Examining Travel Time Variability and Reliability on an Urban Arterial Road Using Wi-Fi Detections- A Case Study

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Abstract: The objective of this paper is to examine travel time variability and reliability on an urban arterial road. Towards this purpose, travel time data was collected using Wi-Fi sensors for fourweeks. Generalized extreme value (GEV) distribution was observed as the best-fitted distribution for explaining variations in travel time values. The variations in travel time were also assessed by the time of the day (TOD) and day of the week (DOW). The results obtained indicate that travel time variation is significantly influenced by TOD and DOW. It was observed that buffer time index (BTI) explained variations in travel time better compared to other reliability parameters such as planning time index (PTI) and travel time index (TTI). As an important outcome, the study developed reliability-based level of service thresholds (LOS), which can enable traffic engineers to evaluate the performance of an urban arterial road based on travel time variability and reliability.

Keywords: Travel Time Variability, Reliability, Wi-Fi sensors, Generalized Extreme Value (GEV), Level of Service (LOS)

1. BACKGROUND

The performance of a road is significantly affected by the nature of perturbation and disturbance in travel times. These perturbations or disturbances can be recurrent or non-recurrent in nature. Recurrent disturbances can be attributed to changes in travel patterns, traffic volume, change in traffic composition and traffic control devices, over space and time; whereas non-recurrent disturbances are caused because of occurrence of some unexpected
events or incidents (like work-zone; accident; mechanical breakdown of a vehicle, or inclement weather). For capturing these disturbances, the travel time variations under different conditions need to be studied in detail. Although travel time has been considered as a performance measure for any transportation network, variability in time travel time due to both recurrent and non-recurrent disturbances have indeed become a growing concern as they significantly influence commuters time of departure, route choice behaviour, and scheduling of trips.

The consistency in travel time variations or variability in travel time is better measured in terms of travel time reliability. Asakura and Kashiwadani (1991) defined reliability as the network that can guarantee an acceptable level of service (LOS) for road traffic, even if the functions of some links are physically damaged or a large amount of travel demand is occasionally generated. However, a comprehensive statistical and mathematical analysis of travel time variability and travel time reliability warrants significant upgradation in methods of travel time data collection.

Traditional traveltime data collection methods consist of direct measurement techniques and estimation methods. Floating car technique is one of the most popular direct measurement methods, which uses a probe vehicle travelling with the traffic flow to record travel time and location information. Since 1990s, this technique was combined with global positioning system (GPS) devices to provide more comprehensive information in the form of vehicle trajectory along with time stamps, thereby providing frequent sampling along the route. This can implicitly avoid human error associated with traditional traveltime and location recording technique (Quiroga and Bullock, 1998). However, as the floating car technique only provides travel time information for the probe vehicle, it becomes extremely difficult to collect a large data set for spatial-temporal analysis of travel time variability and reliability.

To address the aforementioned limitation, direct measurement techniques were replaced by passive data collection technologies or intelligent transportation system (ITS) techniques. With the advent of ITS, the outlook towards the measurement of intrinsic traffic parameters mainly travel time, headway, speed, delay, and traffic volume for performance evaluation of transportation systems has undergone a radical change. These passive technologies are broadly classified as (a) fixed sensors (such as loop detector, Bluetooth/Wi-Fi, Automatic Number Plate Recognition System (ANPR), and radio frequency identification (RFID)) that provide traffic information at the location where the sensors are installed and (b) mobile sensors (such as GPS equipped vehicles and Automatic Vehicle Location (AVL)), which provide data for the entire journey of the vehicle equipped with such sensors. The passive technologies can often be implemented more economically and faster than the traditional methods. Further, richness in the resultant data set is maintained as the observed behavior is captured using these passive data collection techniques as opposed to the stated behavior. The aforementioned ITS methods have been widely explored for measuring travel time and other important traffic parameters. However, under the Indian traffic conditions, where heterogeneity in vehicle classes and loose-lane discipline prevails, the effectiveness of many such sensors subsides. Further, GPS units have been deployed in the public transport buses as a source of reliable travel time information under the Indian scenario. However, the percentage of buses accounts for less than 5% of the traffic, and as a result, the data obtained from GPS units suffers from inherent mode bias.

Recently, Bluetooth/Wi-Fi based passive data collection technologies have gained immense popularity, primarily due to their cost-effectiveness, ease of implementation and non-evasiveness. These sensors are essentially based on the concept of re-identification of MAC address associated with any instrument when the instrument or vehicle passes through a
Bluetooth or Wi-Fi equipped zone. The re-identified vehicles are registered with time stamps, which facilitates calculation of travel time and, hence implicitly, speed along with other important traffic patterns. Further, working with the MAC address of Bluetooth/Wi-Fi devices ensures privacy because the MAC address is not associated with any other personal data. Therefore, the audited data cannot be related directly to particular individuals. As a result, many interdisciplinary researchers in the domain of traffic state prediction have explored concepts related to travel time variability and reliability in recent times using data from Bluetooth/Wi-Fi sensors.

2. LITERATURE REVIEW

2.1 Review of Studies on Bluetooth/Wi-Fi MAC Data Collection Technologies

The research on the application of Bluetooth in traffic monitoring began to appear in the academic literature in 2010 (Barcelo et al., 2010; Haseman et al., 2010; Wang et al., 2011), although a small number of early field trials by local government transportation departments and agencies date back to as early as 2008 (Wasson et al., 2008). Bluetooth MAC Scanner (BMS) data provides significant benefit to the road operators for estimating the travel time on road networks in a very cost-effective manner (Bhaskar and Chung, 2014; Erkan and Hastemoglu, 2016). The travel time from BMS data was compared with that from video cameras for motorways (Wang et al., 2011) and arterial (Mei et al., 2012) and promising results were reported.

The travel time obtained from the traditional matching of BMS data was considered as the ground truth travel time (Haghi and Aliari, 2012). Bluetooth enabled device tracking was not only explored for estimation of car travel-times, but also for other applications such as bicycle travel-time (Mei et al., 2012; Ryeng et al., 2016) and work zone delays (Haseman et al., 2010). Origin-Destination estimation (Barcelo et al., 2010; Blogg et al., 2010; Barcelo et al., 2012; Laharotte et al., 2015) and route choice analysis (Hainen et al., 2011; Carpenter et al., 2012) are other related applications. In addition to these, freeway and urban arterial travel time variability (Bullock et al., 2011; Mathew et al., 2016) and arterial traffic congestion analysis (Tsubota et al., 2011) are also explored and analyzed as some other application of Bluetooth based data collection technologies. Pulugurtha et al. (2015) compared the section-level travel time data obtained from different sources like Bluetooth, global positioning system (GPS), INRIX data source and floatingtestcarmethods. Results indicated that section-level travel time data captured using Bluetooth detectors on urban street segments are less accurate and not dependable when compared with GPS unit and INRIX.

The performance characteristics of the sensor by varying antenna size, height and lateral position of the sensor was also explored in the past (Brennan et al., 2010; Abedi et al., 2015). It was concluded that the antenna size, height and lateral position of the sensor significantly influences sensor efficiency in terms of penetration rate. The speed of passing the vehicle in addition to the height, lateral position and antenna gain affected the performance of the Bluetooth sensor (Bakula et al., 2012). Further, travel mode bifurcations using Bluetooth detector data was also attempted by many researchers (Bahar Namaki Araghi et al., 2016; Yang and Wu, 2017; Nadia Bathae et al., 2018). Moreover, accuracy and reliability studies of Bluetooth technology as a passive data collection technique for travel time estimation (Bahar Namaki Araghi et al., 2014; Stevanovic et al., 2014) concluded that Bluetooth based technology can be considered as suitable and scalable technology for...
estimation of travel times. Microscopic modelling of control delay at a signalized intersection using Bluetooth data was also attempted (Montasir Abbas et al., 2013).

2.2 Review of Studies on Travel Time Variability and Reliability

Most agencies focus on Volume to Capacity (V/C) ratio as the level of service (LoS) measure to describe the efficiency of a road (Highway Capacity Manual 2000). The efficiency of a road can be effectively measured in terms of travel time reliability. Reliability of a transportation system is defined as the network, which can guarantee an acceptable LoS for the road traffic even if the functions of some links are physically damaged or a large amount of travel demand is occasionally generated (Asakura and Kashiwadani 1991). In other words, travel time reliability is “an important measure of service quality for travelers” (Chen et al., 2003).

Polus (1979) analysed travel time and operational reliability on arterial routes. Travel time behaviour and its variability were explained through gamma distribution, utilising arterial travel time data from the Chicago area. Ravi Sekhar and Asakura (2007) modelled travel time variability under the influence of various uncertain factors such as traffic volume, number of vehicle breakdowns, number of road accidents, the intensity of rainfall effect and falling objects from vehicles, with the help of multiple linear regression models. Lyman and Bertini (2008) used archived freeway data from Portland, USA to illustrate ways of reporting reliability. They analysed changes in travel time reliability using cross-sectional data between the years 2004 and 2006 using different travel time reliability measures and explored methods for prioritizing freeway corridors. Ravi Sekhar et al. (2010) modelled travel time variability under the influence of various uncertain factors such as traffic volume and crossing pedestrians. They quantified sources of travel time parameters with the help of regression models and stochastic response surface models. They concluded that stochastic models are capable of modelling worst-case scenarios. Susilawati et al. (2010) assessed the travel time reliability of ten corridors of the Adelaide metropolitan road network by using the buffer time (BT) and planning time index (PTI). Anish Kumar et al. (2013) analysed the variation of PTI and buffer time index (BTI) values for different V/C ratios. Mehbub Anwar (2010) evaluated the travel time variability as a function of delay, congestion index and V/C ratio. Sathya Prabha and Mathew (2013) developed a multilinear regression model for the travel time by considering the dependent variables of length, speed, and volume. Chepuri et al., (2018a) examined travel time variability for an urban corridor. Towards this purpose, they collected data for two-wheelers using GPS probe data and examined variability in travel time using statistical distribution under different V/C ratio conditions. Further, Chepuri et al. (2018b), examined travel time variability and reliability for three urban arterial roads. They proposed a new reliability index named reliable buffer index (RBI) as a modification to buffer index. Pulugurtha and Imran (2017) modelled level of service of freeway section using reliability parameters.

Overall, the application of Bluetooth MAC data collection for analyzing travel time variability, estimation of delays in work-zone, route choice behaviour and estimation of origin-destination matrix were conducted in the past. Further, the credentials of Bluetooth based data collection technologies has been well reported. Moreover, a substantial literature on travel time variability and travel time reliability exists. However, it is worth noting that, though Wi-Fi based MAC data collection technologies provide similar database compared to Bluetooth but are not widely explored. Additionally, very few studies (Mathew et al., 2016) on travel time variability and reliability studies using Wi-Fi sensor are reported especially under Indian conditions. As the usage of electronic devices with enabled Wi-Fi is increasing and
will further increase, Wi-Fi based passive data collection technologies seem to be a potential prospect as effective data collection method in the future. With this motivation, the objective of the present study is to analyze travel time variability and reliability for an urban arterial corridor and develop reliability-based level of service (LoS) thresholds.

3. METHODOLOGY

The methodology adopted for the present study is presented in following sub-sections.

3.1 Design of Experiment and Data Acquisition

The data collection was carried using Wi-Fi sensors for an urban arterial corridor along the Rajiv Gandhi IT Expressway in Chennai. The selected test bed section is a 6-lane, divided, interrupted urban arterial corridor, having two signalized intersection along its length of 1.8km as shown in Figure 1. Wi-Fi sensors were placed at three locations from First Foot over Bridge (13000’14.0”N, 80014’50.8”E) to Tidel intersection (12059’15.9”N, 80015’05.0”E) along the subject corridor as illustrated in Figure 1.

As the vertical and lateral position of the sensor significantly affects data collection
efficiency (Brennan et al., 2010), it becomes a prerequisite to fix the sensor at optimal positions (both vertically and laterally). For this purpose, the optimal vertical and lateral position of the sensor was appraised based on the past literature. Wi-Fi sensors were placed along the median, at both midblock and the signalized intersection. However, in case of the signalized intersection, it was deemed appropriate to locate sensor along the downstream end of the intersection. The sole motive to place the sensor at the downstream end was to incorporate the effect of signalized intersection on travel variations and, hence, travel time reliability. Further, the sensors were mounted on an electrical pole at a height of 2.5ft at the signalized intersection for enhancing data collection efficiency; while, at the midblock section, sensors were placed on FOB (16ft height). An antenna of gain 5dbi was polarized vertically to maximize data collection efficiency (Porter et al., 2013). Travel time data was collected for four weeks (from 10th June 2018 to 10th July 2018) to analyze travel time variability by the time of the day, and day of the week.

The road inventory details of the test bed are summarized in Table 1.

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Location</th>
<th>Designation</th>
<th>Description</th>
</tr>
</thead>
</table>
| 1       | Foot over bridge 1 (near Madya Kailash) | FOB         | Mid-block section  
6-lane divided carriageway  
Service lane on either side |
| 2       | 2nd Avenue (near Indira Nagar Railway Station) | 2nd Avenue  | Signalized T-intersection  
6-lane divided carriageway  
Service lane on either side |
| 3       | Tidel Intersection (near Tidel park) | TIDEL       | Four-Legged Signalized Intersection  
6-lane divided carriageway  
Service lane on either side |

3.2 Matching and Data Processing

The travel time values for the test bed section was computed by developing a matching algorithm. Since Wi-Fi sensors were placed at three locations, the matching algorithm was developed such that the trajectory of the MAC address was traced at all the three locations. This was done to retain the trip characteristics of the device by extracting information from the intermediate sensor. Further, the MAC address only detected between FOB and Tidel (i.e., the extreme end of the sensor) were filtered separately. Prior to analyzing the data, the matched MAC address datasets need to be processed for removing slow-moving vehicles, pedestrians, cloned addresses, and round-trips. For this purpose, the matched data set was processed in twostages.

Stage 1: Processing data using upper capping threshold

The first stage processing was done by removing outliers by adopting an upper capping threshold. An upper capping threshold of 2400 sec was adopted. This threshold was adopted based on the maximum time to traverse the section under maximum congestion for any mode of travel (including pedestrian and bicyclist). Further, this threshold eliminates the possibility of a round trip. Figure 2 represents a sample plot illustrating stage 1 and stage 2 filter. It can be noted that a significant amount of matched data was filtered after first stage processing.
However, there still exists outliers, which again needs to be processed.  

**Stage 2: Processing first stage filtered data for removing outlier**  

The second stage processing involves removing outliers and slow-moving vehicles like pedestrians and bicyclists. Based on the review of the literature, it was deemed appropriate to consider modified z-score technique to filter such outliers. The second stage processing was performed separately for the northbound and southbound traffic.

![Figure 2. Stages in data processing](image-url)
4. DERIVING TRAVEL TIME

Prior to analyzing travel time variability and reliability, it is a prerequisite to determine travel time values using Wi-Fi-based sensors. Deriving travel time through a Wi-Fi sensor is quite simple. The concept of deriving travel time is based on the concept of re-identification of the same MAC address over the space equipped with the Wi-Fi sensor. It is apparent that a device with enabled Wi-Fi can be logged multiple times within the detection zone, which can be attributed to the speed of vehicle, efficiency of the sensor in the form of time taken by the receiver and emitter to log a device (inquiry cycle), the time spent in detection zone and the location of the sensor (vertical and lateral position). Considering that the MAC address in the detention zone is detected multiple times, four components, mainly, first in first out (FIFO), last in last out (LILO), first in last out (FILO) and last in first out (LIFO) can be deduced for deriving travel time between two locations (Pulugurtha et al. 2015) as shown in Figure 2. However, now the question arises as to which component out of FILO, FIFO, LIFO, and LILO need to be considered for determining travel time values. Pulugurtha et al (2015) suggested LIFO and FIFO as travel component for urban arterial and freeways. However, considering different traffic conditions in countries like India, it becomes imperative to derive travel component prior analyzing travel time variability and reliability. To address this question, all four components were comprehensively assessed.

![Figure 3. Deriving travel time](image)

To assess these components, primarily, the time difference for each case FIFO, FILO, LIFO and LILO was checked for its potential distribution. Based on the goodness of fit test indices, generalized extreme value (GEV) distribution was concluded as the best-fitted distribution for explaining the variation in time difference for each of the components. Probability distribution plots of time difference for all four cases were then plotted on the same set of axes, to facilitate derivation of the travel time component. The first stage processed data having an upper capping threshold of 2400 sec was considered for deriving the travel time.
The standard deviation (scale) and mean (location) parameter of the time difference differed significantly between the four components (i.e., FIFO, FILO, LIFO and LILO). The statistical validation of this observation was carried out by performing one-way ANOVA at a 5% level of significance. The null hypothesis is defined as “no variation in the time difference between FIFO, FILO, LIFO, and LILO exists”. There exists a significant difference between the time difference for respective cases. A higher mean and higher standard deviation was observed in the case on FILO, highlighting the capability of FILO component to account for the maximum delay and maximum variability in the resultant dataset. To probe further, the time difference for all the four components was analyzed as a function of time spent by the MAC address in the detention zone. It is apparent that the MAC address will spend a certain amount of time within the detention zone, which will indeed have a significant influence on the values of the time difference and hence values of travel time. Since the sensor was positioned at the intersection, the time spent by the given MAC address can be bifurcated into three categories: (a) time spent at the midblock, (b) time spent at the intersection, and (c) the total time spent (cumulative of time spent at midblock and intersection). However, for the present study, the time difference for all four components was assessed as a function of total time spent by the MAC address at both midblock and the intersection. Towards this purpose, primarily, the total time spent was delineated into four clusters. Thereafter, for each of the delineated clusters, probability distribution plots of time difference for four components were plotted on the same set of axes (Figure 5).
TRAVEL TIME VARIABILITY

Figure 5. Probability distribution plot of time difference for different ranges of time spent (a) less than 3 sec (b) between 3-103sec (c) between 103-203sec (d) greater than 203sec.

From Figure 5, for a total time spent less than 3 seconds, the probability distribution plots for all four components overlapped (nearly similar means and standard deviation). With an increase in the total time spent, the mean and standard deviation of time difference for all four components (FIFO, FILO, LIFO, and LILO) varied. However, the magnitude of variation depends on the total time spent in the detection zone. The mean in time difference in addition to the standard deviation was observed to increase with an increase in the total time spent. Further, it can be noted that out of all the four components, FILO had higher travel time values and standard deviation values compared to other components, namely, FIFO, LIFO, and LILO. Since the first and last timestamp are considered in the case of FILO, it is apparent that FILO will have higher values of mean and standard deviation. Therefore, by considering FILO as a component for deriving travel time values, maximum delays and maximum variability can be better accounted for. Therefore, it was deemed appropriate to consider FILO as a component for determination of travel time.

5. TRAVEL TIME VARIABILITY

The travel time values for the subject study location were derived by considering FILO as a component. Furthermore, travel time was aggregated at the one-hour interval for analyzing travel time variability and travel time reliability. The second stage processing was carried out to remove outliers from the resultant travel time dataset using the modified z-score method. For the present study, segregation of data was carried out at two levels: the time of the day (the hour of the day and period of the day) and the day of the week.

Before carrying out the reliability analysis, it is very important to understand the travel time variability for different hours of the day, periods of the day, and day of the week. These travel time variability patterns help in determining the peak and off-peak hours of the day, peak day of the week, and peak season of the year. As the available data is limited, variations in an hour of the day and day of the week are considered in this study. Towards this purpose, variation in travel time was visualized by plotting box-plot at the one-hour interval for typical weekday and weekend (Figure 6).
From Figure 6, it can be noted that the variation in travel time and the average travel time values are relatively higher for morning 8 am-10am period and evening 5 pm-8pm period compared to other periods of the day. Therefore, they are considered as peak hours for further analysis. Further, the variation in travel time and the average travel time was observed to vary between weekday and weekend highlighting the influence of day of the week on travel time variations.

5.1 Travel Time Variability Using Statistical Distributions

The travel time dataset for the subject study sections was tested for five major potential distributions, namely, Burr, lognormal, gamma, normal, and GEV. The goodness of fit indices based on the K-S test for the potential distribution is summarized in Table 2.
Table 2. Goodness of fit result based on K-S tests for travel time distribution

<table>
<thead>
<tr>
<th>Day</th>
<th>Descriptive Statistics</th>
<th>K-S test Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. dev</td>
</tr>
<tr>
<td>Sunday</td>
<td>193.87</td>
<td>81.09</td>
</tr>
<tr>
<td>Monday</td>
<td>309.91</td>
<td>161.69</td>
</tr>
<tr>
<td>Tuesday</td>
<td>364.91</td>
<td>220.24</td>
</tr>
<tr>
<td>Wednesday</td>
<td>367.70</td>
<td>183.44</td>
</tr>
<tr>
<td>Thursday</td>
<td>372.32</td>
<td>208.82</td>
</tr>
<tr>
<td>Friday</td>
<td>237.05</td>
<td>111.63</td>
</tr>
<tr>
<td>Saturday</td>
<td>225.77</td>
<td>84.05</td>
</tr>
</tbody>
</table>

Note: K-S test performed at a 5% level of significance

Based on the goodness of fit indices, GEV distribution was observed as the best-fitted distribution for explaining travel time variations compared to other potential statistical distributions. To probe further, the quartile-quartile plot was generated for assessing best-fitted distribution (Figure 7).

Figure 7. Q-Q plot of travel time for considered potential statistical distribution

From Figure 7, it can be noted that the travel time based on GEV distribution was observed to scatter along the standard line as compared to other potential distributions. Further, GEV distribution has a flexible shape and can better capture extreme tail data (left or right). Therefore, the effect of outliers can be well captured and accounted. Moreover, easy and flexible computation of different percentile values, forms another advantage of the GEV distribution. Overall, the GEV distribution can be considered as the best-fitted distribution for explaining variations in travel time values. Based on the best-fitted distribution, travel time variability patterns were analyzed for the time of day and the day of the week.
5.2 Analyzing Variability in Travel Time

Primarily, for the subject survey days, travel time data of individual MAC address during peak and off-peak hour, weekend and weekday were tested for its potential distribution and GEV distribution was observed to be the best-fitted distribution for explaining variations in travel time for all the cases. Figure 8 shows the probability distribution plots of travel time based on time of the day, the day of the week, weekday-weekend, peak and off-peak hour.

![Probability distribution plot of travel time for (a) subject survey (b) based on the day of the week (c) the time of the day](image)

From Figure 8, higher upper tails were observed on Sunday, Saturday, and Friday compared to other days (Figure 8a), indicating that the travel times are lower on these days than the mean travel times. Further, it can be noted that the mean and standard deviation values shift towards the right side, indicating higher average travel time and higher variation in travel time for Monday through Thursday. Further, the shape factor, for Friday, Saturday and Sunday were observed to be lesser (towards zero) compared to other days (higher than zero positively skewed), indicating that the travel time for Friday, Saturday and Sunday can be better explained using the normal distribution.

To probe further, the variations in travel time were assessed for a different day of the...
week (weekend and weekday). To comprehend the effect of the time of day on travel time variability, the probability distribution of travel times for weekday and weekend was plotted as shown in Figure 8b. It was observed that, the mean and standard deviation of travel time shifted towards the right side for weekdays compared to the weekends, indicating higher average travel time and higher variation in travel time for weekdays compared to weekends. Further, the longer upper tail was observed for weekends indicating that the majority of travel time values are lower than the mean travel time and as result, thinner kurtosis (width of distribution) can be noted. In addition, the shape factor values for weekday were observed to be higher (greater than zero) compared to the weekends (approaching zero), indicating that the travel time data for the weekend can be better explained using the normal distribution.

To scrutinize further, the travel time variability was analyzed for the time of day (peak and off-peak hour) using GEV distribution as shown in Figure 8c. As anticipated, higher average travel time and larger variations in travel time can be noted for peak hours compared to off-peak hours (probability distribution shifted towards the right side for the peak hour compared to an off-peak hour). Based on the GEV analysis, it was observed that the travel variation for an off-peak hour can be better explained using normal distribution (shape factor approaches zero) as compared to the peak hours. Therefore, the skewness of the curve gradually decreases (approaches zero) as the traffic flow condition varies from extreme peak condition to free-flow conditions. This can be attributed to the effect of signalized intersections on travel time values.

6. TRAVEL TIME RELIABILITY

The buffer time index (BTI), planning time index (PTI) and travel time index (TTI) were computed for examining travel time reliability.

Travel Time Index (TTI): It can be computed as the mean travel time divided by the free flow travel time.

$$TTI = \frac{\text{Average Travel time}}{\text{Free flow travel time}}$$

Buffer Time Index (BTI): It is used to account for the extra time that travelers should add to the mean travel time to ensure on-time or earlier arrivals. It is computed as the difference between the 95th percentile travel time and the mean travel time, divided by the mean travel time. Lower buffer index value indicates higher reliability.

$$BTI = \frac{\text{95th percentile Travel time} - \text{Average Travel time}}{\text{Average travel time}}$$

Planning time index (PTI): It is computed as the 95th percentile travel time divided by assumed the free-flow travel time. Higher planning time index leads to lower reliability.

$$PTI = \frac{\text{95th percentile travel time}}{\text{Free flow travel time}}$$

The above reliability parameters were derived for an aggregation interval of 1-hr for all survey days. For the present study, free-flow travel time was derived based on the posted speed limit of 60kmph. Further, a tolerance of +5kmph was added to the posted speed limit to derive the free-flow travel time.
6.1 Variation in Travel time reliability parameters

The derived travel time reliability parameters were then visualized for its variation by the time of the day for a typical a weekday and weekend as illustrated in Figure 10.

![Graphs showing variation in different travel time reliability parameters by the time of the day for a typical weekday and weekend.](image)

From Figure 10, it can be observed that the reliability measures were observed to vary by the time of the day and day of the week, indicating the effect of travel time variability on reliability parameters. It can be noted that relatively lower values of BTI are observed during off-peak hours compared to peak hours, indicating higher reliability during peak hours compared to off-peak hours. This can be attributed to lesser variations in travel time data during the peak hours. Further, higher values of both PTI and TTI are observed during the peak hours on both weekdays and weekends. Therefore, it can be concluded that travel time reliability measures vary significantly by time of the day (TOD) and day of the week (DOW). However, the question now arises as to which travel time reliability measures should be used for developing reliability-based LoS thresholds. The following subsection addresses the above question.

6.2 Performance Evaluation of Different Reliability Parameters

For developing reliability-based LoS thresholds, it is a prerequisite to explore the performance of different reliability parameters in terms of its capabilities of explaining variations in travel...
To comprehend the performance of different reliability parameters for explaining variations in travel time, the variation in shape factor of GEV distribution for different hours of the day was plotted against the various reliability parameters. One such sample plot for a given day is as shown in Figure 11.

![Figure 11](image_url)

**Figure 11. Variation in reliability parameters with shape factor of GEV distribution for (a) PTI/TTI (b) BTI**

From Figure 11, the travel time reliability parameters are observed to vary with the shape factor of GEV distribution, indicating a correlation between the travel time variability and travel time reliability parameters. However, the magnitude of correlation varied between the different reliability parameters. It was observed that, among all the reliability parameters, the trend in BTI values perfectly matched the trend in shape-factor values. Therefore, BTI can be considered as an effective travel time reliability parameter for explaining variations in travel time. Since shape factor values may vary depending on the mean and standard deviation with the travel time data, it was deemed appropriate to incorporate $\lambda_{var}$ proposed by Van Lint, & Van Zuylen (2005) as a suitable index of travel time variability. Further, the presence of outliers within the dataset may result in biased mean and standard deviation. Therefore, the coefficient of variation (CV) was not considered as a suitable travel time variability index. To probe further, Pearson correlation analysis between different travel time reliability measures and variability measure ($\lambda_{var}$) is performed to arrive at effective travel time reliability parameter. Correlation analysis results are summarized in Table 3.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$\lambda_{var}$</th>
<th>BTI</th>
<th>PTI</th>
<th>TTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_{var}$</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BTI</td>
<td>0.85</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PTI</td>
<td>0.44</td>
<td>0.47</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>TTI</td>
<td>0.14</td>
<td>0.14</td>
<td>0.92</td>
<td>1</td>
</tr>
</tbody>
</table>

From the above Table, it can be inferred that, BTI has a strong correlation with respect to $\lambda_{var}$ when compared to other travel time reliability measures namely, PTI and TTI. Further, BTI indicates the additional time that a travel needs to ensure on-time arrival. Therefore, values of BTI can provide information regarding delay experienced by users and hence, becomes important parameter in perspective of both users and operators. Therefore, it was deemed...
appropriate to consider BTI as an effective travel time reliability measure for developing reliability based LOS thresholds.

7. DEVELOPING RELIABILITY-BASED LOS THRESHOLDS

To develop reliability-based LoS thresholds, primarily, a scatter plot between BTI and travel time variability index ($\lambda_{var}$) was plotted. Thereafter, based on the observed relation between BTI and $\lambda_{var}$, k-means clustering technique was adopted to develop reliability-based LoS thresholds. K-means clustering technique is based on the minimization of the Euclidean distance (distance from a data point to the cluster mean) based on some random iteration and is suitable for dense datasets (Xia et al., 2008; Cokorilo et al., 2014). For the purpose of crisp results, BTI and $\lambda_{var}$ values were considered as a variable for delineating reliability-based thresholds in STATISTICA 10, for a total of 250 iterations, to arrive at normalized boundary delineation. To arrive at the optimal number of clusters, initially, clustering technique for different cluster sizes i.e., 2-cluster to 7-cluster were performed. The optimum number of clusters to visualize segmented data in the best possible manner was determined based on the Silhouette values. From the silhouette values, 3-cluster was considered as the most optimum number of clusters to visualize the segmented data in the best possible manner. Therefore, three clusters were considered to delineate reliability-based LoS thresholds for urban arterial corridors.

The sample clustering plot of delineated reliability-based thresholds is presented in Figure 12. Table 4 summarizes the reliability-based LoS thresholds. The developed reliability-based LoS thresholds can enable planners and traffic engineers to characterize the performance of an urban arterial corridor in terms of travel time variability and reliability.

![Figure 12. Scatter plot between BTI and $\lambda_{var}$](image)

<table>
<thead>
<tr>
<th>Cluster</th>
<th>$\lambda_{var}$</th>
<th>BTIx100 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High reliability</td>
<td>&lt;0.68</td>
<td>&lt;0.38</td>
</tr>
<tr>
<td>Moderate reliability</td>
<td>0.68-1.35</td>
<td>0.38-0.76</td>
</tr>
<tr>
<td>Low reliability</td>
<td>&gt;1.35</td>
<td>&gt;0.760</td>
</tr>
</tbody>
</table>

Table 4. Reliability-based level of service thresholds
8. CONCLUSION

This paper presents an analysis of travel time variability and travel time reliability parameters for an urban arterial corridor. The travel time data was collected using Wi-Fi sensors for seven days along an urban arterial corridor in Chennai, India. Following are the important conclusion drawn from this study.

- First in last out can be considered as an appropriate component to derive travel time between the sections.
- The goodness of fit indices based on K-S test revealed Generalized extreme value distribution as the best-fitted distribution for explaining variations in travel time compared to other potential statistical distributions such as Burr, Gamma, Lognormal and normal. Further, travel time was observed to be positively skewed for all the survey days.
- The variations in travel time is significantly influenced by the time of the day, the day of the week and the direction of the travel. It was observed that normal distribution can better explain variation in travel time for off-peak hours and weekend.
- The travel time reliability parameters were found to vary by the time of the day and day of the week. Buffer time index (BTI) had lower values during peak hours compared to off-peak hours. Further, PTI and TTI values were higher during off-peak hours compared to peak-hours. Therefore, peak hours are reliable compared to off-peak hours.
- Among all travel time reliability parameters, the variation in BTI values explained the variation in shape factor of GEV distribution. Therefore, variations in travel time values can be better explained using BTI.
- The reliability-based LOS thresholds developed using BTI and $\lambda_{var}$ can facilitate planners and traffic planners to characterize the performance of an urban arterial corridor based on travel time reliability.

The present study develops a novel approach of characterizing the performance of an urban arterial corridor using reliability-based LoS thresholds. Further, the study projects BTI as an effective reliability parameter for explaining variations in travel time values. The study establishes immense potential in Wi-Fi based monitoring of urban arterial for measuring performance in terms of reliability and variability. Examining travel time variability and reliability for different roadway conditions and the effect of land-use on travel time variability and reliability for developing generalized reliability-based LOS thresholds warrants further research. Further, travel time reliability and variability can be analyzed with respect to traffic flow parameters like traffic density or traffic volume to develop appropriate traffic management strategies.

CONTRIBUTION OF THE STUDY

Travel time and its variation are considered as an important indicator for measuring the performance of any roadway infrastructure. Variations in travel time have significant impact on consistency of travel time, hence travel time reliability. The present study develops reliability-based level of service (LOS) thresholds. The developed LOS thresholds accounts for both travel time variability and reliability simultaneously, which can enable planners to gauge and characterize the performance of urban arterials based on travel time variability and reliability.
REFERENCES


