Arab J Sci Eng (2014) 39:7555–7567
DOI 10.1007/s13369-014-1332-z

RESEARCH ARTICLE - CIVIL ENGINEERING

Urban Arterial Travel Time Estimation Using Buses as Probes

S. Vasantha Kumar · Lelitha Vanajakshi

Received: 29 November 2013 / Accepted: 31 March 2014 / Published online: 22 August 2014

Abstract The accurate estimation of travel time of different types of vehicles in a traffic stream has always been of interest in various stages of planning, design, operations and evaluation of transportation systems. The traditional way of travel time data collection by means of active test vehicles or license plate matching techniques has its own limitations in terms of cost, manpower, geographic coverage, sample size and accuracy. With the growing need for real-time travel time data, the passive probe vehicles with onboard global positioning systems (GPS) are increasingly being used. However, due to privacy issues and participation requirements, the public transit vehicles are the only ones which can be equipped with GPS devices and this could possibly be used as a source to estimate the travel time of other types of vehicles. The present study is an attempt in this direction. Two approaches have been proposed: one based on the ratio of the section travel times of personal vehicles to public transit and the other based on the quantifiable relationship between the public transit and personal vehicles section travel times. The results showed that the approach-2 which is based on the relationship between the bus travel time and other vehicles travel time outperforms the approach-1, with 98 % of the times the deviation of estimated travel time of personal vehicle with respect to observed/actual travel time being less than ±5 min and mean absolute percentage error (MAPE) within the acceptable range of 10–15 %.

S. Vasantha Kumar (✉)
School of Mechanical and Building Sciences, VIT University, Vellore 632 014, India
e-mail: svasanthakumar@vit.ac.in

L. Vanajakshi
Department of Civil Engineering, Indian Institute of Technology Madras, Chennai 600 036, India
e-mail: lelitha@iitm.ac.in

الخلاصة

كان التقدير الدقيق لوقت السفر لأنواع مختلفة من المركبات في تيار حركة المرور دائما مهما في مختلف مراحل التخطيط والتصميم والعمليات وتقييم نظم النقل. والطريقة التقليدية لجمع بيانات وقت السفر عن طريق مركبات الاختبار النشطة أو تقنيات مطابقة لوحة الترخيص لها حدودها الخاصة من حيث التكلفة ، والقوى العاملة ، والتغطية الجغرافية ، وحجم العينة والدقة. ويتزايد -مع الحاجة المتزايدة لبيانات وقت السفر في الوقت الحقيقي -استخدام مركبات التحقيق السلبي على متن أنظمة تحديد المواقع العالمية. ولكن نظرا لقضايا الخصوصية وشروط المشاركة ، فإن مركبات النقل العام هي الوحيدة التي يمكنها أن تكون مجهزة بأجهزة تحديد المواقع العالمية ، وربما يمكن أن تستخدم هذه كمصدر لتقدير الوقت الذي يستغرقه السفر من أنواع أخرى من المركبات. وهذه الدراسة هي محاولة في هذا الاتجاه. لقد تم اقتراح نهجين: واحد على أساس نسبة قسم أوقات سفر المركبات الشخصية إلى وسائل النقل العامة وغيرها على أساس العلاقة الكمية بين وسائل النقل العامة وقسم أوقات سفر المركبات الشخصية. وأظهرت النتائج أن النهج الثاني الذي يقوم على العلاقة بين الوقت الذي يستغرقه السفر بالحافلات من غيرها من المركبات يتفوق على النهج الأول ، ومع 98٪ من الأوقات كان انحراف وقت السفر بالسيارة الشخصية المقدر فيما يتعلق بوقت السفر الملاحظ / الفعلي هو أقل من ± 5 دقائق ، ومتوسط نسبة الخطأ المطلق هو ضمن نطاق مقبول من 10-15٪.

Keywords Travel time · Public transport buses · Dwell time · Personal vehicles · Advanced traveler information system · Global positioning system

1 Introduction

Travel time is one of the fundamental measures in transportation engineering, which is easy to understand and communicated by both technical and non-technical user. In the context of intelligent transportation systems (ITS), travel time is one of the most preferred traffic information by a wide variety of travelers. Travel time information provided through variable message signs (VMS) at the roadside helps commuters to assess the prevailing traffic situation, and allows drivers to make better decisions in terms of route, mode or time of travel, thus alleviating driver stress. The Federal Highway Administration (FHWA) of the United States Department of Transportation listed ‘real-time travel time information’ as one among the six major groups aimed at getting as much congestion relief from the current system [1].

In general, the data collection system for travel time can fit into any of the following: test vehicle or floating car techniques, license plate matching, ITS probe vehicle and other indirect techniques from inductance loops or aerial video. Both test vehicle and license plate matching techniques for travel time data collection are labor-intensive, costly for any large-scale collection of travel time data, and as a result, unable to supply travel time on a continuous basis. This restricts the applicability of both the methods for advanced traveler information system (ATIS) applications such as real-time travel time estimation where the travel time of vehicles in the stream are needed in a continuous and uninterrupted manner. In such cases, the ITS probe vehicle technique is a promising alternative, which utilizes passive instrumented vehicles in the traffic stream and remote sensing devices to collect travel times.

The ITS probe vehicles can be personal vehicles, public transit buses or commercial vehicles that are not driving for the sole purpose of collecting travel times, thus making the initial cost lower. The ITS probe vehicle techniques include signpost-based transponders, Automatic Vehicle Identification (AVI) transponders, ground-based radio navigation, GPS and cellular phone tracking. Among them, GPS is more popular due to low operating cost per unit of data, coverage in any part of the world and affordability of the GPS instruments due to competitive market, thus making the initial and operating costs lower. The only disadvantage with the GPS-based probe vehicle system is the privacy issues with the personal and commercial vehicle owners. However, it is a good source of data from public transit buses as most of the cities all over the world have their public transit buses equipped with GPS mainly for real-time tracking of the fleets. In India, in recent years, the public transit vehicles are gradually being equipped with GPS devices in major metropolitan cities. The metropolitan transport corporation of Chennai has GPS in 600 buses out of the total fleet size of 3,400. Process is underway to install the GPS system in another 1,000 buses. Since there are no exclusive bus lanes for buses in Chennai, the public transit buses have to travel alongside other vehicles and quite often both experience similar traffic conditions, intersection control and incidents or special events. This implies that the public transit buses could be used as probes for estimating the travel time of other vehicles in the stream. The use of public transit buses as probes also offers other advantages such as frequent trips during peak hours, wide range network coverage, easy accessibility to the data, low initial and maintenance cost when compared to that of location based smart sensors, trouble-free installation and maintenance when compared to the fixing of loop detectors and other video-based sensors. The present study is an attempt to utilize this useful source of data from bus probes for estimating travel time of other vehicles in the stream. A detailed review of studies in the area of travel time estimation using probe vehicle data is presented in the following section.

2 Literature Review

Since the early 1990s, travel time measurement using probe vehicles has become more popular with the increasing development of ITS technologies. Depending on the technologies used for travel time data collection, probe vehicles can be classified into two groups: automatic vehicle identification (AVI) systems and automatic vehicle location (AVL) systems. AVI systems measure travel times by identifying vehicles through fixed roadside systems. One example of AVI is probe vehicles that are equipped with electronic tags, which can be used to communicate with roadside transceivers to identify unique vehicles and collect travel times between transceivers [2–5]. This method is suitable for travel time estimation on stretches of tolled roads which are equipped with electronic tagging technology for toll collection purposes. On the other hand, AVL systems measure travel times by identifying probe vehicle positions through in-vehicle systems. The main advantage of AVL systems is that it can continuously provide the location information of the mobile sensors over time. This differs from AVI systems, where a vehicle can only be identified at specific locations on the road network. The AVL systems are based on technologies which include ground-based radio navigation [6], GPS [7–11] and cellular phone tracking [12–14]. Of the above technologies used by AVL systems, GPS is more popular due to low operating cost per unit of data, coverage in any part of the world and affordability of the GPS instruments at lower price due to competitive market, thus making the initial and operating costs lower. However, equipping private vehicles with GPS for data collection may be a difficult task due to privacy issues and lack of public participation. It can be a good source of data from public transit buses as most of the cities all over the world have their public transit buses equipped with GPS mainly for real-time tracking of the fleets. There are many advantages such as frequent trips during peak hours, wide range network coverage and ease of accessibility to the data when public transit buses are used as ITS probe vehicles. The available literature in the area of use of public transit buses as probe vehicles for stream travel time estimation is detailed in the following section.

Table 1 Studies on stream travel time estimation using buses as probes

S. no.	Authors	Years	Technique used	Important findings
1	Bae	1995	ANN, Regression	ANN performs better than simple regression
2	Hall and Vyas	2000	Comparison of car and bus trajectories	Buses and cars experiences similar traffic conditions
3	Kho and Cho	2001	ANN, Regression	Regression model turns out to be more powerful than ANN
4	Dailey and Cathey	2002	Kalman filtering	Correlation exists between travel times/speeds obtained from probes and that of inductance loop detectors
5	Chakroborty and Kikuchi	2004	Regression	91 % of the predicted values had errors less than 15 %, and at least 77 % had errors less than 10 %
6	Bertini and Tantiyanugulchai	2004	Comparison of car and bus trajectories	Pseudo bus trajectories were able to explain the car travel time better than hypothetical bus trajectory
7	Lin	2009	Regression, State space model	State space model performs better than regression
8	Coifman and Kim	2009	Comparison of travel times and speeds of transit probes and loop detectors	Over 95 % of the transit-based observations are concurrent with that of the loop detector observations
9	Pu et al.	2009	Regression; Microscopic simulation using VISSIM	Estimated car travel times were within 15 % of the observed times
10	Acierno et al.	2009	Analytical formulation that combines road traffic conditions with transit traffic conditions	Proposed method of using transit data allows a reduction in travel demand estimation error between the O–D pairs considered
11	Esawey and Sayed	2010	Regression; Microscopic simulation using VISSIM	Estimated car travel times showed an error of 17.6 %
12	Kieu et al.	2012	Regression	Model performs better during off-peak hours

2.1 Studies on Stream Travel Time Estimation Using Buses as Probes

The details of the studies reported in the area of stream travel time estimation using buses as probe vehicles are shown in Table 1 and explained below.

One of the earlier attempts in this particular area is by Bae [15]. Both simple linear regression and artificial neural network (ANN) methods were employed and it was reported that ANN produced a better mapping of car travel time from bus probes than simple regression methods. Hall and Vyas [16] compared the car and bus trajectories and reported that when car experiences long delays, buses traveling nearby on the same route also get delayed. Kho and Cho [17] found that regression model with variables of bus travel time, traffic volume and number of bus stops found to perform better than ANN in estimating average travel time of the traffic stream. Based on AVL data and KFT, Dailey and Cathey [18] proposed algorithms based on Kalman filtering that use transit vehicles as probes to determine traffic speeds and travel times along freeways and other primary arterials in Washington. The study by Chakroborty and Kikuchi [19] developed simple linear regression equation that estimated the car travel time based on the travel time of the bus. The results showed that at least 91 % of the predicted values had errors less than 15 %, and at least 77 % had errors less than 10 %. The study by Bertini and Tantiyanugulchai [20] compared the time-distance diagrams of two types of assumed bus trajectories, namely hypothetical and pseudo buses with the time-distance diagram of car. Hypothetical buses were defined as buses traveling as if there were no stops and pseudo buses were defined as buses traveling as if they traveled at the maximum speed recorded for each link. The authors found that pseudo bus trajectories were able to explain the car travel time better than hypothetical bus trajectory. Lin [21] found that state space model using Kalman filtering performs better than simple regression model. The author also concluded that the difference between bus and car speeds at midblock is minimal when traffic is either highly congested or very light, and largest when traffic condition is somewhere in between. Coifman and Kim [22] reported that the travel speeds and travel times from transit data are generally consistent with the concurrent estimates from loop detector data. Pu et al. [23] developed bus–car speed relationships based on historic data using regression and reported that the estimated car travel times were within 15 % of the observed times. Esawey and Sayed [24] proposed regression models to relate bus travel time to car travel time. However, the study used simulated data using VISSIM for model development and validation and reported an error of 17.6 %. Kieu et al. [25] used regression analysis to relate bus travel time and car travel time in a study corridor of 2.2 km in Brisbane, Australia using bus vehicle identification data obtained from Bluetooth and radio frequency identification (RFID)-based techniques. The authors found that bus travel times and car travel times are comparable during off-peak hours.

The following gaps were identified in the studies reviewed above. Most of the reported studies except Acierno et al. [26] considered only the stopping times at bus stops and did not consider the associated acceleration, deceleration times. Acierno et al. [26] considered an acceleration (or deceleration) rate of 1 m/s^2, which is constant across all the bus stops. This assumption of constant acceleration (or deceleration) across all the bus stops and trips is not a realistic one as it can vary according to driver and vehicle characteristics. Hence in the present study, a methodology has been proposed, which will calculate the actual deceleration time, stopping time and acceleration time based on the approaching and departing speeds at bus stops. In most of the studies, the bus travel time was related to only car travel time. In India, the traffic comprises of vehicles of different static and dynamic characteristics. A sample analysis is one of the major arterials in Chennai shows that two-wheeled vehicles constitute 45 %, three-wheeled vehicles constitute 6 %, light motor vehicles (mostly of passenger cars) constitute 47 % and heavy motor vehicles counts to only 2 %. This classification clearly shows that, under heterogeneous traffic conditions as existing in India, inferring only car travel time will not be sufficient. Taking into account, the other modes as well become more important as the speed and travel time for the above said classification will be quiet different due to varying physical characteristics of each class of vehicles. Hence in the present study, three types of personal vehicles in the stream, namely two-wheeler, three-wheeler and car were taken into account.

Also, many of the reported studies corroborated their results using data from freeways where the interruption to traffic flow and the interaction among the vehicles are less. It is to be noted here that the estimation of traffic stream characteristics becomes more difficult in urban arterials with frequent signalized intersections and high interaction among vehicles especially under heterogeneous traffic conditions. Hence in the present study, two bus transit routes passing through important arterials of Chennai city was considered. Some of the reported studies were of simulation based and few of them validated the developed model only at selected time periods. To overcome these gaps, the proposed approaches for stream travel time estimation were evaluated for its accuracy using the real-world data covering traffic conditions at different time periods of a day.

3 Data Collection and Extraction

The study stretch selected for the present study was two bus transit routes, namely 5C and 23C in Chennai, India. The selected stretches are typical representation of urban routes in India comprising road links of different categories like major arterials, and collector streets with varying geometrics and volume levels. The route number 5C connects the Parrys bus terminus in the northern part of Chennai, and the Taramani bus terminus in the southern part. The time headway between the buses varies between 15 and 30 min. The total route length of 5C is 15 km and has 24 bus stops and 14 signalized intersections. The route number 23C connects the Ayanavaram bus terminus in the northwestern part of the city and the Tiruvanmiyur bus terminus in the southern part. The time headway between the buses varies between 15 and 30 min. The total route length of 23C is 19 km in onward direction (Tiruvanmiyur to Ayanavaram) and 21.5 km in return direction (Ayanavaram to Tiruvanmiyur) and has 18 and 21 bus stops in onward and return directions, respectively. The number of signalized intersections in 23C route is 21 and 22 in onward and return directions, respectively.

Data collection was carried out at different times of the day over several days using GPS units, which were fixed in the public transit buses and by manually carrying GPS devices in three types of personal vehicles—two-wheeler, three-wheeler and car. Fourteen trips were made for each mode in each bus route considered. The personal vehicle trip was started at the same time and location as that of the public transit bus and followed the same route along with the traffic stream. According to the travel time data collection handbook [27], the minimum number of test vehicle runs should be in the range of 5–15 to ensure that the travel time obtained from the test vehicle is within a specified error range of the true average travel time for the entire vehicle population. Also, it states that the test vehicle runs should be evenly distributed over various times in order to capture the off-peak and peak traffic characteristics. The 14 trips for each mode in each bus route as adopted in the present study was close to the suggested number of test vehicle runs at 95 % confidence level with ±5 % error. Also, the 14 trips were well distributed across varying time over several days in order to capture the off-peak and peak traffic characteristics. For data extraction, the total study stretch in each bus route was divided into 500-m subsections in order to facilitate the comparison of section travel times of the bus and the other vehicles. For each trip, the travel time of bus probe and personal vehicle within each of these 500-m subsections were calculated. This process is repeated for all the 252 trips made (28 trips (14 trips for bus and 14 trips for personal vehicle) ×3 directional routes ×3 modes).

4 Estimation Scheme

The estimation scheme proposed here uses two approaches: one based on the ratio of the section travel times of personal vehicles to public transit and the other based on the quantifiable relationship between the public transit and personal vehicles section travel times. The procedure to remove the dwell times at bus stops with associated acceleration and deceleration times is detailed first. The details of the two approaches to estimate the modewise travel time of personal vehicles using only the bus travel time data are discussed after that.

4.1 Procedure to Find the Dwell Times with Associated Acceleration and Deceleration

Since all modes of vehicles are sharing the same roadway without any exclusive bus lanes, the only characteristic that differentiates the bus probes from the remaining vehicles is the dwell time at bus stops. The methodology to determine the dwell time or stopping time at bus stops including the time of deceleration and acceleration based on the speed of movement of the transit buses is explained below.

After fixing the latitude and longitude range of each bus stop, a program in MATLAB has been written which will check for the lowest speed value (denoted as K_t, where t is the GPS time) corresponding to the selected bus stop range. For finding the time of start of deceleration, each pair of speed values (K_t and K_{t-1}, K_{t-1} and K_{t-2}, K_{t-2} and K_{t-3}, etc.) will be checked, until the speed $K_{t-n} > K_{t-(n+1)}$, where $n = 0, 1, 2, 3\ldots$ The time corresponding to K_{t-n} is considered as the time of start of deceleration. In other words, for finding the time of start of deceleration, each pair of successive speed values (prior to the lowest speed) will be checked, until the prior speed ($K_{t-(n+1)}$) in the pair is lower. A similar procedure is adopted for finding the time of end of acceleration. For finding the time of end of acceleration, each pair of speed values (K_t and K_{t+1}, K_{t+1} and K_{t+2}, K_{t+2} and K_{t+3}, etc.) will be checked, until the speed $K_{t+n} > K_{t+(n+1)}$, where $n = 0, 1, 2, 3\ldots$ The time corresponding to K_{t+n} is considered as the time of end of acceleration. The difference between the two times is taken as the dwell time, which includes the acceleration and deceleration times.

Once the dwell time with associated acceleration and deceleration times were found for all the bus stops in each bus trip, they were removed from the actual section travel times of the bus. The dwell time removed bus travel times were considered as a probe input for estimating the travel time of other vehicles in the stream using the two approaches as explained in the following section.

4.2 Estimation of Personal Vehicle Travel Time Using Approach-1

Approach-1 is based on the assumption that, in a subsection, the travel times of bus and the personal vehicle can be related by a parameter $s(k)$ as shown in Eq. 1.

$$s(k) = \frac{a(k)}{b(k)} \tag{1}$$

where $a(k)$ and $b(k)$ are the personal vehicle and bus travel times (dwell time removed) in subsection 'k' and 'k ' varies from 1 to n, where 'n' is the total number of 500-m sections in the study stretch considered. If both the personal vehicle and public transit travel times in kth subsection are equal, then $s(k)$ will be equal to one. The scheme for the estimation of the model parameter $s(k)$ is explained below.

For each mode in each bus route considered, two set of $s(k)$ values were calculated, one representing the off-peak traffic conditions and the other representing the peak traffic conditions. The time period from 8 to 11 am and 5 to 8 pm were considered as the morning and evening peak periods, respectively, and the remaining time periods were considered as off-peak. Based on this, 126 trips (here, each trip is a pair of public transit and personal vehicle) were classified either as off-peak trip or peak hour trip based on their trip staring times. In order to calculate the parameter $s(k)$, out of 14 trips representing each mode in each bus route, 4 trips were used for model calibration and the remaining 10 trips were kept of validation. Out of the 4 trips for model calibration, two trips were from off-peak traffic conditions, and the remaining two were representing the morning peak and evening peak, respectively. For each subsection 'k,' the section travel times of those two trips were averaged to calculate the personal vehicle travel time $a(k)$ and similarly the bus travel time $b(k)$. Once $a(k)$ and $b(k)$ are known, $s(k)$ was calculated for off-peak and peak traffic separately using Eq. (1) for each mode in each bus route considered. Thus, a total of 18 set of $s(k)$ values were calculated for all the modes in all three directional routes considered [2 (one for off-peak and one for peak traffic) $\times$ 3 modes $\times$ 3 routes]. During peak traffic, the number of sections where the calculated $s(k)$ was greater than one was observed as 6, 11 and 18 for two-wheeler, three-wheeler and car, respectively. The comparatively lower value for two-wheeler shows that the two-wheeler in heterogeneous traffic can easily maneuver the available space between vehicles and travels much faster than bus and exhibit a travel time less than that of bus in most of the sections when compared to three-wheeler and car. For car, in almost half of the sections, the bus travels faster than car with lesser travel times with $s(k)$ value greater than one. Thus, by using the parameter $s(k)$, one can estimate the travel time of other vehicles in the stream using the bus travel time as input using Eq. 2 which was obtained by rearranging Eq. 1.

$$a(k) = s(k) \times b(k) \tag{2}$$

For travel time estimation of the remaining 10 trips for each mode in each bus route, the section-wise bus travel times (dwell time removed) were used in place of $b(k)$ and were

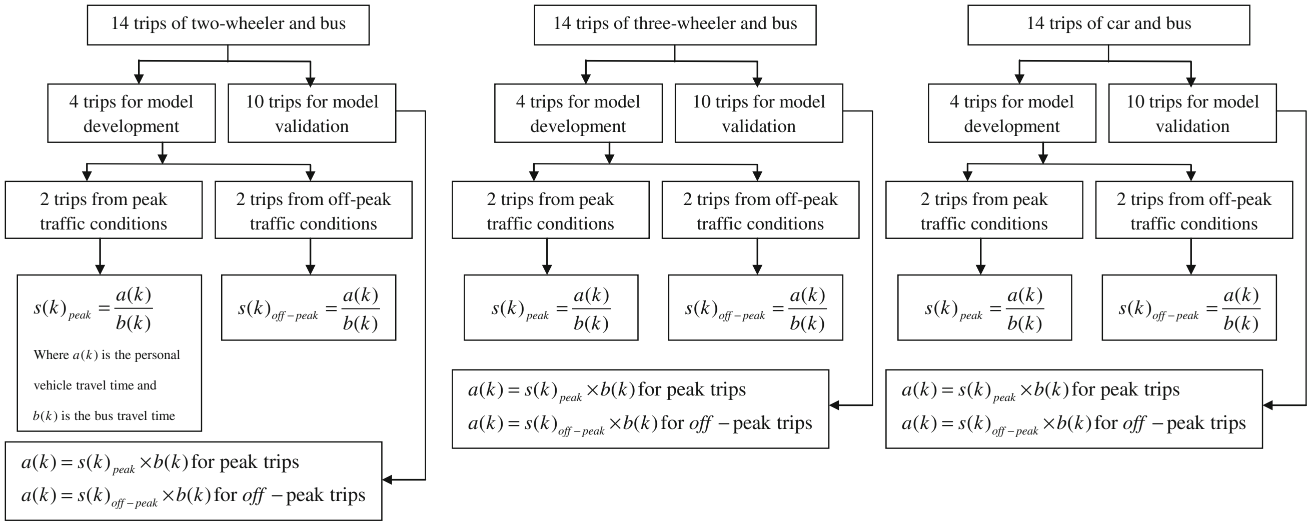

Fig. 1 Flowchart showing the proposed methodology for the estimation of stream travel time using approach-1

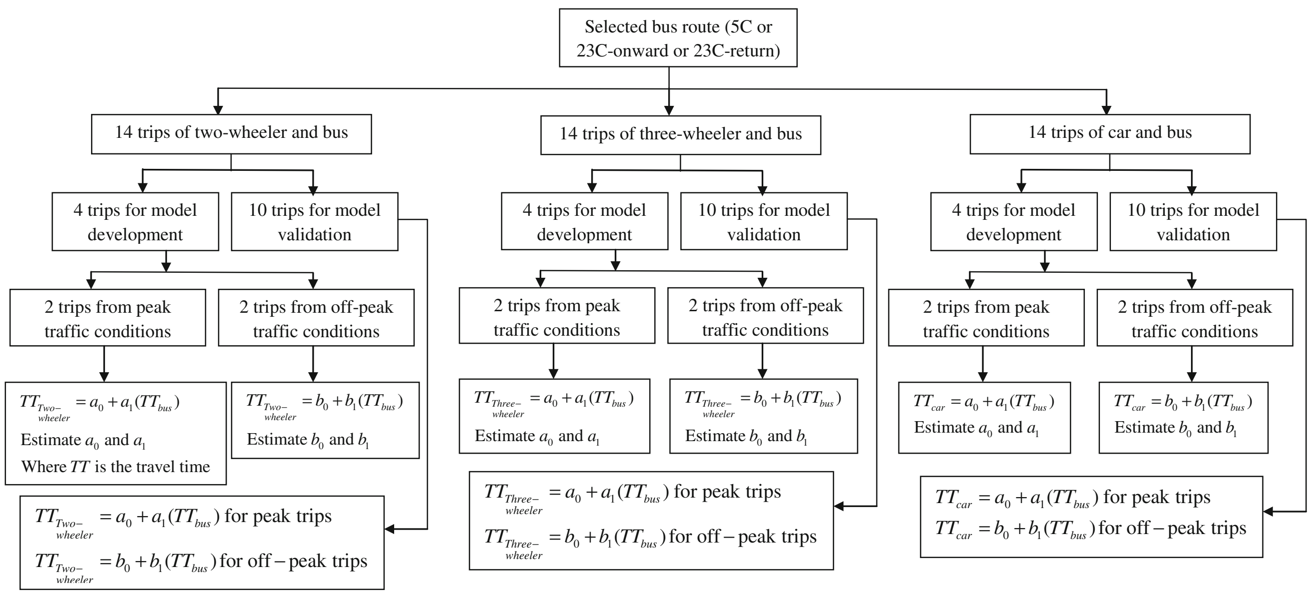

Fig. 2 Flowchart showing the proposed methodology for the estimation of stream travel time using approach-2

multiplied by $s(k)$ to obtain the corresponding personal vehicle travel time estimates. The estimated personal vehicle travel times were then compared with the observed/actual personal vehicle travel times obtained from those 10 trips of each mode in each bus route considered. A flowchart showing the proposed methodology for approach-1 is shown in Fig. 1.

4.3 Estimation of Personal Vehicle Travel Time Using Approach-2

Approach-2 is based on the concept of developing an empirical relationship between the bus travel times (dwell time removed) and personal vehicle section travel times. Regression analysis was used to develop the relationship with independent variable as the bus travel time and dependent variable as the personal vehicle travel time. The same trips which have been used for $s(k)$ calculation was used to find the relationship in this scheme too. A total of 18 regression equations were developed for all the modes in all three directional routes considered. A flowchart showing the proposed methodology for approach-2 is shown in Fig. 2.

A sample scatter plot of personal vehicle travel time versus the bus travel time in 23C route for all the three modes during both off-peak and peak traffic conditions is shown in Fig. 3. The fitted equations along with R^2 values are also shown. In all the cases, a positive linear relationship was observed with R^2 value of more than 0.7 (except two-wheeler off-

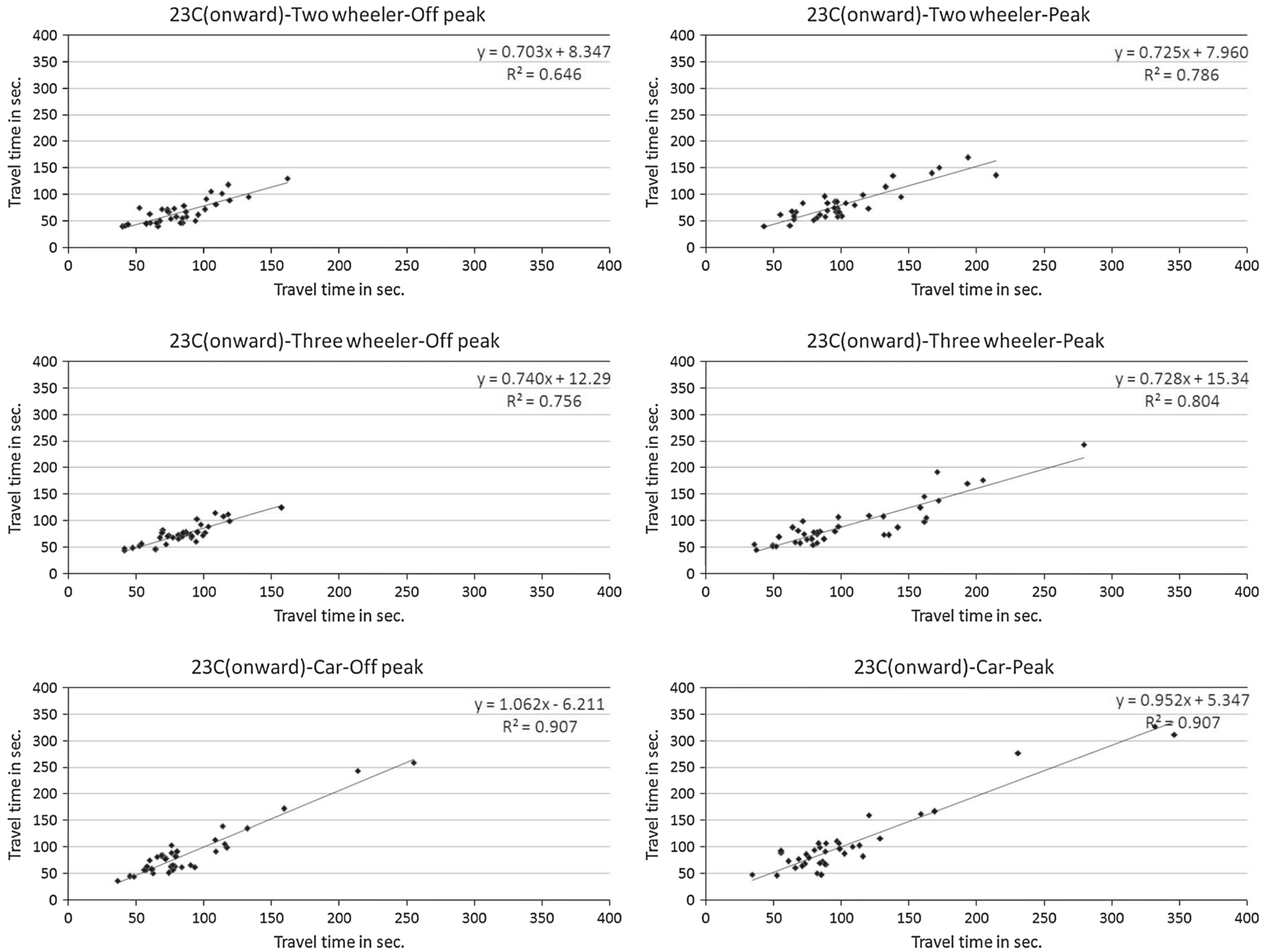

Fig. 3 Scatter plot of personal vehicle travel time versus the bus travel time in 23C route

peak) between the travel times of public transit and personal vehicles. This shows that if the traffic is high in a particular section, both transit probe and other vehicles will get slowed down. Similarly, if free flow condition exists, both the modes travel fast and exhibit a relatively lesser travel time. In regression analysis, it is essential to check whether the coefficient is significant using the p value. It was found that the p value is less than 0.05 in all the cases, thus showing the statistical significance of the regression coefficient in the developed regression model.

5 Results and Discussion

The efficacy of the two approaches proposed in the previous sections for the estimation of personal vehicle travel time using the bus travel time data was tested using the remaining 10 trips for each mode in each bus route considered. In each of these ten trips, the section-wise bus travel times (dwell removed) were used to obtain the corresponding personal vehicle travel time estimates using the approaches 1 and 2. A total of 90 trips (10 trips $\times$ 3 modes $\times$ 3 routes) were used for corroboration. For comparing the estimated personal vehicle travel times with the observed travel times, 15 origin–destination (O–D) pairs in each bus route were considered. Thus, for all three directional routes, a total of 45 O–D pairs (15 $\times$ 3 directional routes) were used and the estimated and observed travel times of personal vehicles in each of these O–D pairs were computed. The purpose of using the O–D pair concept for travel time comparison is that the final application of the proposed model involves the provision of travel time information through VMS at important junctions along the route. At each of these junctions, the travel time to important destinations on downstream will be provided. Hence, the O–D pairs were selected covering these important destinations in the selected bus routes. The estimated travel times in the O–D pairs were compared with the observed travel times using absolute error (AE) expressed in minutes and mean absolute percentage error (MAPE) as shown below in Eqs. 3 and 4.

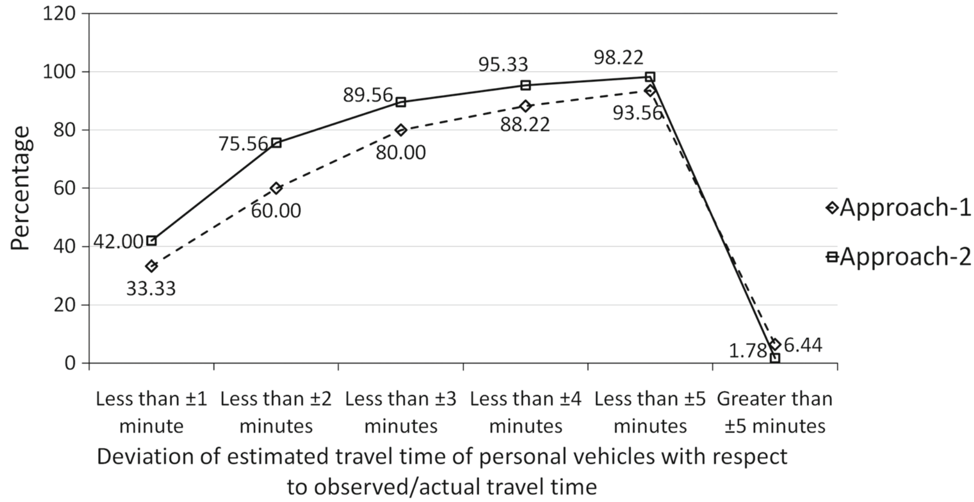

Fig. 4 Number of times the estimated travel time of personal vehicles deviated with respect to observed/actual travel time for various time intervals (expressed in percentage) in 5C route

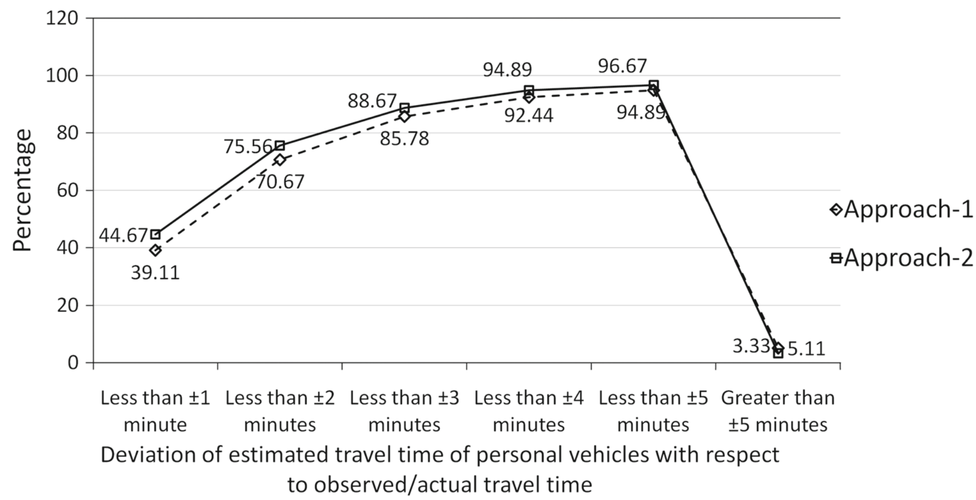

Fig. 5 Number of times the estimated travel time of personal vehicles deviated with respect to observed/actual travel time for various time intervals (expressed in percentage) in 23C route-onward direction

$$\mathrm{AE} = |\mathrm{TTE\text{-}TTO}| \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{TTE}-\mathrm{TTO}}{\mathrm{TTO}}\right| \times 100 \tag{4}$$

where TTE and TTO are the estimated and observed travel times of personal vehicles expressed in minutes and 'n' is the number of O–D pairs considered.

Considering ±5 min as an allowable AE (maximum deviation of estimated travel time of personal vehicle with respect to observed/actual travel time), the number of times the deviation went less than ±1 min, less than ±2 min, less than ±3 min, less than ±4 min, less than ±5 min and more than the tolerable limit of ±5 min was found for all the 90 trips by both the approaches. A total of 450 absolute error values were used in each bus route considered (15 O–D pairs × 10 trips × 3 modes). The results are shown in Figs. 4, 5 and 6 for 5C route, 23C route-onward and 23C route-return directions, respectively.

It can be seen that approach-2 which is based on the relationship between the bus travel time and other vehicles travel time outperforms the approach-1, with 98 % of the times the deviation being less than ±5 min in 5C route. Similar results were obtained in 23C route, with approach-2 showing comparatively higher percentage values with 97 and 91 % of the times the deviation being less than ±5 min in onward and return directions, respectively. Considering all three routes, on an average, approach-2 performs better than approach-1 with 91 % of the times the deviation within ±4 min; 82 % of the times the deviation within ±3 min; 66 % of the times the deviation within ±2 min and 39 % of the times within ±1 minute. The MAPE averaged across 10 trips for each mode in each bus route considered is shown in Fig. 7. It can be seen from Fig. 7 that approach-2 performs better than approach-1 with lesser MAPE in most cases. According to Chakroborty et al. [19], considering traffic signals and the usual perturbations in urban traffic, the tolerable error of the estimate may be about 10–15 % of the actual travel time. According to Pu et al. [23], the estimated car travel times within 15 % of the observed times are acceptable. Esawey et al. [24] reported a deviation of 10–17.6 % as acceptable. Based on these stud-

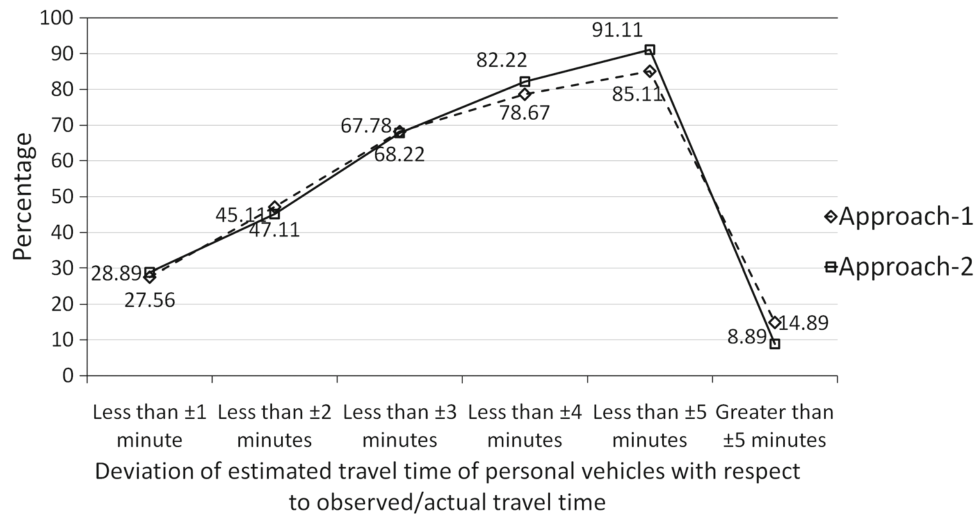

Fig. 6 Number of times the estimated travel time of personal vehicles deviated with respect to observed/actual travel time for various time intervals (expressed in percentage) in 23C route-return direction

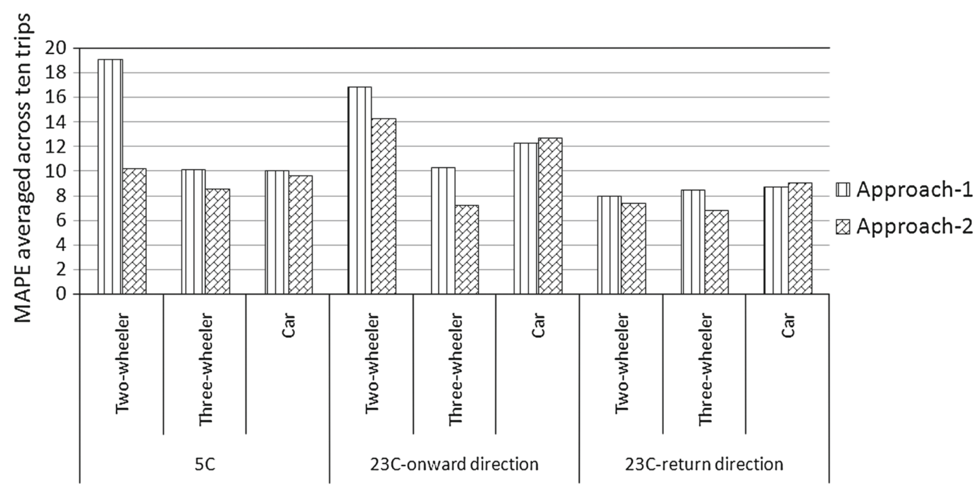

Fig. 7 Mean absolute percentage error (MAPE) between estimated and observed/actual personal vehicles travel time

ies, it can be assumed that the acceptable MAPE for a robust model to be in the range of 10–15 %. In the present study, it can be observed from Fig. 7 that approach-2 produces a MAPE within this acceptable range. Sample plot of observed versus estimated travel times for car is shown in Fig. 8. It can be seen that the estimated travel times are closely following the observed travel times for the O–D pairs considered.

In order to check the effect of dwell times with associated acceleration, deceleration times on personal vehicle travel time estimation, a comparison was made with and without the removal of dwell times for a sample case of three-wheeler in 5C route for an off-peak scenario. The actual section-wise bus travel times (without removing dwell times) were used as the independent variable in the regression model to obtain the corresponding three-wheeler travel time estimates. Similarly, the dwell time removed bus travel times were used to obtain the corresponding three-wheeler travel time estimates. The estimated travel times for various O–D pairs were then compared with the observed/actual three-wheeler travel times and the results of MAPE are shown in Table 2. It can be seen from Table 2 that, in 7 out of 8 trips, the scenario of using dwell time removed bus travel times performs better than the scenario of using actual bus travel times. This shows the importance of dwell time removal if public transit buses are used as probes for other vehicles travel time estimation.

In order to check whether there is an improvement in model estimates of approach-2, we have considered two more independent variables, namely the carriageway width and the presence or absence of signalized intersection(s) in each 500-m section in addition to bus travel time. A sample route, namely 23C-onward direction was taken into account and the carriageway width was measured manually in every 500-m sections using tapes in the field. For sections with varying carriageway widths, a weighted carriageway width has been arrived at based on the section lengths as shown below.

$$\text{Weighted carriageway width} = \frac{\sum_{i=1}^{n}(c_i \times l_i)}{\sum_{i=1}^{n}(l_i)} \quad (5)$$

where c_i is the carriageway width for section i of length l. The presence or absence of signalized intersection(s) in each

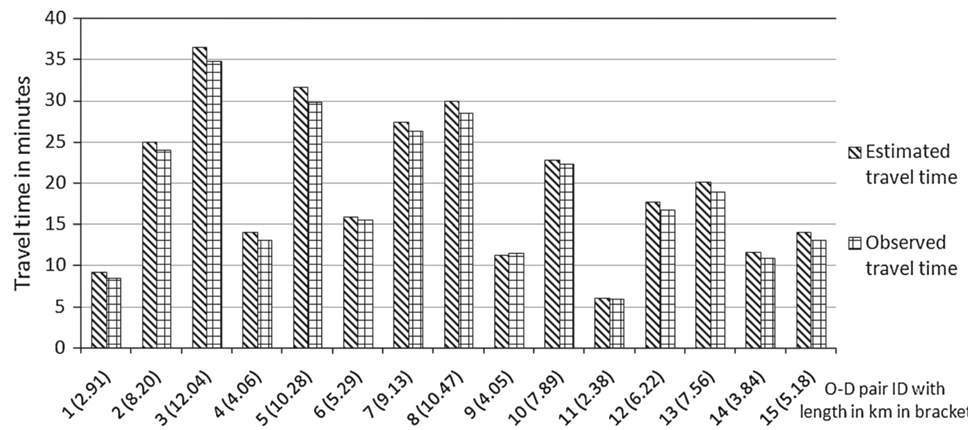

Fig. 8 Plot of observed versus estimated travel time for car

Table 2 MAPE between estimated and actual three-wheeler travel times in 5C route

Trip ID	MAPE using actual bus travel times (without removing dwell times)	MAPE using dwell times removed bus travel time data
1	10.994	6.055
2	13.228	9.479
3	19.804	14.753
4	8.358	5.991
5	19.741	4.504
6	7.510	10.171
7	10.039	4.742
8	15.536	7.740

Table 3 Coefficients of regression variables

	Two-wheeler		Three-wheeler		Car	
	Off-peak	Peak	Off-peak	Peak	Off-peak	Peak
Intercept	16.235	19.349	19.906	7.724	16.656	14.706
Bus travel time	0.608	0.707	0.672	0.723	1.006	0.944
Carriageway width	−0.609	−1.327	−0.473	0.712	−2.340	−0.921
Presence/absence of signalized intersection	10.688	4.756	4.601	3	6.404	0.074

500-m section was also noted down. The results of regression analysis showing the coefficients of regression variables are shown in Table 3.

It can be seen from Table 3 that the carriageway width generally exhibits a negative coefficient. It is logical that when carriageway width reduces, the capacity gets reduced and will result in an increased travel time. Intersection presence/absence (a binary variable which takes the values of 1 or 0) exhibits a positive regression coefficient in all the cases considered. It is consistent with the fact that when there is a signalized intersection in a 500- m section, the probability of congestion is higher due to signal delays. The results of *p* values of the coefficients to check for the statistical significance of the independent variables are shown in Table 4.

It can be seen from Table 4 that the *p* values are not less than 0.05 in most of the cases for the two newly added independent variables, namely, the carriageway width and presence/absence of signalized intersection(s), thus showing that they are not statistically significant. The validation also showed similar results that the addition of two independent variables does not show much improvement in the travel time estimates as can be seen in Figs. 9 and 10. Thus, for the present case, the addition of more variables like carriageway width and the presence/absence of signalized intersection(s) in the regression model of approach-2 does not show significant improvements in the model estimates.

One of the simple method available in literature in estimating stream traffic conditions using bus probe data is to con-

Table 4 *p* values of regression coefficients

	Two-wheeler		Three-wheeler		Car	
	Off-peak	Peak	Off-peak	Peak	Off-peak	Peak
Bus travel time	2.82E−07	2E−11	1.06E−08	7.64E−12	1.78E−18	6.95E−17
Carriageway width	0.449	0.136	0.466	0.559	0.007	0.486
Presence/absence of signalized intersection	0.027	0.382	0.243	0.690	0.195	0.992

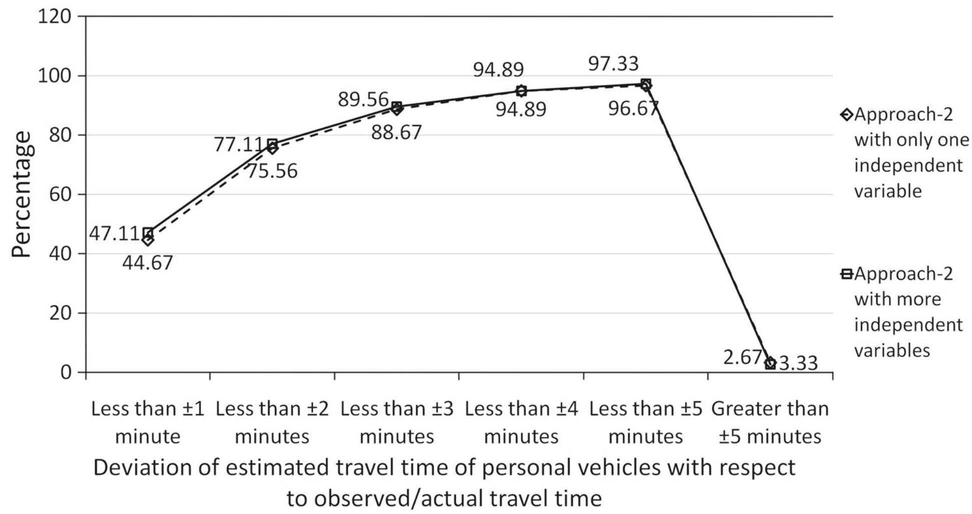

Fig. 9 Comparison of percentage deviation of approach-2 of one independent variable with that of more independent variables

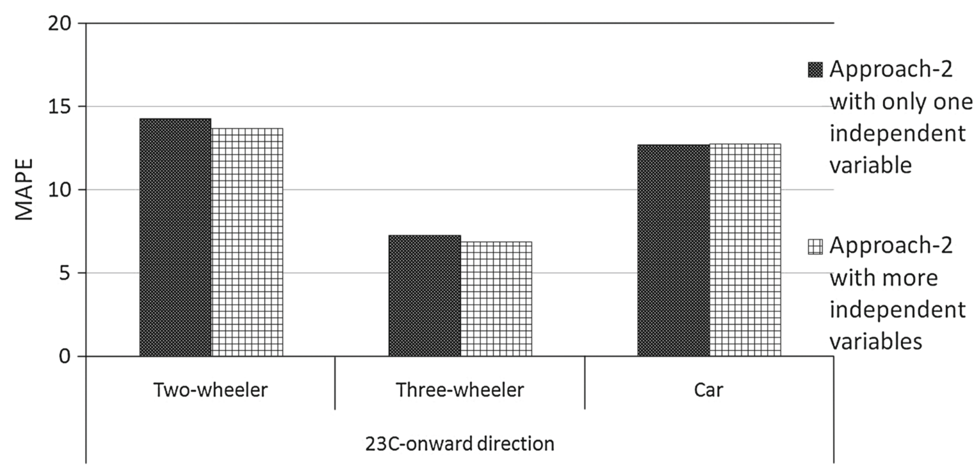

Fig. 10 Comparison of MAPE of approach-2 of one independent variable with that of more independent variables

sider directly the bus travel time (after deducting dwell times) as representative of the stream traffic conditions [20] and comparing whether the bus and car travel times are matches or not. The main advantage of this method is that it does not require any model building using regression analysis except the dwell time (including acceleration, deceleration times) removal algorithm. Hence, this simple method of using direct bus travel time as representative of stream traffic conditions has been tried out and compared with that of the results of approach-2, which is based on regression analysis. The results of MAPE averaged across 10 trips for each mode in 23C route (onward direction) are shown in Fig. 11.

It can be seen from Fig. 11 that for two-wheeler, the use of direct bus travel time (simple method) is not recommended as it shows very high MAPE value when compared to that of approach-2. Since the two-wheeler being the smallest mode in the stream with widely different characteristics as compared to bus, the travel times vary widely compared to those of bus. Hence for estimating two-wheeler travel times, the approach-2 of using regression equations should be considered. For three-wheeler also, the approach-2 showed better results with relatively lesser MAPE when compared to that of simple method of using bus travel time as direct three-wheeler travel time. But for car, both the methods yields

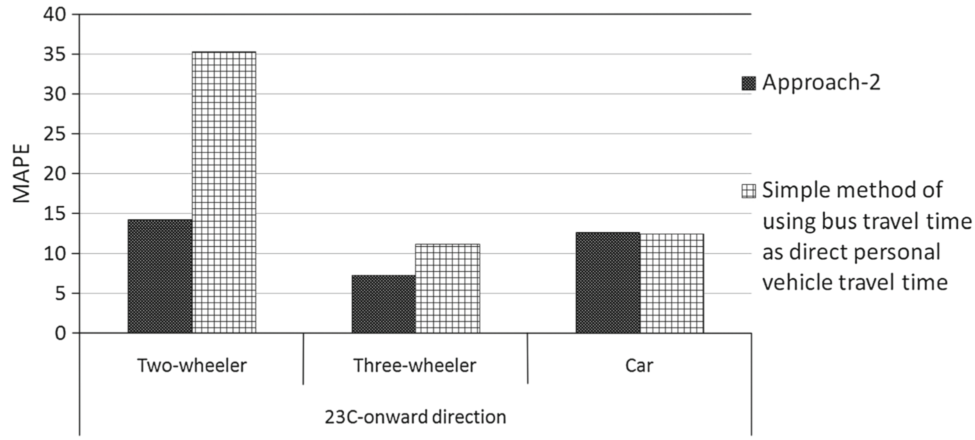

Fig. 11 Comparison of approach-2 with simple method of using bus travel time as direct personal vehicle travel time

comparable MAPE values and hence the bus travel time after removing dwell times can be considered directly as that of the car travel time without using any regression equations. Thus, it can be concluded that, for the case study routes in Chennai, India, the two-wheeler and three-wheeler travel times can be estimated using the developed regression models with dwell time removed bus travel time as independent variable. Whereas for cars, the bus travel time after removing dwell times at bus stops can be considered directly as that of car travel time without using any regression equations.

6 Concluding Remarks

Travel time is one of the fundamental measurements required by both transportation professionals and users of a transportation system. With the advent of low cost GPS systems, the probe vehicle-based techniques for travel time estimation gains more attention and gradually replaces the traditional techniques of license plate matching or active test vehicles. However, due to privacy issues and participation requirements, the personal or commercial vehicles may not be employed as passive probe vehicles leading to the research problem of estimating the stream travel time from bus data alone. The present study analyzed this problem of estimating the travel time of other types of vehicles such as two-wheeler, three-wheeler and car from bus data. In order to use bus data for such an application, there is a need to remove the dwell times at bus stops. This has been given a careful attention in the present study by proposing a methodology which can calculate the dwell times with associated acceleration and deceleration times. Using this dwell time removed bus travel time, two approaches were proposed for the stream travel time estimation. The methods used only two sample trips representing each traffic conditions for model calibration. The second approach based on a relationship between bus and other vehicle travel times showed a better performance when compared to the first approach which was based on the ratio of the two subject vehicle travel times.

In countries like India, the unique nature of roadway geometry and traffic behavior restricts the applicability of infrastructure-based techniques such as loop detector or aerial video for automated travel time data collection and estimation. On the other hand, the probe vehicle-based techniques for travel time data collection using personal vehicles or commercial vehicles as probes could not be employed due to privacy issues and participation requirements. In such cases, the GPS-fitted public transit buses could be considered as probes and the present study showed a methodology on how to use this GPS data of bus probes to estimate the other vehicles travel time. The estimation scheme proposed in the present study for modewise travel time estimation using only bus data could potentially be used in applications such as providing real-time traveler information in ATIS in a cheap and effective manner.

Acknowledgments The authors acknowledge the support for this study as part of the project 23(1)/2009-IEAD by Department of Information Technology, Government of India.

References

1. FHWA (Federal Highway Administration): Focus on Congestion Relief. Department of Transportation, United States. http://www.fhwa.dot.gov/congestion/toolbox/. Accessed 29 Nov 2013
2. Ohba, Y.; Ueno, H.; Kuwahara, M.: Travel time calculation method for expressway using toll collection system data. In: International Conference on Intelligent Transportation Systems, pp. 471–475. Tokyo, Japan (1999)
3. Soriguera, F.; Thorson, L.; Robuste, F.: Travel time measurement using toll infrastructure. In: Proceedings of the 86th Annual Meeting of the Transportation Research Board, Washington, DC, USA (2007)
4. Namkoong, S.J.; Smith, B.L.; Lee, H.; Song, P.: A method to estimate path-travel time on expressway using toll collection system data. 15th World Congress on Intelligent Transport Systems and ITS America's 2008 Annual Meeting, New York, USA (2008)

5. Faouzi, E.; Billot, R.; Bouzebda, S.: Motorway travel time prediction based on toll data and weather effect integration. Intell. Transp. Syst. IET **4**(4), 338–345 (2010)
6. Vaidya, N.; Higgins, L.L.; Turnbul, K.F.: An evaluation of the accuracy of a radio-trilateration automatic vehicle location system. In: Proceedings of the 1996 Annual Meeting of ITS America, Intelligent Transportation Society of America, Washington, DC, USA (1996)
7. Nakata, T.; Takeuchi, J.: Mining traffic data from probe-car system for travel time prediction. In: Proceedings of the 10th ACM International Conference on Knowledge Discovery and Data Mining, pp. 817–822. NY, USA (2004)
8. Jensen, A.F.; Larsen, T.V.: Travel-time estimation in road networks using GPS data. http://projekter.aau.dk/projekter/files/61070977/1181652577.pdf. Accessed 07 Feb 2014
9. Miwa, T.; Sakai, T.; Morikawa, T.: Route identification and travel time prediction using probe-car data. Int. J. ITS Res. **2**(1), 21–28 (2008)
10. Hunter, T.; Herring, R.; Abbeel, P.; Bayen, A.: Path and travel time inference from GPS probe vehicle data. NIPS 2009 Workshop on Analyzing Networks and Learning with Graphs, Canada (2009)
11. Zheng, F.; Zuylen, H.: Urban link travel time estimation based on sparse probe vehicle data. Transportation Research Part C. doi:10.1016/j.trc.2012.04.007
12. Yoo, B.S.; Kang, S.P.; Park, C. H.: Travel time estimation using mobile data. In: Proceedings of the Eastern Asia Society for Transportation Studies, 5, pp. 1533–1547 (2005)
13. Wunnava, S.V.; Yen, K.; Babji, T.: Travel time estimation using cell phones for highways and roadways. Final report, Florida International University, Miami, FL (2007)
14. Tao, S.; Manolopoulos, V.; Rodriguez, S.; Rusu, A.: Real-time urban traffic state estimation with A-GPS mobile phones as probes. J. Transp. Technol. **2**, 22–31 (2012)
15. Bae, S.: Dynamic estimation of travel time on arterial roads by using automatic vehicle location (AVL) bus as a vehicle probe. Ph.D. dissertation, Department of Civil Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA (1995)
16. Hall, R.W.; Vyas, N.: Buses as a traffic probe: demonstration project. Transp. Res. Rec. J. Transp. Res. Board **1731**, 96–103 (2000)
17. Kho, S.Y.; Cho, J.R.: Estimating average travel times from bus travel times. Proc. East. Asia Soc. Transp. Stud. **3**(2), 45–55 (2001)
18. Dailey, D.J.; Cathey, F.W.: AVL-equipped vehicles as traffic probe sensors. Report number WA-RD 534.1, Washington State Transportation Center, University of Washington, USA (2002)
19. Chakroborty, P.; Kikuchi, S.: Using bus travel time data to estimate travel times on urban corridors. Transp. Res. Rec. J. Transp. Res. Board **1870**, 18–25 (2004)
20. Bertini, R.L.; Tantiyanugulchai, S.: Transit buses as traffic probes: empirical evaluation using geo-location data. In: Proceedings of the Transportation Research Board 83rd Annual Meeting, Transportation Research Board of the National Academics, Washington, DC (2004)
21. Lin, J.: Probe based arterial travel time estimation and prediction—a case study of using Chicago transit authority bus fleet as probes. CTS-IGERT Seminar, www.cts.cs.uic.edu/Lin.ppt. Accessed 07 Feb 14
22. Coifman, B.; Kim, S.: Measuring freeway traffic conditions with transit vehicles. Transp. Res. Rec. J. Transp. Res. Board **2121**, 90–101 (2009)
23. Pu, W.; Lin, J.; Long, L.: Real-time estimation of urban street segment travel time using buses as speed probes. Transp. Res. Rec. J. Transp. Res. Board **2129**, 81–89 (2009)
24. Esawey, M.I.; Sayed, T.: Travel time estimation in urban networks using buses as probes. In: Proceedings of the 2010 Annual Conference of the Transportation Association of Canada, Nova Scotia (2010)
25. Kieu, L.M.; Bhaskar, A.; Chung, E.: Bus and car travel time on urban networks: integrating Bluetooth and bus vehicle identification data. In: 25th ARRB Conference—Shaping the Future: Linking Policy, Research and Outcomes, Perth, Australia (2012)
26. Acierno, L.D.; Carteni, A.; Montella, B.: Estimation of urban traffic conditions using an Automatic Vehicle Location (AVL) System. Eur. J. Oper. Res. **196**(2), 719–736 (2009)
27. Turner, S.M.; Eisele, W.L.; Benz, R.J.; Holdener, D.J.: Travel time data collection handbook. Technical Report FHWA-PL-98-035, Federal Highway Administration, USA (1998)