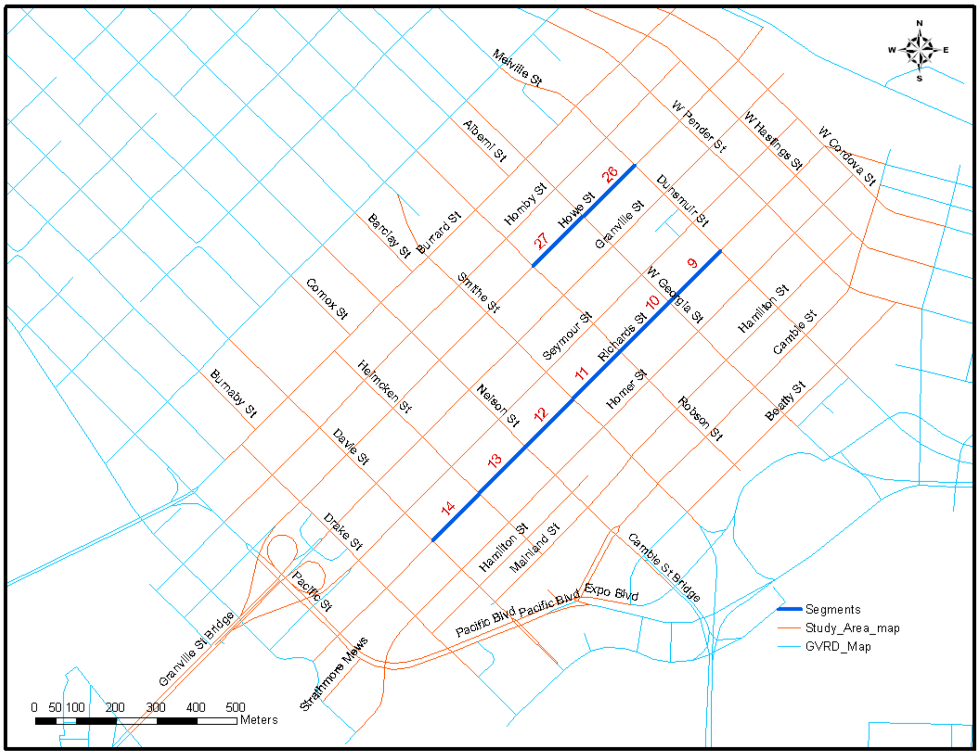

FIGURE 1 The Proposed Study Area & Analyzed Transit Sections ID

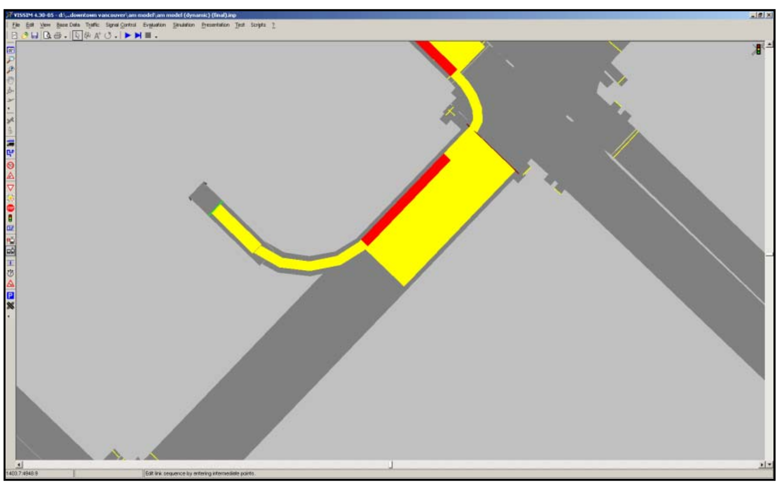

FIGURE 2 Dummy Links for Bus Routes Ending at Midblock

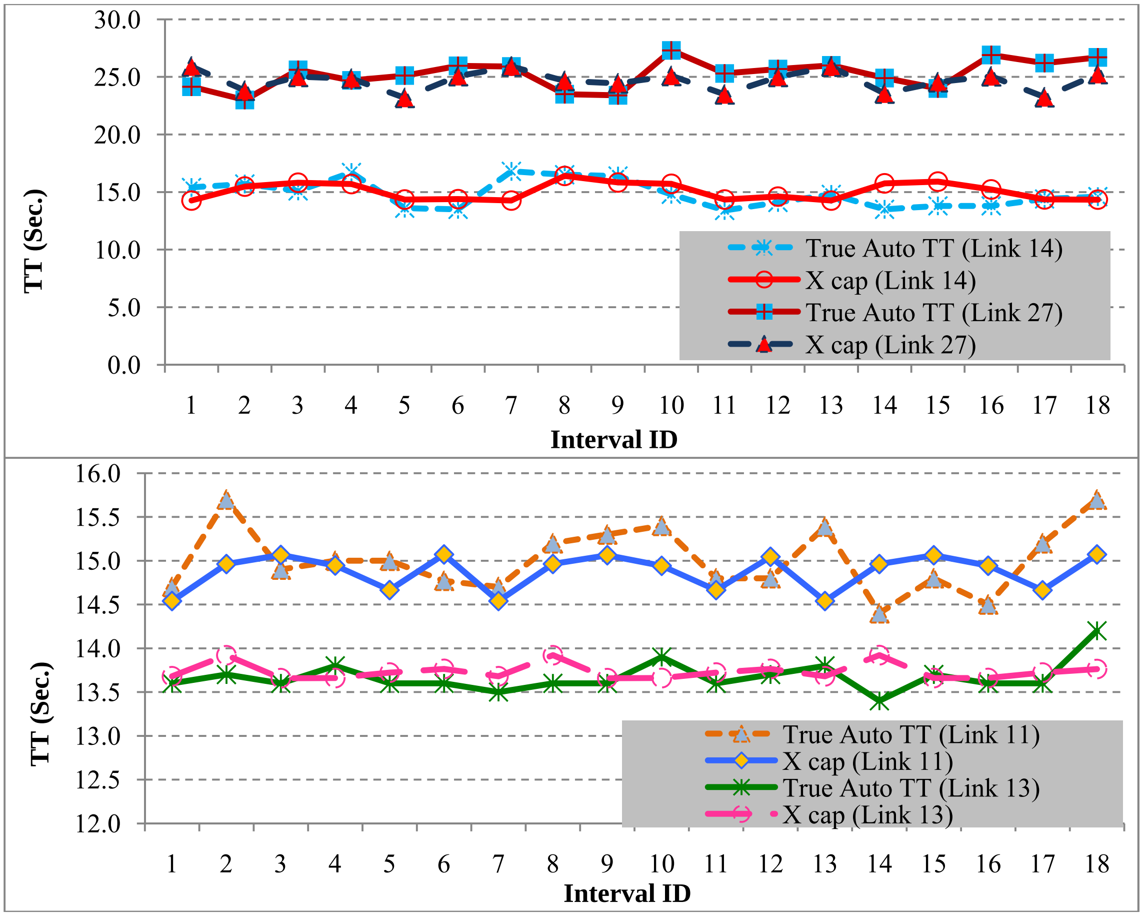

FIGURE 3 Estimated Vs. True Auto Travel Times

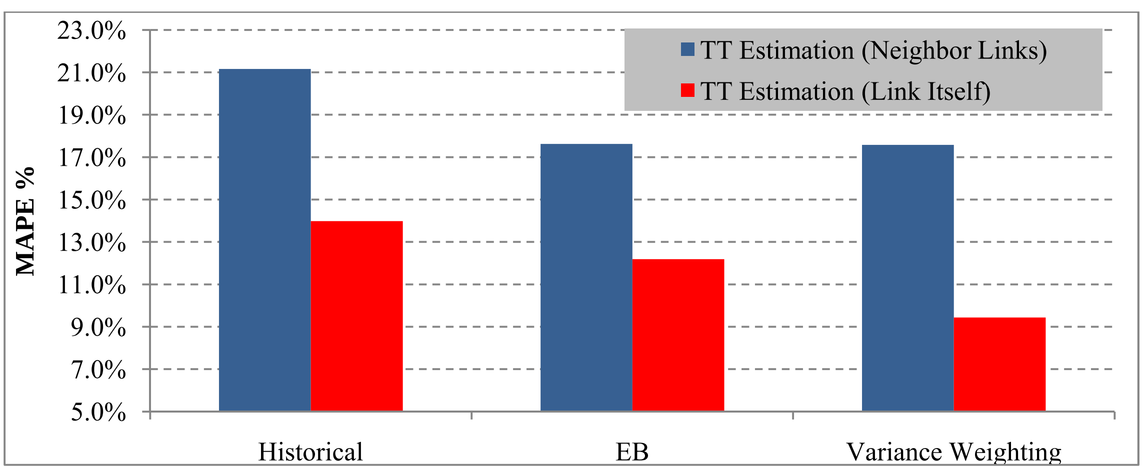

FIGURE 4 Accuracy of Using Buses As Probes for Travel Time Estimation

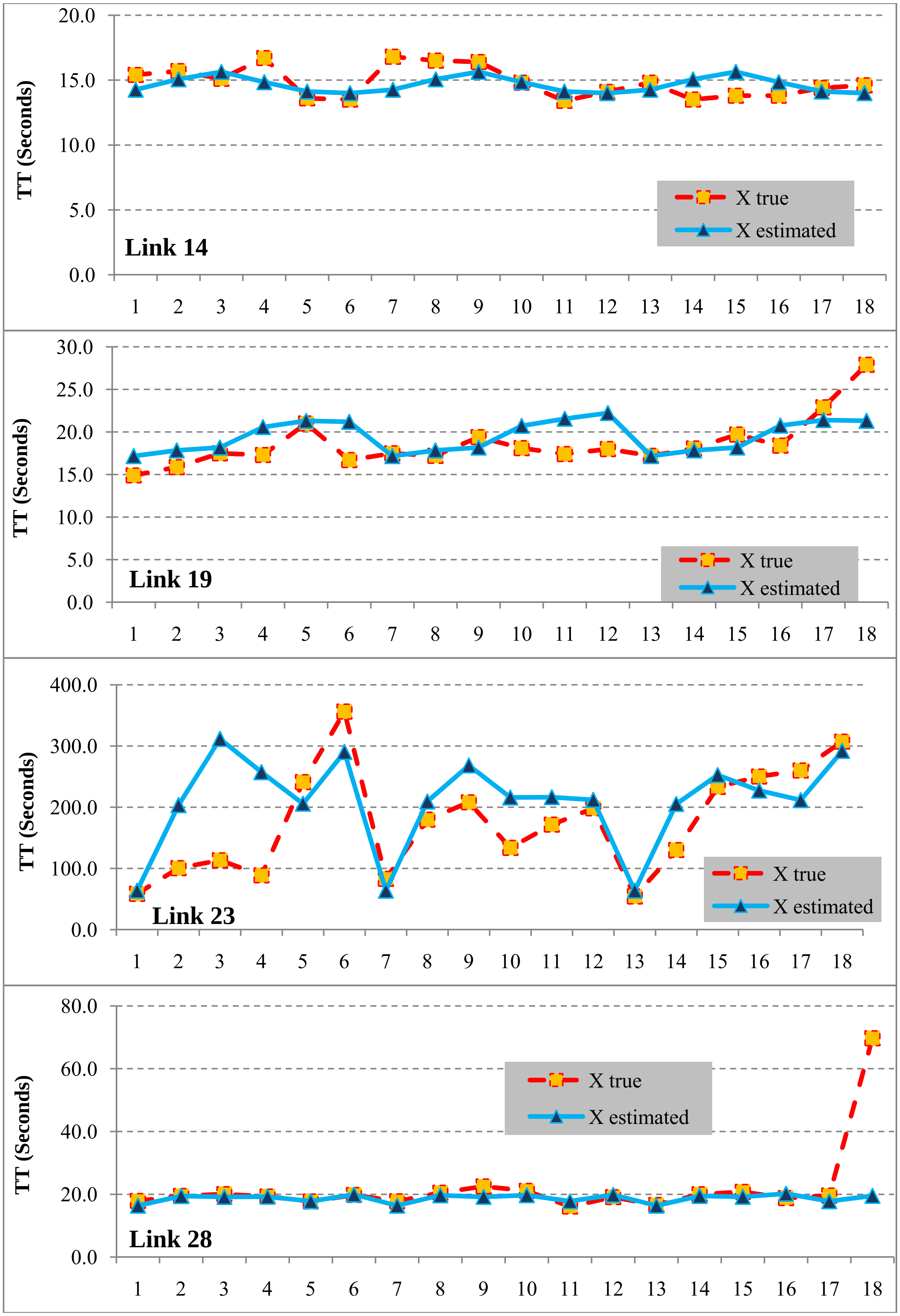

FIGURE 5 Estimated Versus True Link Travel Times for the Four Sections (Variance Weighting Used)

TABLE 1 Summary Statistics of the Analyzed Segments

Street	Group ID	Section ID	Number of Transit Lines	Length (m)
Richards	1	9	4	180.1
Richards	1	11	1	166.1
Richards	1	13	1	163.3
Howe	1	26	1	181.6
Richards	2	10	1	173.2
Richards	2	12	1	166.4
Richards	2	14	1	164.6
Howe	2	27	4	174.3

TABLE 2 Correlation between Average Automobile and Bus Travel Times

	Bus TT (Group 2)	Bus TT- Total Dwelling Time (Group 1)
Correlation Estimate	0.93	0.91
95% LL	0.89	0.87
95% UL	0.95	0.94
p-value	<0.0001	<0.0001

TABLE 3 Models' Parameters and Goodness of Fit

	Variable	Coefficients	t-Stat	*P-value*	Adjusted R^2	MSE
Group 1	Intercept	9.559	16.1	0.000	0.84	10.48
	(Bus TT-Bus dwell*No. of Stops)	0.120	21.1	0.000		
	Variable	**Coefficients**	**t-Stat**	***P-value***	**Adjusted R^2**	**MSE**
Group 2	Bus tt	0.787	90.0	0.000	0.97	4.14

TABLE 4 Defined Neighbours for Transit Sections

Transit Segment ID	Neighbour Link ID	Correlation Estimate	95% Confidence Limit LL	95% Confidence Limit UL	*p-value* $H_0: r = 0$
9	37	0.63	0.34	0.81	0.000
9	21	0.62	0.33	0.80	0.000
9	20	0.55	0.24	0.76	0.001
9	5	0.51	0.19	0.74	0.003
9	19	0.45	0.11	0.70	0.011
9	38	0.64	0.36	0.81	<.0001
11	23	0.55	0.23	0.76	0.001
11	28	0.46	0.12	0.70	0.009
11	7	0.39	0.04	0.66	0.029
12	14	0.37	0.01	0.64	0.040
13	7	0.51	0.18	0.73	0.003
13	28	0.42	0.07	0.68	0.018
13	35	0.36	0.00	0.64	0.045
14	12	0.37	0.01	0.64	0.040