Bluetooth Vehicle Trajectory by Fusing Bluetooth and Loops: Motorway Travel Time Statistics

Ashish Bhaskar, Ming Qu, and Edward Chung

Abstract—Loop detectors are widely used on the motorway networks where they provide point speed and traffic volumes. Models have been proposed for temporal and spatial generalization of speed for average travel time estimation. Advancement in technology provides complementary data sources such as Bluetooth MAC Scanner (BMS), detecting the MAC ID of the Bluetooth devices transported by the traveller. Matching the data from two BMS stations provides individual vehicle travel time. Generally, on the motorway loops are closely spaced, whereas BMS are placed few kilometres apart.

In this research, we fuse BMSs and loops data to define the trajectories of the Bluetooth vehicles. The trajectories are utilised to estimate the travel time statistics between any two points along the motorway. The proposed model is tested using simulation and validated with real data from Pacific motorway, Brisbane. Comparing the model with the linear interpolation based trajectory provides significant improvements.

Keywords—Bluetooth, Data Fusion, Loops, Trajectory, Travel time statistics, MAC reader.

I. INTRODUCTION

Motorways are highly equipped with inductive loop detectors that work on the principle of induction. Here, the wire loop has a circulating electric current. Each time a metal (vehicle) passes over the loop, due to induction, the voltage of the loop drops. The drop in voltage indicates that the metal is present over the loop. Technically these detectors can provide pulses data corresponding to the presence and absence of the metal (vehicle) over the detector. Generally, these detectors are configured to provide flow and occupancy aggregated over a time period termed as detection interval. If the detector has dual loops then the average speed over the detection interval is also available.

Extensive research has been performed to estimate and predict travel time on both motorways [1-11] and arterials [12-15]. Most of the research is limited to motorways where aggregated data from loops are used. These models provide average travel time during certain time period. Statistically, the mean is sensitive to the extreme values and for traveller information systems other measures such as the median, the 85th percentile should be explored. These statistics are better descriptive of the travel conditions. However, average is mostly generated because a) it is a standard measure for practitioners and b) the available speed from the detectors are aggregated over a detection interval (say 60 s) which limits the estimation of individual vehicle travel time and hence other measures of statistics. Nevertheless, the advanced detectors that provide pulse information have the potential to measure individual speeds at the detector locations and models are to be developed to estimate other statistics of travel time using these individual speed measurements.

Recently, Bluetooth MAC Scanner (BMS) [16] has gained significant interest of practitioners as one of the most cost effective way of obtaining travel time on the road network. The concept behind BMS is rather simple. BMS scans the MAC IDs of the discoverable Bluetooth devices (being transported by the travellers) within its communication zone. MAC ID is a unique identification for each device. One can easily obtain travel time of the Bluetooth device from one BMS to another by matching the MAC-IDs from the two respective time-synchronized BMSs. Assuming a device is in the vehicle, individual vehicle travel time from one BMS to another BMS can be obtained.

In literature, travel time from BMS data is compared with that of field measurements and promising results are reported [17]. Bluetooth tracking is not only being explored for vehicle travel time estimation, but also for other applications such as bicycle travel time [18], travel patterns of people movement [19-21], work zone delays [22], Origin-Destination estimation [23], route choice analysis [24], and freeway travel time variability [25]. The bias in BMS based travel time estimation from multiple Bluetooth devices being transported in public transport vehicle is also explored [26]. Interested readers should refer to [16] for details about the BMS data acquisition and accuracy and reliability of travel time estimations using BMS.

Contributing to the research on the use of BMSs and loops, this paper aims to integrate BMSs data with loops data on motorway to estimate the trajectory of the vehicle equipped with Bluetooth. The trajectory of the vehicle provides multiple

Submission Date: 8 December 2013. This work was supported by Smart Transport Research Centre (STRC) under Integrated Traveler Information (ITI) research domain.

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benefits such as:

1) Estimating individual vehicle travel time between any two points along the motorway, not necessarily the locations of BMSs. Similarly, other statistics of travel time such as the 85th percentile between any two points along the motorway can be estimated;

2) Availability of the detailed trajectory of the vehicle provides important input for emission and noise modelling [27, 28].

3) A Bluetooth device might not always be detected by the BMS. Say a Bluetooth device is detected at stations A, C and F but not at station B, D, E (assuming A to E are in order). Defining the trajectory of the vehicle using A, C and F provides the time when the device is at B, D and E. Thus, though not major, estimating trajectory also contributes to increase in the sample size of Bluetooth travel time points along mid-block scanners (station B, D, and E).

The paper is structured as follows: First BMS data is discussed, thereafter the proposed model to fuse loops and BMSs is explained, and finally the results of its testing using simulation and validation using real data are discussed and paper is concluded.

II. DISCUSSION ON BLUETOOTH MAC SCANER (BMS) DATA

Considering the data from Brisbane as an example, following are the BMS data fields:

- **Device-ID** (m): MAC-ID or encrypted MAC-ID of the device discovered;
- **BMS-Station ID** (s): ID of the location where the BMS scanner is installed;
- **Time stamp** (\(t_{m,s}\)): Time when the device \(m\) is first observed at station \(s\). A device can be discovered multiple times during its travel through the BMS zone; and
- **Duration** (\(d_{m,s}\)): Time gap between the first and last observation of the device \(m\) at the station \(s\).

Travel time from one BMS zone to another is the difference of the times when the device is observed at the respective stations. For instance, for a vehicle with MAC-ID=m, travel time (\(TT_m\)) from the entrance of the upstream BMS (\(u/s\)) zone to the entrance of the downstream BMS (\(d/s\)) zone is the difference of the times when the device is first observed at these BMS stations (1).

\[
TT_m = t_{u/s} - t_{d/s}
\]

This crude way of matching can provide noise in the travel time data points. For instance, say a device makes two trips between \(u/s\) to \(d/s\), during its first trip the device is observed at \(u/s\) but missed at \(d/s\), and during the second trip it is observed at \(d/s\). Aforementioned matching does not represent the true travel time (during its first trip) of the vehicle from \(u/s\) to \(d/s\). Similarly, other combinations of matching can produce noise in the data. Researchers [29, 30] have proposed different filtering algorithms to reduce the noise. The general framework for removing the noise is to define Upper Bound Value (UBV) (2) and Lower Bound Value (LBV) (3) for the data points during a given time period. The points outside these bounds are considered as noise and are removed. For instance, UBV and LBV for the Median Absolute Deviation (MAD) filter are defined as follows:

\[
UBV = \text{median} + \hat{\sigma}_f
\]
\[
LBV = \text{median} - \hat{\sigma}_f
\]

Where \(\sigma\) is the standard deviation from the MAD, in which a normally distributed data can be approximated as:

\[
\hat{\sigma} = 1.4826 \times \text{MAD}
\]

\[
\text{MAD} = \text{median}(|X_i - \text{median}(X_i)|)
\]

Where \(X_i\) is the individual travel time data value. The value of \(f\) is to be defined considering the trade-off between the confidence in travel time and sample size. The value \(f=1\) gives us the most confidence in the travel time profile, but can consider valid travel time points as noise. On the other hand, with \(f=3\), we have lower confidence in the travel time profile with few noisy points considered as valid. The value of \(f\) has been suggested by some authors to be from 1 to 5 [31, 32].

A. Does BMS capture all Bluetooth devices?

A Bluetooth device passing through the BMS zone might not be detected by the BMS, and there can be multiple reasons for these miss detections [16]. In order to measure the travel time, the MAC-ID should be observed at the two BMSs. Missing detections reduce the sample size of the travel time. The matrix presented in Fig. 1 has the header (first) row as BMS station IDs along the Gateway Motorway, Brisbane and the header (first) column as the individual MAC-IDs. The flow of the traffic is from BMS-1 to BMS-15. The grey colour of the cell indicates the device is detected whereas, the black colour represents that the detection of the device is missed. White colour of the cell indicates that no information can be inferred. For instance, MAC-3 is observed at BMS-1 to BMS-4; BMS-6 to BMS-9; BMS-12 and BMS-14. As the traffic is on the motorway, the device observed at BMS-9 and BMS-12 must have passed through BMS-10 and BMS-11. On the same argument MAC-3 is reported as missed detection at BMS-5, BMS-10, BMS-11 and BMS-13. The MAC-3 is not observed at further downstream of BMS-14, hence although it might have travelled further downstream but we cannot infer whether it was missed at further downstream BMSs or has exited the motorway at the next off-ramp after BMS-14. These observations clearly indicate that the capture of a Bluetooth device at BMS station is probabilistic in nature and BMS does not captures all the devices. From our analysis on the Brisbane motorway BMS data, it is found that around 10% observations were missed in a daily dataset.

The initial motivation for this research was to fill the aforementioned black colour cells in Fig. 1. Addressing this need, we come up with the proposed methodology (Section III) where we can even estimate the trajectory of the Bluetooth vehicle.
B. Errors in Travel Time Estimation from BMS Data

BMS data does not provide the exact location of the device within its communication zone. Moreover, due to the probabilistic nature of the detection, the device in the communication zone can be detected anytime. There can be multiple detections or a single detection for a device. Interested readers should refer to [16] for more detailed discussion. Considering a worst case scenario, say a vehicle is detected only once at u/s BMS and only once at d/s BMS. If the detection at u/s BMS corresponds to the time when it has entered the zone and detection at d/s BMS corresponds to the time when it exits from d/s BMS zone. Then the estimated travel time (tt) (using equation (1)) is actually the travel time from the entrance of the u/s BMS zone to the exit of the d/s BMS zone. Say the distance between u/s BMS and d/s BMS is D, and the estimated average speed for this vehicle is (Dtt/r).

However, the actual average speed should be (D+2r)/tt, where r is the radius of the BMS communication zone (assumed to be same for both u/s BMS and d/s BMS). For simplicity, we neglect the variation of the speed along the motorway and assume average speed as a good representative of the vehicle speed through the BMS zones. The absolute percentage error in the travel time estimation is approximated as equation (6), which clearly indicates that D increases the error in travel time from BMS decreases, and if D >> 2r, the absolute percentage error in the travel time estimation is negligible. Generally, on the motorways it is recommended that D should be more than two kilometres for a reasonable accuracy in travel time estimation [16].

\[
\text{Absolute % error} \approx \left| \frac{tt - TT_{tr}}{TT_{tr}} \right| = \frac{2r}{D} \tag{6}
\]

From the above discussion it can be concluded that: a) not all Bluetooth devices can be captured from BMS and b) for better accuracy of travel time from BMS on motorways, the spacing between BMS should be no closer than few kilometres.

III. PROPOSED METHODOLOGY

The objective here is to develop a model for estimating trajectory of the Bluetooth vehicle by fusing BMS data with loops.

The trajectory of a vehicle is mathematically expressed as a function that defines its position at a given time (X(t)). It can be represented as a list of a structured data of time and position [t, x], where trajectory is assumed to be piece-wise linear between the data points.

Say, \(x_b\) represents the spatial coordinate for a BMS station with station-ID equals b. Considering the time-space diagram for the motorway section, the coordinates for a BMS data (station-ID = b, MAC-ID = m) is represented as \((t_{mb}, x_b)\). If a Bluetooth device (MAC-ID = m) is observed at two BMS stations u/s and d/s, then one can obtain two points \((t_{mb}, x_u)\) and \((t_{mb}, x_d)\) on the time-space diagram for the motorway section from u/s to d/s. A naïve way of generating the trajectory \(X(t)\) of this vehicle is to draw a straight line joining these two time-space coordinates (7).

\[
X(t) = \frac{x_u - x_d}{t_u - t_d}(t - t_u) + x_u \quad \forall t \in [t_u, t_d] \tag{7}
\]

As discussed in Section II.B, generally the spacing between the BMS scanners on the motorway is in kilometres. Thus, this linear naïve trajectory does not include the dynamics of the traffic. In order to realistically represent the trajectory, the spatial-temporal dynamic of the traffic should be considered. For this, we propose to fuse BMS data with loops data and reconstruct the trajectory of the Bluetooth device. The proposed model is termed as Bluetooth Trajectory Reconstruction Model (TRM). The architecture for TRM is illustrated in Fig. 2 which includes the following steps:

- Identify the study site (see Section III.A)
- Defining the speed contour map (see Section III.B)
- Defining the Bluetooth points in time-space region (see section III.C)
- For each Bluetooth points apply the following (see Section III):
  - Defining imaginary vehicle trajectories by using speed contour map (see Section III.D.1))
  - Defining Upper Bound (UB) and Lower Bound (LB) plots (see Section III.D.2))
  - Defining Bluetooth trajectory (see Section III.D.3))
  - Updating the trajectory database (see Section III.D.4))
- Estimating travel time statistics (see Section III.E)

Let’s explain the architecture with the help of an example. Refer to Fig. 4, for the steps discussed below.

A. Identify the study site

The trajectory of the Bluetooth vehicle is to be defined between two BMSs. The study site consists of the motorway corridor including the BMSs stations and respective Loop Detector Stations (LDSs).

Refer to Fig. 3, say u/s BMS and d/s BMS represent exit of the BMS zone at upstream (position \(x_u\)) and downstream (position \(x_d\)) locations, respectively, where D (8) is the distance between the two BMSs.

\[
D = x_d - x_u \tag{8}
\]

Considering the two BMSs following LDSs are identified:

a. LDS between u/s BMS and d/s BMS;

b. LDS immediately upstream of u/s BMS: Say \(d_1\) (position \(x_1 \leq x_u\)) is the first LDS immediately upstream of u/s BMS; and

c. LDS immediately downstream of d/s BMS: Say \(d_n\) (position \(x_n \geq x_d\)) be the last LDS immediately downstream of d/s BMS.

The study site is defined from \(d_1\) to \(d_n\) where Bluetooth

### Table: Sample Bluetooth MAC-IDs observed at the Gateway motorway, Brisbane

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<thead>
<tr>
<th>MAC-IDs</th>
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trajectories are estimated from \( x_{a,t} \) to \( x_{d,t} \).

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**B. Defining the speed contour map**

Here, we assume that the average speed from each LDS is provided. We term this speed as *site speed*, where the average is aggregated over a time period termed as detector detection interval (DI). Say \( v(t,x) \) represents the *site speed* from detector \( d_i \) at time \( t \). Note: Due to errors or malfunctioning of detectors, the detector data is not always continuously available and for providing a seamless *site speeds*, “patching” of the data is needed. Patching means, replace the erroneous and missing data values with the most reasonable values. In literature different methods for patching are proposed [33]. We assume that the detector data provided is a good estimate of *site speed* and any patching, if needed, is performed and is outside the scope of this paper.

We use the *site speed* from detectors to define the speed contour map for the study site. For this, first the grids are defined and thereafter the speed is generalized over the grids as explained below.

Here, first the time-space region is divided into rectangular grids of size \( \Delta t \) by \( \Delta x \) along time axis and space axis, respectively. The value of \( \Delta t \) is DI and \( \Delta x \) is defined by the user which can be set to 100 m. Refer Fig. 4, a grid is termed as \( \text{grid}(f,g) \) where the centroid of the grid has coordinates \( (t_i, x_i) \) and the time-space region covered by the \( \text{grid}(f,g) \) satisfies equation (9)

\[
\text{grid}(f,g):
\begin{align*}
    x_i - \frac{\Delta x}{2} &\leq x < x_i + \frac{\Delta x}{2} = x_{i+1} - \frac{\Delta x}{2} \\
    t_i - \frac{\Delta t}{2} &\leq t < t_i + \frac{\Delta t}{2} = t_{i+1} - \frac{\Delta t}{2}
\end{align*}
\]

The site speeds from two consecutive LDSs (say \( d_i \) and \( d_{i+1} \)) are to be generalized over the grids. To generalize the speeds over the space we adopt Piecewise Linear Speed Based (PLSB) [5] method (10), where speed between two detectors \( (d_i \) and \( d_{i+1} ) \) for a given time is assumed to be linear over the space

\[
\forall x \in [x_i, x_{i+1}] \text{ and } t \in [t_i, t - DI]
\]

\[
v(t,x) = v(t,d_i) + \frac{v(t,d_{i+1}) - v(t,d_i)}{x_{i+1} - x_i} (x - x_i)
\]

(10)

Where: \( x_i \) and \( x_{i+1} \) are the distance coordinates for the loops \( d_i \) and \( d_{i+1} \), respectively in the time-space region.

Say, \( V(t_i, x_i) \) represents the distance coordinates for the loops \( d_i \) and \( d_{i+1} \), respectively in the time-space region.

Say, \( V(t_{i+1}, x_{i+1}) \) represents the distance coordinates for the loops \( d_i \) and \( d_{i+1} \), respectively in the time-space region.

C. Defining Bluetooth data points (\( P_{u/s} \) and \( P_{d/s} \)) in the time-space region

Here, the raw BMS data are matched and filtered (as discussed in Section II) to define the Bluetooth data points (11) in the aforementioned time-space region. Following list of points for each MAC-ID in the time-space region (see Fig. 4c) is defined:

\[
P_{u/s} = [P_{m,u/s}] \text{ and } P_{d/s} = [P_{m,d/s}]
\]

where: \( P_{m,u/s} = (t_{m,u/s}, x_{u/s}) \) and \( P_{m,d/s} = (t_{m,d/s}, x_{d/s}) \)

Where, \( P_{m,u/s} \) and \( P_{m,d/s} \) are the data points for a device with MAC-ID=m observed at the exit of u/s BMS and the exit of
\(d/s\) BMS, respectively (see Fig. 4b) and [.] represents a data list.

D. Processing for each Bluetooth point

Here, for each Bluetooth point (i.e., \(\forall m\)) we perform the following process:

1) Define the trajectories using speed contour

The speed contour defined in section III.B is utilized to trace the following trajectories:

1) \(LT_1\): trajectory of an imaginary vehicle that starts in time-space region at \(P_{m,u/s}\)

2) \(LT_2\): trajectory of an imaginary vehicle that ends in time-space region at \(P_{m,d/s}\)

For the above, a method similar to the trajectory method [5] is utilized, the details for which are explained below.

\[\frac{\Delta t}{2} \leq t_{f} < x_{f} + \frac{\Delta t}{2}\] (12)

\[\frac{\Delta t}{2} \leq t_{r} < t_{r} + \frac{\Delta t}{2}\] (13)

The vehicle moves from one grid to another based on the speed of the grid. We define \(D_R\) (14) as the remaining distance to the \(grid(f,g+1)\), and \(T_R\) (15) as the remaining time to the \(grid(f+1,g)\).

\[D_R = (x_{f} + \frac{\Delta t}{2}) - x_{c}\] (14)

\[T_R = (t_{r} + \frac{\Delta t}{2}) - t_{c}\] (15)

In the current grid, the vehicle travels at a constant speed \(V(t_c, x_c)\), and at this speed:

1) If the vehicle travels for time \(T_R\), then it can cover distance \(D_R\) (16); and

2) Vehicle will take time \(T_T\) (17) to cover distance \(D_R\)

\[D_T = V(t_c, x_c)T_R\] (16)

\[T_T = \frac{D_R}{V(t_c, x_c)}\] (17)

Considering \(D_T\), \(D_R\), \(T_N\) and \(T_T\) the next position of the vehicle (18) and its grid \((g,f)\) (19) is updated as below:

\[next\ position: (t_{c} + min(T_T, T_R), x_c + min(D_T, D_R))\] (18)

\[Next\ grid(f,g)\]

\[if\ T_T \geq T_R\]

\[f = f + 1\]

\[if\ D_T \geq D_R\]

\[g = g + 1\] (19)

The logic for equation (18) and (19) can be explained with the help of a self-explanatory example in Fig. 5, Fig. 6 and Fig. 7 where it is demonstrated, that given the current position, there can be three possible cases for the movement to the next grid:

1) Fig. 5, next grid is \(grid(f,g+1)\). Here, \(min(T_T, T_R) = T_R\) and \(min(D_R, D_T) = D_R\)

2) Fig. 6, next grid is \(grid(f+1,g+1)\). Here, \(T_T = T_R\) and \(D_R = D_T\)

3) Fig. 7, next grid is \(grid(f+1,g)\). Here, \(min(T_T, T_R) = T_R\) and \(min(D_R, D_T) = D_T\)

Finally, the trajectory \(LT_1\) (20) is the list of the position of the vehicle as defined above, where tracing of the trajectory starts from \(P_{m,u/s}\) until vehicle reaches \(x_{d/s}\). The equation is also expressed as (21).

\[LT_1 = \{t_i, x_i\} \forall i = 1, ..., n\]

\[where\ (t_i, x_i) = P_{m,u/s} = (t_{m,u/s}, x_{m,u/s})\]

\[and\ x_n = x_{d/s}\] (20)
From the above algorithms it can be seen that the vehicle can start from any point within the grid, but later on its position is always updated at the grid boundaries. This makes sense because the speed of the vehicle within the grid is assumed to be constant, resulting in a linear trajectory within the grid. For \( LT_1 \) the time corresponding to the \( x_{ds} \) needs to be interpolated (see equation (7)), if \( x_{ds} \) is not at the trajectory boundary.

\[ LT^{-1}_1(x_i) = t_i \quad \forall i = 1, ..., n \]  

where \( LT^{-1}_1(x_{ds}) = t_{m,ds} \)

3) \textbf{Defining Bluetooth trajectory}

Once the LB and UB are defined, we define the Bluetooth Trajectory (BT) considering the following cases:

1) \( P_{m,u/s} \) is on LB and \( P_{m,ds} \) is on UB (Refer to example in Fig. 8b): Here, equations (29) and (30) are satisfied. The Bluetooth trajectory should start from LB and end at UB and for any point in between, it should be bounded by LB and UB (31). We make an assumption that farther the Bluetooth trajectory point is from \( P_{m,ds} \), closer it will be to UB, and vice versa. So for any point in space \( (x_i) \), the corresponding time for Bluetooth trajectory (32) is obtained by adding the portion \[ [\frac{(x_i - x_{ds})}{D} * (UB^{-1}(x_i) - LB^{-1}(x_i))] \]

between UB and LB to the respective LB time \[ [LB^{-1}(x_i)] \]

(see Fig. 8d). Here, when \( (x_i - x_{ds}) \) equals 0 and D the Bluetooth trajectory point is at LB and UB, respectively.

\[ LB^{-1}(x_{ds}) = t_{m,ds} \]  

\[ UB^{-1}(x_{ds}) = t_{m,ds} \]  

\[ LB^{-1}(x_i) \leq BT^{-1}(x_i) \leq UB^{-1}(x_i) \]

\[ BT^{-1}(x_i) = LB^{-1}(x_i) + \frac{(x_i - x_{ds})}{(x_{ds} - x_{ds})} * (UB^{-1}(x_i) - LB^{-1}(x_i)) \]

\( \forall i = 1, ..., n \)

2) \( P_{m,u/s} \) is on UB and \( P_{m,ds} \) is on LB (Refer to example in Fig. 8c): Here, equations (33) and (34) are satisfied. The Bluetooth trajectory should start from UB and end at LB and for any point in between it should be bounded by LB and UB (31). Similar to the previous case, we make an assumption that farther the Bluetooth trajectory point is from \( P_{m,u/s} \), closer it will be to LB, and vice versa. So for any point in space \( (x_i) \), the corresponding time for Bluetooth trajectory is obtained by subtracting the portion of the time difference between UB and LB to the respective UB time (see Fig. 8e).

\[ UB^{-1}(x_{ds}) = t_{m,ds} \]  

\[ LB^{-1}(x_{ds}) = t_{m,ds} \]  

\[ BT^{-1}(x_i) = UB^{-1}(x_i) - \frac{(x_i - x_{ds})}{(x_{ds} - x_{ds})} * (UB^{-1}(x_i) - LB^{-1}(x_i)) \]

\( \forall i = 1, ..., n \)
Note: Bluetooth data points are obtained only at the location of BMS. The trajectories between the BMS stations are estimated considering the speed contour map from the loops. The spatial and temporal granularity of the speed contour map along the corridor only depends on the loops data (see III.B). Trajectory of the Bluetooth device is traced over speed contour map, considering the time when the device is observed at upstream and downstream BMS, respectively. I.E., the start and end coordinates of the Bluetooth vehicle in the time space region, is defined by considering the Bluetooth scanning zone. Say the last observation of the device at the upstream and downstream BMS scanning zone is at $t_{u/s}$ and $t_{d/s}$, respectively. If the space coordinates of the exit of the upstream BMS zone and the exit of the downstream BMS zone are $x_{u/s}$ and $x_{d/s}$, respectively, then the BMS device time-space coordinates are defined as $[t_{u/s}, x_{u/s}]$ and $[t_{d/s}, x_{d/s}]$. The space coordinates between the time $t_{u/s}$ and $t_{d/s}$ are to be traced using the speed contour map.

Here the order of the Bluetooth vehicles is well conserved because we have not done any manipulation with the time when the device is observed at the upstream and the downstream BMS scanners, respectively.

$P_{m,u/s} = (t_{m,u/s}, x_{u/s})$ $P_{m,d/s} = (t_{m,d/s}, x_{d/s})$

Where: $BT_i(t)$ represents the trajectory of the $i^{th}$ vehicle.

IV. MODEL TESTING USING SIMULATION

The model is thoroughly tested using simulation. A three lane motorway simulation model in AIMSUN is created. The modelled section is illustrated in Fig. 9. The study section is 5 km long, with BMS at point A and point B. The study site has loops every 500 m.

Simulation is performed with bottleneck between A to C. Here, demand from on-ramp is high, resulting in congestion along the section from A to C. The demand profiles for the simulation are defined as: a) Gradual increase and gradual decrease; b) Steep increase and gradual decrease; c) Steep increase and steep decrease; and d) Gradual increase and steep decrease. For each of the demand scenarios we have 10 replications with random seeds. Thus total of 40 simulation runs were performed.

Simulation provides trajectories of all the vehicles and hence ground truth of individual vehicle travel time between any two points on the simulated section is known.

Here, first the individual vehicle travel time estimation using TRM is compared with that of the linear interpolation (Naïve) model. For this all vehicles are considered to be equipped with Bluetooth. BMS data includes the time when these vehicles are observed at A and B. TRM model is applied on the BMS and the loops data to generate Bluetooth vehicle trajectories. Say $x_A$, $x_B$ and $x_C$ are the locations of point A, point B and point C in the time-space region. Then the individual vehicle travel time ($\tau_i$) for Bluetooth vehicles from A to C and C to B are estimated using equation (36).

For linear interpolation (Naïve) model, the vehicle trajectory is estimated using equation (7) with $u/s$ as point A and $d/s$ as point B. Thereafter, individual vehicle travel time from A to C is obtained using equation (37), and similarly individual vehicle travel time from C to B are obtained.

$$\tau_i = X_{i}^{-1}(x_C) - X_{i}^{-1}(x_A)$$

Individual vehicle travel time from Naïve model and TRM are compared with the actual travel time for the respective sections. The results are presented in Fig. 10.

In Fig. 10, X-axis is actual travel time and Y-axis is estimated travel time (from Naïve model and TMR). Blue dots are from Naïve model and red squares are from TRM. Fig. 10a and Fig. 10b illustrate results for the section from A to C and for the section from C to B, respectively. It can be seen that during congested conditions Naïve model highly underestimates travel time and overestimates travel time for the section from A to C and the section from C to B, respectively. TRM provides good estimates of the travel time during such conditions. The coefficient of determination ($R^2$) for the Naïve model is 32.2% whereas, for the TRM it is 97.8%. The Mean Absolute Percentage Error (MAPE) for travel time estimation for Naïve model for section from A to C.
and section from C to B is 16% and 27%, respectively. Whereas, the MAPE for TRM is 3% and 4.8% for section from A to C and section from C to B, respectively. These results clearly indicate that the proposed TRM provides better results than that of assuming a constant speed (Naïve model) along the corridor.

Let’s now evaluate the performance of estimating the 85th percentile of travel time using the TRM model. For this five percent of the simulated vehicles are randomly considered as Bluetooth equipped vehicles and the 85th percentile of the individual vehicle travel time for each 5 minute estimation periods is estimated using equation (38).

\[ t_{85,p} = 85^{th} \text{ percentile of } \{ t_i \} \quad (38) \]

\[ \forall \ BT_i^{-1}(x_c) \in (p - 300, p) \]

Fig. 13 represents the time series of the 85th percentile of the travel time obtained from all the simulated vehicles (Blue diamonds) and from the Bluetooth vehicles using TRM (Red squares) for one of the simulations. It can be seen that a good estimate is achievable. Aggregating the results for different simulations into MAPE during peak period only we observe that the TRM provides MAPE less than 5%.

V. MODEL VALIDATION USING REAL DATA

The proposed TRM is validated using the real data from Pacific Motorway, Brisbane, Australia. The study site is around 9240 m in length, directed outbound (out of Brisbane, CBD) and has three lanes. Refer to Fig. 12, the site is along the motorway section from Leopard St. on-ramp to Klump Road off-ramp. The site is equipped with loops and the average spacing between loops is 770 m. We have three BMSs A, B and C. The distance between A and C is 3740 m, and C and B is 5500 m. Bluetooth records (from BMSs at A, C and B) and loops data are collected for the month of April 2013. Matching Bluetooth records between two BMSs provides true actual individual Bluetooth vehicle travel time between the BMSs. This is considered as ground truth travel time. Hence, the BMSs records provide actual travel time from A to C and C to B.

The data from BMSs at A and B and the loops are used to reconstruct trajectories along the section from A to B. From these trajectories travel time statistics from A to C and C to B are estimated. The estimated travel time are compared with actual travel time from A to C and from C to B, respectively.

Here, we present the results for 18th April 2013. Fig. 11a and Fig. 11b illustrate time series of travel time from A to C and C to B, respectively. In the graphs, red squares are the 85th percentile of travel time estimated from TRM and blue diamonds are the 85th percentile of ground truth travel time from Bluetooth data. It can be seen that the TRM can well represent the 85th percentile of travel time. Validating the 85th percentile of travel time over different days indicates that MAPE during peak period is 5.5% and during the off-peak period is less than 3%.  

Fig. 11. Results from one simulation  

Fig. 12. Systematic illustration of the validation site
over 10% (Linear interpolation errors are around 16% to 27% whereas TRM has errors around 3% to 4.8%)

BMS can only provide travel time statistics for travel time from upstream to downstream BMS locations whereas, loops provide average travel time only. The proposed TRM can provide travel time statistics between any two points along the motorways. The MAPE in the estimation of the 85th percentile of travel time from TRM is generally less than 5%.

VII. ACKNOWLEDGEMENTS

The authors acknowledge the partners of the Smart Transport Research Centre and Queensland University of Technology for supporting this research. Constructive comments from the reviewers are also acknowledged.

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VI. CONCLUSION

BMS data is the most cost effective means of estimating individual vehicle travel time between two BMS locations. Generally, motorways are highly equipped with loop detectors that can provide average travel time. In this paper we have proposed an innovative model to fuse loops with BMSs to estimate the trajectories of the vehicles equipped with Bluetooth along the motorway. These trajectories provide a detailed dynamic of spatial-temporal motorways traffic states and opportunities to estimate travel time statistics (the 85th percentile) between any two points along the motorway section.

The proposed model is tested using simulation and validated using real data from Brisbane and promising results are obtained.

Comparison of the proposed model with Naïve linear interpolation based trajectory indicates that the linear interpolation is not accurate during congested condition and the proposed model provides improvements in accuracy of

Fig. 13. Validation results: Red squares are 85th percentile of travel time estimated from TRM. Blue diamonds are 85th percentile of ground truth travel time.
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