Accuracy of Travel Time Estimation using Bluetooth Technology

Case Study Limfjord Tunnel Aalborg

Araghi, Bahar Namaki; Skoven Pedersen, Kristian; Tørholm Christensen, Lars ; Krishnan, Rajesh; Lahrmann, Harry

Published in:
ITS World Congress

Publication date:
2012

Document Version
Early version, also known as pre-print

19th ITS World Congress
Vienna, Austria
22 to 26 October 2012
smarter on the way

Accuracy of Travel Time Estimation using Bluetooth Technology: Case Study Limfjord Tunnel Aalborg

Bahar Namaki Araghi[1]*, Kristian Skoven Pedersen[1], Lars Tørholm Christensen[2], Rajesh Krishnan[3], Harry Lahrmann[1]

1.Traffic Research Group, Aalborg University, Fibigerstræde 11, DK-9220 Aalborg OE, Denmark, Tel: +45-9940-8447, E-mail: araghi@plan.aau.dk

2. CTO, Blipsystems, Denmark

3. Centre for Transport Studies, Imperial College London, United Kingdom

Abstract

Short-term travel time information plays a critical role in Advanced Traffic Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS). In this context, the need for accurate and reliable travel time information sources is becoming increasingly important. Bluetooth Technology (BT) has been used as a relatively new cost-effective source of travel time estimation. However, due to low sampling rate of BT compared to other sensor technologies, existence of outliers may significantly affect the accuracy and reliability of the travel time estimates obtained using BT. In this study, the concept of outliers and corresponding impacts on travel time accuracy are discussed. Four different estimators named Min-BT, Max-BT, Med-BT and Avg-BT with different outlier detection logic are presented in this paper. These methods are used to estimate travel times using a BT derived dataset. In order to quantify the accuracy and robustness of these estimators against outliers, a comparative study between BT and Floating Car Data (FCD) is conducted. Results show that the Min-BT and Med-BT are more robust concerning the existence of outliers in the dataset and can provide more accurate travel time estimates compare to Max-BT and Avg-BT.

Keywords: Bluetooth Technology, Travel Time Estimation, Traffic Sensors

1. Introduction

Short-term travel time information plays a critical role in Advanced Traffic Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS). The access to short-term travel time information can significantly influence the decision making on both supply side (i.e. efficient management of network capacity, saving travel time, reducing congestion etc.) and demand side (i.e. mode choice, route choice etc.) of transportation. In this context, the need for accurate and reliable travel time information sources is becoming increasingly important. In recent years, traffic in and around the Limfjord tunnel in Aalborg, Denmark, has risen significantly and the tunnel is now operating close to its capacity. This has resulted in increasing travel times, peak hour congestion and wasted time. In response, a number of projects have been launched in close collaboration between Danish Road Directorate and Aalborg Municipality to improve the ease of passage for road users through the tunnel. These projects mainly aim to solve the congestion through speed regulation and queue warning inside and around the tunnel. In this context, upgrading and extending the Intelligent Transport Systems (ITS) as well as establishing a new traveller's information system (i.e. new travel time measurement system, new dynamic traffic map and expanded use of data) have been planned. As a part of upgrading and extending the ITS infrastructures, Inductive Loop Detectors (ILD) and Automated Number Plate Recognition (ANPR) have been implemented to measure the travel time and speed in and around the tunnel. There are issues regarding these technologies. First, ANPR and ILD are expensive mainly in terms of installation and maintenance. Second, they can get affected by the weather conditions in Denmark (i.e. high degree of humidity and fog can significantly reduce the sampling rate of ANPR cameras). Therefore, there is a need for cheaper and more flexible technologies which can be used as an alternative system. Application of Bluetooth Technology (BT) for estimating travel time has been tested before [1, 2, 3]. Bluetooth sensors in commission are less costly than other sensor technologies and are capable of providing travel time estimations. However, the accuracy and reliability of BT based travel time estimation requires further investigation. Outliers are a common problem in Vehicle Re-Identification Systems (VRIS) such as ANPR systems, Global Positioning System (GPS) and BT, and can negatively influence the accuracy of the estimations. In other words, accuracy and reliability of travel time estimates obtained by VRIS are highly dependent on detecting and removing outliers in the dataset. Due to the low sampling rate of BT compare to other VRIS, this problem becomes more promising. In motorways, the BT sample size has been estimated to be around 3-5% of general traffic volume; a factor that is related to the number of open Bluetooth devices carried by vehicles [2, 4]. In Denmark, a penetration rate can be as high as 20% which is prone to get affected by the outliers [4]. Existence of outliers may significantly affect the accuracy and reliability of travel time estimates using BT. Therefore, it is necessary to clean individual vehicle travel time estimates obtained by BT using outlier removal algorithms. There is a direct relationship between the complexity of the algorithm and required computing process-time. Hence, there should be a trade-off between accuracy requirements and the level of complexity of the algorithm. It is not always necessary to use complex algorithms to accurately identify outliers. Simple but fast outlier removal algorithms could sometimes be more efficient in many cases depending on the objectives of the study and nature of outliers. This study aims to evaluate simple methods of detecting and removing the outliers in BT dataset.

2. Application of Bluetooth Technology for Travel Time Estimation

Since 2005, BT has been used as a sensor for traffic measurement. Bluetooth sensors in commission are less costly than other sensor technologies. Bluetooth is a short-range data transmission protocol amongst electronic devices. The Bluetooth protocol uses an electronic identifier in each device called a Machine Access Control address (MAC). The MAC address serves as an electronic nickname so that electronic devices can keep track of who is who during data communications. Vehicles carrying discoverable Bluetooth devices (i.e. navigators, mobile phones, headsets etc.) can be detected by Bluetooth sensors installed at multiple locations along the road network. The MAC address and its detection time are recorded by the sensors, which then can be used for travel time estimation [6]. There are two pertinent factors regarding the use of BT for travel time estimation. First, depending on the motor vehicle speed and the range of Bluetooth detection antennas, there may be multiple detection events recorded for a single Bluetooth-enabled device while passing a sensor location. Whereas, ANPR has a narrower detection area (i.e. point) and they record a passing vehicle only once. Hence, for ANPR there is no ambiguity on the best estimation. However, for application of BT it is important to find the most accurate estimations among multiple recorded events. There is no general rule for selecting the best detection record. Nevertheless, some previous studies used the first detection event [2, 3]. In this study, the median of the all BT detection records for a single MAC address is used for travel time estimation. The second point is related to the accuracy of vehicle classification. Most of the ANPR systems can classify vehicles. Hence, it is easier to detect abnormalities (i.e. outliers) such as the high-speed emergency cars or low-speed heavy trucks in the dataset. However, it is not easy to classify vehicles and distinguish such abnormal situations using BT. Therefore, the simple average travel time can get affected by outliers resulted by low-speed vehicles (i.e. heavy-trucks) or high-speed vehicles (i.e. ambulances or police cars). As a result, the simple average is highly prone to the outliers. This highlights the importance of using more robust estimators as well as using appropriate outlier removal algorithms. The focus of this study is on the second issue, i.e. determining the most reliable travel time estimate based on Bluetooth detections. Hence, the problem of multiple detection events is not considered.

3. Literature review

Over the last few years, application of BT as a new method of travel time estimation has been evolved rapidly. However, expansion of this technology for traffic monitoring and specially travel time estimation is depending on the approval of its accuracy and reliability. Research has been conducted to evaluate different aspects of reliability and accuracy of the BT for travel time estimation. Outliers are defined a common problem in all VRIS, and BT is not excepted [2,3]. Accuracy and reliability of travel time estimates obtained by VRIS are highly depending on detecting and removing the outliers exist in the dataset. Dependency of BT to the number of open Bluetooth devices carried by the vehicles and sample rate of 3-5% of the traffic volume [2,4], also intensify the problem with outliers. As such existence of outliers may significantly affect the accuracy and reliability of travel time estimates by BT. Hence, one of the common issues which have been mentioned in the previous studies is the outlier treatment of BT datasets. The problem with application of static outlier removal method "static cut-off value limits" which did not consider intra-day travel time variability (i.e. the difference between off-peak and peak hours) is explained by [1]. The authors recommended automated outlier screening algorithms as an alternative to static cut-offs. They also emphasised on simplicity and effectiveness of outlier detection algorithms as the two main requirements of the candidate method. They used a moving standard deviation method (1).

$$\sigma = \sqrt{\frac{1}{u}\sum_{i=x-\frac{u}{2}}^{u}(\rho_x-\mu)^2} \qquad (1)$$

Where:
u: a user set neighbourhood sample size used as the bases for standard deviation comparisons
x: the current detection that is being assessed
p: travel time value for the detection x.

Based on this method only the data above the mean will be screened and the points below the mean value will be allocated to the group of fastest mode. Accordingly, they considered an upper limit based on standard deviation. If the *p* is more than the set number of standard deviations above the mean, the point is determined to be an outlier. In this paper, it is not explained how the mean value was calculated. A drawback of these outlier cleaning methods is that using the mean value as the basis of analysis can be misleading because mean value itself can be affected by outliers. Moreover, the size of the neighbourhood (u) and its impact on accuracy needs to be clearly identified.

In order to address the outliers in BT dataset, a four step filtering method is developed by [2]. In this study, outliers are defined as observations with unreasonably low speed, observation that were far from the average of the rest of observations in a particular time interval, as well as a small number of observations in a time interval that are not sufficient for extracting the ground truth value. The first two steps of the filtering algorithm aimed to identify and discard outliers among single observations in each time interval. The third and the fourth steps were designed to exclude time intervals with lower sample size or with large variation among individual observations within the time interval. In the first step, Moving Average (MA) was implemented for identification of lower and upper cut-off points. Although MA is known as a flexible method for smoothing out short-term fluctuations in the data, but it allocates equal weights to all the data in a dataset. This means that in calculation of MA, variation of travel time during the day may not be considered and it gives the same weight to peak and off-peak travel time. Moreover, finding the optimum radius for MA was based on a short range of data (1-5) which may need further investigations. In the second step, a normal distribution for the observations around the mean is assumed. However, this assumption may not be valid in all cases and can be violated for different datasets.

An adoptive mechanism for treating the outliers is defined by [7]. This method assumes a lower bound threshold for the free flow speed v_f for the designated section which is mainly calculated based on the historical data. Accordingly, an upper-bound for the travel time τ_f is estimated. Travel times larger than this threshold are removed as outliers. This system also monitors every minute the aggregated average speed of the vehicles and in case the v_f is dropping into a certain values, then the lower bound threshold is updated accordingly. One of the problems of using the aggregated average speed is that it is very sensitive to variation of the extreme end values. For instance, the aggregated average speed can be influenced by an emergency car with very high-speed or a heavy trucks with significantly lower-speed. Moreover, this method did not considered the impact of sample size on the designated sections. A static cut-off limit (8 minute) for removing the outliers related to the pedestrians and cyclists is implemented by [3]. As other static outlier removal algorithms, the variation of travel time over the peak and off-peak hours were not considered.

Weakness in the existing literature is that outlier treatment methods are mainly determined based upon the average value [1, 3]. Nevertheless, using the average value as the basis of analysis can be misleading as the average itself can be affected by outliers. The outlier bias becomes more important for small sample sizes. Therefore, it is important to test whether other simple estimators can provide a more accurate and reliable travel time estimate, and understand the relationship between sample size and estimation accuracy for those methods. Four such alternate estimators are presented in the next section.

4. Methodology

Four different estimates are presented in this section, based upon the aggregation of BT records of vehicles in 15 minutes intervals. These estimators are simple and can be reflective of various traffic conditions. The estimators are calculated as follow:

1. Min-BT: Travel time estimate is the minimum travel time of all BT based travel time observations during a given time period. The minimum travel time is unaffected by slower vehicles with non-typical driver behaviour and represents the fastest vehicle in normal traffic condition. Min-BT is a good indicator for congestion detection applications.

$$\text{Min-BT} = Minimum(TT_1, TT_2, TT_3, \dots, TT_n)_{15minutes} \quad (2)$$

2. Max-BT: Travel time estimate is the maximum travel time of all BT based travel time observations during a given time period.

$$\text{Max-BT} = Maximum(TT_1, TT_2, TT_3, \dots, TT_n)_{15minutes} \quad (3)$$

3. Avg-BT: Travel time estimate is the average travel time of all BT based travel time observations during a given time period. This method is used by most BT based travel time estimation studies. The Average travel time is calculated based upon all the records in a 15 minutes time interval.

$$\textit{Avg-BT} = Average(TT_1, TT_2, TT_3, \dots, TT_n)_{15minutes} \quad (3)$$

4. Med-BT: Travel time estimate is the median travel time of all BT based travel time observations during a given time period. The median is less prone to outliers caused by the slow or fast vehicles compared to the other estimators. Hence, it has the potential to be used as an alternative for the simple average travel time.

$$\textit{Med-BT} = Median(TT_1, TT_2, TT_3, \dots, TT_n)_{15minutes} \quad (4)$$

Where:

TT_i: Travel Time for i^{th} recorded vehicle calculated based upon the median of multiple travel time detections $TT_i = Median(tt_{i1}, tt_{i2}, tt_{i3}, \dots, tt_{im})_{i^{th}-Vehicle}$

m: The different values of travel time recorded for i^{th} vehicle according to the multiple detection

n: The total number of recorded vehicles in each 15 minutes time interval

In order to evaluate the impact of sample size on the accuracy and reliability of the estimators, two approaches are adopted as follows:

- Approach 1 (App.1): includes all the intervals for data analysis
- Approach 2 (App.2): removes all the intervals for data analysis if the number of records in that interval is less than 30 records (sample size<30).

In order to quantify the impact of sample size on accuracy of various estimators, in the App.1, all intervals regardless of number of observations are used. Whereas, in the App.2 intervals having less than 30 records (sample size<30) are excluded from further analysis. Results of the two approaches are compared.

The candidate estimator is then the estimator which provides more accurate travel time estimates and is more robust regard changes in sample size. For testing the accuracy and robustness of different estimators, both qualitative (i.e. visual) and quantitative (i.e. accuracy measures) statistical methods are implemented. An estimator is considered to be robust that its accuracy is less influenced by the sample size changes. The following sections focus on the data collection as well as the accuracy evaluation methods implemented.

4.1. Data Collection

A section of 5 Km length on E45 motorway between Forbindelsesvejen-Humlebakken including Limfjord tunnel was selected as the study route, see Figure 1. The Average Daily Traffic (ADT) for North-South and South-North directions are 45400 and 51100 respectively. As shown the study route has four main entrances and exits points. The FCD collected by [5] for the research project on Intelligent SpeedAdaptation is used as the ground truth for evaluating the BT travel time. The FCD were collected using GPS-traces received from 152 equipped motorist vehicles over the period of 2 years (i.e. mid 2006-mid 2008)[5]. The averages of GPS-traces were aggregated for 15 minutes interval to provide an average daily travel time. Figures 2 and 3 show the time plots of the FCD. It can be seen that there is a morning peak for North-South direction and an afternoon-peak for the South-North direction.

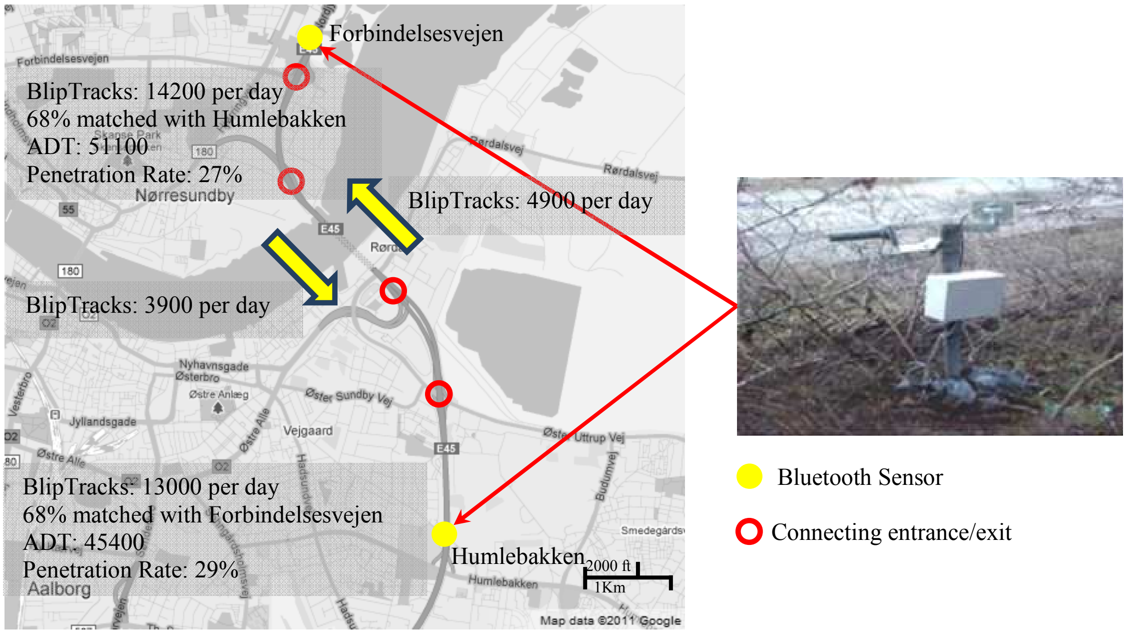

Figure 1- Study area and location of Bluetooth sensors

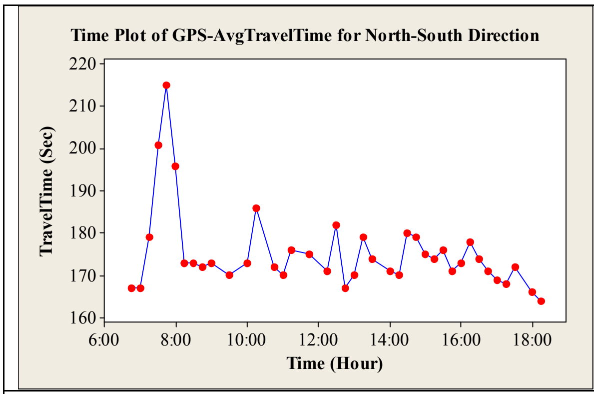

Figure 2- Time Plot of GPS Avg-Travel Time for North-South Direction

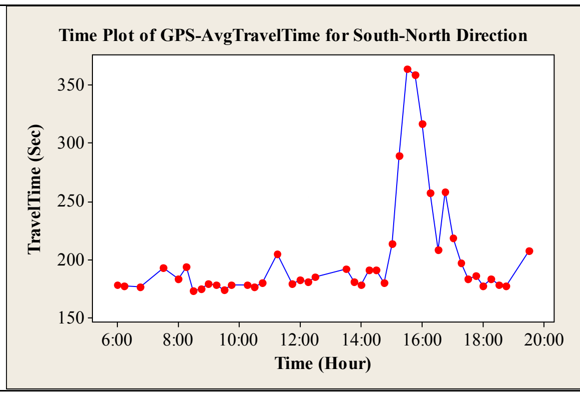

Figure 3- Time Plot of GPS Avg-Travel Time for South-North Direction

The Bluetooth sensors described in this paper, developed by the company called BLIP Systems. The sensors known as BlipTrack consists of Bluetooth detectors using a GPRS connection in real time, three internal directional antennas, USB modem and electricity connection. Due to the specific configuration of BlipTracks antennas, these sensors are able to provide time stamped and directional information of passing Bluetooth devices through a back-end server. The range of detection zone is estimated about 70-200 meters on each side of the sensor. BT travel time data are collected through two Bluetooth sensors installed in proximity to the roadway at the bases of the guard rail posts. Position of Bluetooth sensors are shown in Figure 1. BT data were collected within one month 04/01/2010-04/02/2010. In order to avoid the problem of multiple detections by Bluetooth sensors, the median of the all travel time records for a single MAC address is used. The Min-BT, Max-BT, Avg-BT and Med-BT are calculated for every 15 minutes intervals. Due to resource limitations, a comparative study is conducted based on Bluetooth data and FCD collected in two different period of time. It is assumed that the traffic behaviour is not significantly changes over the period of the study and the data is still valid. This is also confirmed by the road authorities. In order to examine the impact of sample size, two approaches are implemented. In the App.1, data from all the intervals are included. In the App.2 all intervals with less than 30 records are excluded from FCD and BT datasets.

4.2 Accuracy Evaluation

4.2.1 Qualitative Analysis using Probability Plots

A P-P plot shows a variable's (i.e. travel time) cumulative probability against the cumulative probability of the test distribution (i.e. normal distribution). The straighter the line formed by the P-P plot, the more the variable's distribution conforms to the test distribution [8]. The normal probability plot is formed by:

- Vertical axis: represents the observed values
- Horizontal axis: represents the expected outcomes

Being normally distributed provides a wide range of opportunities for using parametric statistical tests to analyse the data. Moreover, based upon the knowledge of normal distribution (μ,σ) it is possible to model the travel time variation and to predict short-term travel time for the intervals with low sample size and missing values. Hence, in this study BT travel time data and FCD are tested against normal distribution. These P-P plots provide a visual comparison of how the both sources of the data are spread compare to the normal distribution hypothetic line. At the same time, the P-P plots show how the BT and FCD are matched. The match or coverage rate between BT and FCD is considered as the proportion of the data that overlap each other. The candidate BT-estimator is the one which has a better match with FCD, compare to the others.

4.2.2 Quantitative Analysis using Accuracy Measure

In order to have a numerical evaluation of the accuracy of BT travel time estimation, three accuracy measures are adopted. These measures include Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). These measures represent the variation of estimations (i.e. BT) from the ground truth (i.e. FCD) [8].

$$MPE = 100.\frac{1}{N}\sum_{i=1}^{N}\frac{(T_i - \hat{T})}{T_i} \qquad (5)$$

$$MAPE = 100.\frac{1}{N}\sum_{i=1}^{N}\frac{|T_i - \hat{T}|}{D_i} \qquad (6)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - \hat{T})^2} \qquad (7)$$

Where:

$\boldsymbol{N}$: The total number of observed motor vehicles

$\boldsymbol{T_i}$: Real travel time for the ith record

$\boldsymbol{\hat{T}}$: Estimated mean travel time using Bluetooth technology

4.2.3 Difference of MPE, MAPE and RMSE

According to [8], one of the advantages of using RMSE is that it is measured in the same units as the data and it is representative of the size of the typical error. MPE and MAPE are also useful for purpose of reporting, since they are expressed in the generic percentage terms which are easy to understand and compare the results. However, the RMSE and MAPE are more sensitive to the occasional large error than MPE. However, if the magnitude of the predicted quantity has a large range in the dataset used, RMSE will be influenced by relatively larger errors for larger values of the prediction variable. In other words, MAPE will hide heteroskedasticity to some extent. But for engineering applications, if the relative magnitude of errors is more important, MAPE gives this information better. The MPE is reported in some statistical procedures as signed measures of error which indicate whether the forecasts are biased (i.e. whether they tend to be disproportionately positive or negative). However, MAPE can only be computed with respect to data that are strictly positive. It has been mentioned that if an occasional large error is not a problem in decision situation, then the MPE or MAPE might be a more relevant criterion. It should be noted that, in many cases these statistics might vary in unison. This means that the model that is best on one of them will also be better on the others, but this may not be the case when the error distribution has "outliers"[9]. Due to the robustness of MAPE compare to RMSE and MPE, it is used as the main criteria for model validation; however, MPE and RMSE are also calculated [8].

5. Results

The qualitative (P-P plots) and quantitative (accuracy measures) analysis are performed for directions for App.1 and App.2. Results of the average and standard deviation (Std) of various estimators are summarised in Table1.

Table1- Mean and Std of Bluetooth estimations for App.1 and App.2

Direction	Travel Time Estimator	Mean (sec)		Std. Deviation (sec)	
		App.1	App.2	App.1	App.2
South-North	Min-BT	194.97	182.44	321.21	132.31
	Max-BT	7867.77	10102.48	5234.13	4184.4
	Avg-BT	927.41	986.76	802.24	612.12
	Med-BT	290.51	248.18	576.07	262.12
	Avg-GPS	192.29	202.53	35.26	47.01
North-South	Min-BT	190.30	168.44	191.47	27.746
	Max-BT	2005.7	2622.56	1241.95	936.03
	Avg-BT	379.94	349.72	270.69	102.32
	Med-BT	257.57	218.35	250.99	47.83
	Avg-GPS	174.39	175.30	8.63	9.688

Results show that by removing the intervals having sample size less than 30, the standard deviation of the BT based estimations reduced significantly. However, for FCD data by removing the intervals with low sample size, the standard deviation slightly increased. In App.2, the difference between the mean values of Min-BT, Med-BT and Avg-BT with Avg-GPS reduced, while the difference between mean values for Max-BT with Avg-GPS increased.

5.1 Results for qualitative analysis using Probability Plots

In first step, normal probability plots are fitted to the data (Figure 4). In general, results of the P-P plots (for both directions and App.1 and App.2) reflect that at 95% confidence level (CI) neither BT nor FCD follow the normal distribution. In other words, travel time obtained by BT and FCD are not normally distributed. The visual comparison between FCD and BT also show that the Min-BT and Med-BT have a better match with FCD compare to Max-BT and Avg-BT,. Results of the P-P plots for App.2 show a slightly better match between BT and FCD compare to App.1. However, this needs to be evaluated quantitatively. A similar pattern for North-South direction is shown, which is not presented in this paper.

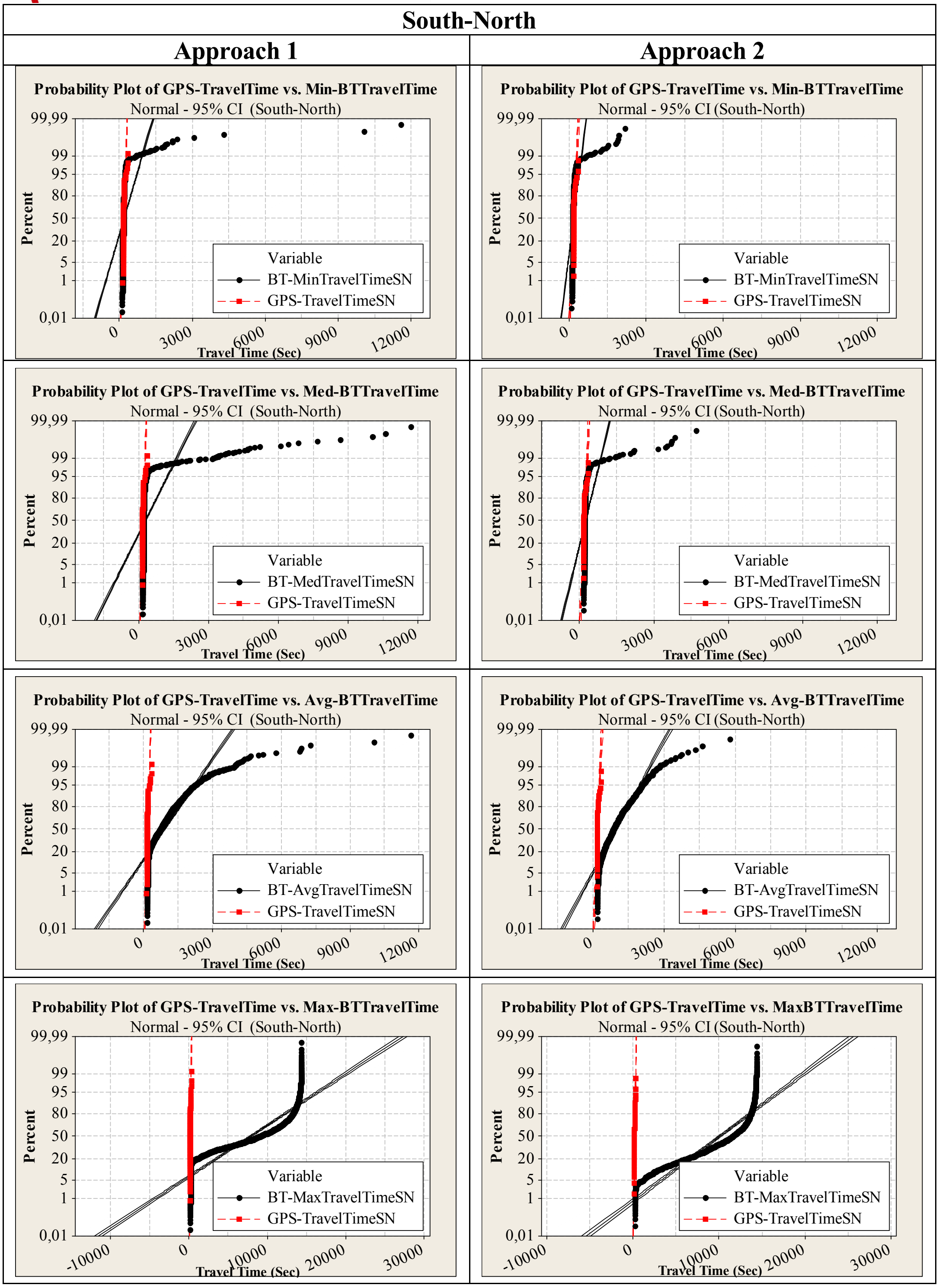

Figure 4- Probability plots of FCD travel time vs. Bluetooth (South-North)

5.2 Results for quantitative analysis using Accuracy Measures

In second step, the accuracy of BT estimations are evaluated using MPE, MAPE and RMSE (see Table2). The MPE, MAPE and RMSE also confirm that the Min-BT gives the most accurate estimates of the travel time followed by Med-BT for both directions. This clearly conform the outputs of P-P plots. For the South-North direction the Min-BT resulted in MAPE about 10% and RMSE less than 4 seconds for App.1. Similarly, for the North-South direction the Min-BT resulted in MAPE about 10% and RMSE less than 2 seconds. These results represent the accuracy of BT for travel time estimation and also show that Min-BT and Med-BT have the potential to be used as an alternative method for Avg-BT. In general, App.1 shows better accurate compare to App.2 except for Med-BT. The RMSE shows to be more sensitive to the sample size and by reducing the sample size RMSE increased significantly. This amplifies the importance of sample size. However, for the Med-BT it can be seen that by removing the low sample intervals (App.2) the MAPE and MPE have reduced by 50%. Negative results of MPE show that BT tends to over-estimate the travel time for both directions. This can be explained by the size of Bluetooth detection zone. As mentioned, Bluetooth sensors used in this study (i.e. BlipTrack) have three directional antennas with wide detection ranges. Therefore, there is a high probability to detect Bluetooth MAC addresses before and after the sensor locations. Even if by using median of multi-detections is tried to reduce the impact of multiple detection, this needs further investigations. The close match between travel time data obtained by the BT and FCD from two different periods confirms our assumption concerning validation of the data. Results also present that the variance of Bluetooth based travel time estimates are significantly higher than the FCD (Table1). This also can be attributed to the larger detection zone and the low penetration rate of BT. This pattern also conform the results of study by [3].

Table2- Accuracy measures of Bluetooth estimations

Direction	Travel Time Estimator	MPE (%)		MAPE (%)		RMSE (sec)	
		App.1	App.2	App.1	App.2	App.1	App.2
South-North	Min-BT	-.0358	0.066	0.0964	0.092	3.79	50.62
	Max-BT	-40.800	-50.694	40.800	50.694	827.68	9900.05
	Avg-BT	-3.927	-4.0497	3.9272	4.0497	79.36	785.59
	Med-BT	-0.5434	-0.270	0.5545	0.3192	11.25	65.13
	Avg-GPS	-	-	-	-	-	-
North-South	Min-BT	-.0937	.0366	0.0987	0.0401	1.93	11.77
	Max-BT	-10.527	-14.0001	10.527	14.0001	195.22	2447.28
	Avg-BT	-1.184	-1.0003	1.1836	1.0003	21.93	174.68
	Med-BT	-0.4803	-0.2489	0.4803	0.2489	8.91	44.10
	Avg-GPS	-	-	-	-	-	-

6. Discussion and Conclusion

Results show that the BT can be used as a complementary method for travel time estimation along with other technologies such as ANPR. The accuracy of Min-BT and Med-BT also show that these values can be used as better alternatives for the Avg-BT both for estimating travel time and outlier removal algorithms. The high accuracy of Min-BT and Med-BT indicates that these estimators can be used for detecting the abnormal traffic situations. In many cases instead of using complicated outlier removal algorithms, the Min-BT and Med-BT can be well representative of the traffic situation. Comparing the results for the App.1 and App.2 confirm the importance of sample size. It is clear that by removing the intervals having less than 30 detections, the variation of the BT data is reduced (Table1). However, it doesn't necessary increase the accuracy of the estimations. Therefore, determining the optimum size for accepting or removing the samples requires further investigations. Compare to Min-BT, the Med-BT tends to be less sensitive to the sample size changes. Hence, it is suggested to implement Med-BT as it is shown to be more robust with lower sample sizes. The significant difference between the Max-BT and Avg-BT compared to other estimators can be explained based on the number of access point (i.e. entrance and exit) which connects the study route with the neighbourhood area. In long corridors with a number of connections, drivers have the possibility to divert from the corridor and return to it in the distance between the Bluetooth sensors. Therefore, the Max-BT is representing the impact of slow vehicles and diverted ones (see Figure 5). Accordingly, the Avg-BT which is calculated based on all the records including Max-BT, directly gets affected by the Max-BT. One of the limitations of this study is that the (As for the limitations of the study) FCD was calculated based on average whereas median might be a more robust estimate. Moreover, it would be more informative if there was a direct comparison between different BT estimation (Min-BT, Med-BT and Max-BT) with similar estimates of FCD, instead of using average FCD as the basis for evaluating various estimators.

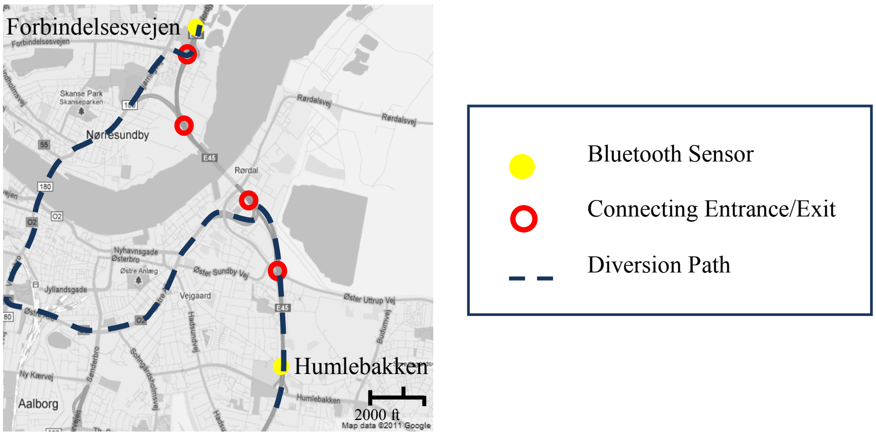

Figure 5- An example of vehicle diversion from the E45

Acknowledgement
The authors acknowledge the continuous support and contributions of the Danish Road Directorate and BlipSystems, both in terms of financial supports and data provision.

References
1. Quayle, S., Koonce P., J.V., Bullock, D.M., DePencier, D. (2010). Arterial Performance Measures Using MAC Readers: Pilot Study in Portland Oregon. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
2. Haghani, A., Hamedi, M., Sadabadi, K.F., Young, S.E., Tarnoff, P.J. (2010). Freeway Travel Time Ground Truth Data Collection Using Bluetooth Sensors. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
3. Malinovskiy, Y., Wu, Y.J., Wang, Y., Lee, U.K. (2010). Field Experiments on Bluetooth-Based Travel Time Data Collection. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
4. Lahrmann, H., Skoven Pedersen, K., C., LT., (2010). Bluetooth detektorer som ny cost-effektiv sensor i vejtrafikken. In Proceedings t*he Annual Transport Conference at Aalborg University,* Aalborg.
5. Lahrmann H, Agerholm N, Tradisauskas N, Berthelsen K. K., Harms L. (2012). Pay as You Speed, ISA with incentive for not speeding: Results and interpretation of speed data, *Accident Analysis & Prevention*, In Press.
6. Hamedi, M., Fish R., L.W., Haghani, A. (2010). Freeway Dynamic Message Sign Evaluation Using Bluetooth Sensors: A Case Study. In Proceeding: *17th ITS World Congress*, Busan. ERTICO (ITS Japan).
7. Barcelo, J., Montero, L., Marques, L. (2010). Travel Time Forecasting and Dynamic OD Estimation in Freeways Based on Bluetooth Traffic Monitoring. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
8. Namaki Araghi, B. (2010). *Using the k-NN Method for Incident Duration Prediction based on TPEG data*, MSc Thesis, Centre for Transport Studies, Imperial College London, UK.

9. Decision 411 Forecasting course outline (2010). What's the bottom line? How to compare models. Available from: http://www.duke.edu/~rnau/compare.htm.
10. Saunier, N., Morency, C. (2011). Comparing data from mobile and static traffic sensors for travel time assessment. In Proceesings *1st Congress of the Transportation and Development Institute of ASCE.*
11. Kavaler, R., Kwong, K., Raman, A., and Varaiya, P., (2010). Arterial Performance Measurement with Wireless Magnetic Sensors. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
12. KMJ Consulting, (2010). Bluetooth Travel Time Technology Evaluation Using the BlueTOADTM' Pennsylvania Department of Transportation.
13. Puckett, D.D., Vickich, M.J., (2010). Bluetooth®-Based Travel Time/Speed Measuring Systems Development' Texas Transportation Institute, UTCM Project #09-00-17.
14. Tarnoff, P.J., Bullock, D.M., Young, S.E., Wasson, J., Ganig, N., Sturdevant, J.R. (2009). Continuing Evolution of Travel Time Data Information Collection and Processing. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
15. Wasson, J.S., Sturdevant, J.R., Bullock, D.M., (2008). Real-Time Travel Time Estimates Using Media Access Control Address Matching, *ITE Journal*, vol. 78, pp.20-23.
16. Wasson, J., Haseman, R., Bullock, D.M. (2010). Real-Time Measurement of Work Zone Travel Time Delay and Evaluation Metrics Using Bluetooth Probe Tracking. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
17. Brennan, T.M., Ernst, J.M., Day, C.M., Bullock, D.M., Krogmeier, J.V., Martchouk, M. (2010). Influence of vertical sensor placement on data collection efficiency from bluetooth MAC address collection devices, *Journal of Transportation Engineering,* vol. 136, no. 12, pp.1104-1109.
18. Farokhi, S.K., Hamedi, M., Haghani, A. (2010). Evaluating Moving Average Techniques in Short-Term Travel Time Prediction Using an AVI Data Set. In Proceedings *89th Annual Meeting Transportation Research Board,* Washington.
19. Barceló, J., Montero L., Marqués L., Carmona C., (2010). A Kalman-Filter Approach for Dynamic OD Estimation in Corridors Based on Bluetooth and WIFI Data Collection. In proceedings *12th World Conference on Transportation Research WCTR*, Lisbon.