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Exploring the affect of Mixed Traffic Zones on BRTS: A case study on Ahmedabad BRTS

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Abstract

To realize low carbon city in a developing nation against increasing automobile usage, promotion of public transport such as BRT is one of crucial policy. However, commuters often hesitate to use public transportation because of its low punctuality index. In this regard, to find out effective countermeasures to improve punctuality of BRTS in Ahmedabad, its travel time characteristics across time-zones was analysed based on GPS log data. To analyse them, an unconventional one-dimensional gridding method was used to improve the resolution of velocity profiles along the BRT tracks. The velocity profiles were further used to characterize and quantify the delay caused by the mixed traffic zones. It was observed that these zones contributed about 25 % of the total travel time. Further, to estimate the spatial distribution of the delay variation along a route, a heuristic segmentation analysis was developed. It divides the BRT route into grids with different levels of travel time variation which can assist in isolating the larger variation segments. Finally, to inspect the extent of interference of non-BRT vehicles, all the mixed traffic zones including intersections were clustered based on their diurnal variation of travel times. Results indicated that majority of the lanes were impacted during evening peak hours.

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Keywords: GPS data, BRTS, Mixed traffic zones, intersections, travel time variability

1. Introduction

In developing nations, automobile ownership has drastically increased due to economic growth and rising population. Hence the local transport governing agencies are being cautious in using suitable technologies and transport systems to smoothen the urban commute. They are promoting public transport to achieve and improve sustainability transport. One of such systems is the Bus Rapid Transit (BRT) which gained considerable attraction and is already being implemented in many developing countries like India due to its less initial investment [1]. BRT offers better travel time reliability over conventional bus system at the cost of lesser accessibility. However, its utilization ratio is not

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improving at the expected rate in many of these places [2]. The dominant factors being accessibility and punctuality. In this paper, the authors analysed the effect of Mixed traffic (MT zone) delay and its variation at various levels. utilization ratio is not improving at the expected rate in many of these places [2]. The dominant factors being accessibility and punctuality. In this paper, the authors analysed the effect of MT zone delay and its variation at various levels.

A BRT system consists of both dedicated BRT lane and MT zones. All the intersections and non-dedicated lanes are considered as MT zones, and their punctuality is affected due to interference from non-private transport (NPT). Further, as the bus frequency is often set to reach a 5-min headway, bus bunching increases and causes travel time fluctuations. Scheduling the buses with respect to traffic demand while minimizing travel time variation remains a challenging task for the policy makers [3]. To exercise such care, variability in the travel time need to be understood in high detail. To serve such purpose, BRT bus is often equipped with a GPS logger for automatic vehicle localization. However, these GPS loggers are expected to be relatively cheap especially in developing countries, and often prone to improper maintenance. Consequently, using such data for performance analysis is not trivial. In this paper, incomplete GPS data was used to isolate the high variation zones. Section 2 details the related work, and our case study is described in section 3. Methodology of study is given in section 4 with results discussed in section 5. Finally, section 6 concludes the paper.

2. Related work

Many studies have focussed on analysing the travel time reliability of the public transport system using GPS data. Mazloumi (2009) used GPS data to understand the variability in the travel time at different times of the day. Zhenliang (2016) modelled distribution of travel times and evaluated the performance of distribution models. On the other hand, tracking algorithms and machine learning techniques were applied on GPS tracks to predict the travel time (vanajakshi (2009), Xianghao (2013), Gurumu (2014)). Some studies have specifically modelled the delay variations at intersections considering near and far side bus stops (Feng (2015), Gu (2014)). Most of these studies focused on normal buses whose flow is very much dependent on the traffic volume. Kathuria (2017) analysed the running performance of BRT in Ahmedabad, India with respect to travel time variability. They also examined different statistical parameters related to travel time. However, there is a limited research on identifying spatio-temporal characteristics of BRT routes and how MT zones impact the travel times of BRT bus. Such studies help in localized decision making such as enabling the policy makers to choose between open and closed systems for a lane. In this context, understanding the effect of each intersections on the total delay is crucial. Along side, the estimating velocity profile of a bus in and around intersections improves the travel time predictions.

With MT zones being the major bottlenecks to BRT performance, velocity profiles at all the MT zones throughout the city were inspected to identify similar patterns. Specifically, travel distance time of a bus through an MT zones depends on the zone type such as signalized intersection or a round-about intersection and its level of interference with the non-BRT vehicles. This paper, especially focused on the all the intersections and quantified the impact of MT zones on the total travel time. Making a similar quantification in terms of variation is not possible due to high correlation between adjacent grids. To this end, a segmentation strategy was used to identify the distribution of variation across the full route. Further, to estimate the level of dynamic interference with the BRT tracks, all the MT zones were classified based on diurnal variation of time.

3. Case study: Ahmedabad BRTS

Ahmedabad is the seventh largest metropolis in India and is projected to have 12 million population by 2050. Its motor vehicle ownership is increasing by 40% percent every year. Its BRTS is operating at coverage 97 km (see in Fig.1) with 250 buses and about 1.3 lakhs average passengers per day. It is a semi-closed BRT system having the routes characteristics tabulated in Table 1. Further, most of the BRT tracks have a dedicated bus zones with bus stations and busways being located on the median. It also has an implementation of pre-board fare collection system. Each bus station maintains the recommended 40 meters from the intersection and has a high-level platform minimizing the boarding time. All buses are logged with a GPS logger to facilitate automatic vehicle location (AVL). In Ahmedabad, India, the public transport utilization ratio is only 15 %. the local government while planning to introduce

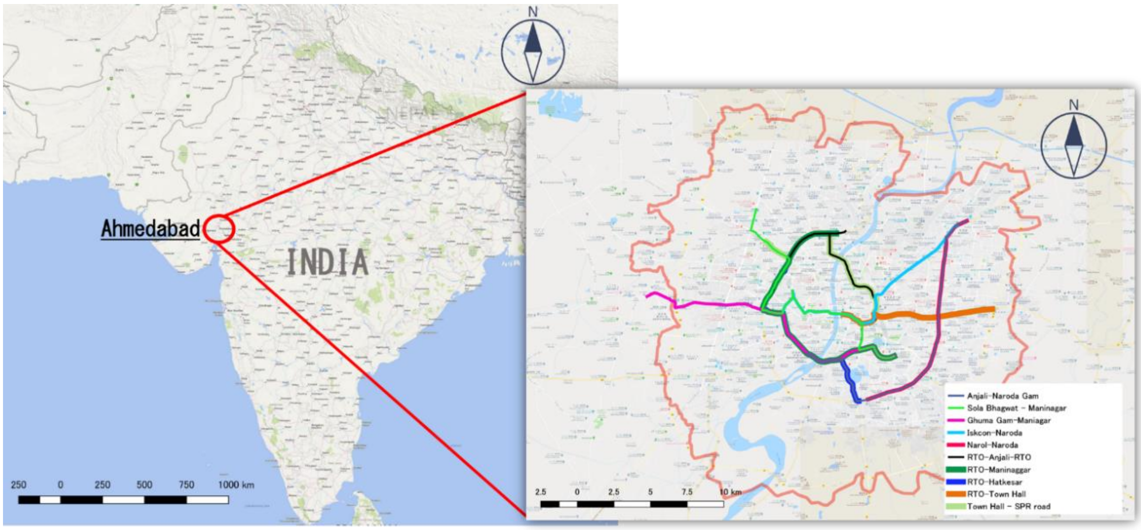

Fig. 1. Ahmedabad location and BRTS route map.

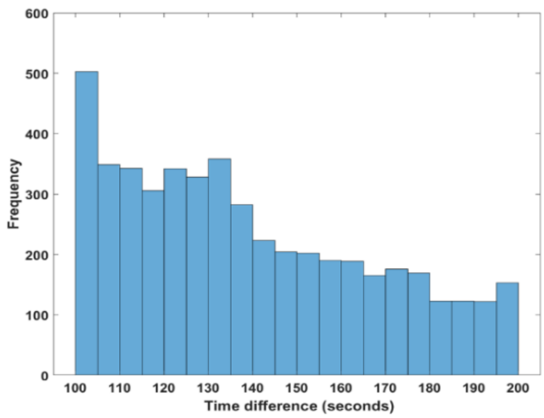

Fig. 2. Distribution of successive GPS log's time difference greater than 100 s.

metro in 2019 is also searching for flaws in the current system. One of the major problems, Ahmedabad BRT will face in the future is punctuality.

4. Data and Methodology

For this study, GPS data for the month of October 2016 was acquired. The data included time, bus number, latitude, longitude and speed. For pre-processing and analysis, all the codes were written in MATLAB while QGIS and google earth were used for data visualization assistance.

4.1. Pre-Processing Challenges

Though the GPS loggers were designed to log every 10 seconds, successive logs time difference varied drastically as shown in Fig. 2. Additionally, data was separated based on date and bus number but not on the direction of the bus. Extracting trips separately for upstream and downstream from complete one month's data is challenging. Using a conventional 2-dimension grid similar to (Cristian (2011)) cannot support high resolution analysis. Further, using 2-dimensional grid analysis provided by many of the off-the-shelf tools, complicate the processing of GPS records and

Table 1. Route characteristics of Ahmedabad BRTS

Number	Routes	Route Length (km)	Number of bus stops	Number of Mixed traffic lanes	Trips extracted
1	Anjali to Naroda	21.2	34	30	981
2	Sola Bhagwat to Maninagar	21.9	35	42	447
3	Ghuma Gum to Maninagar	21.5	30	38	1867
4	Iskon to Naroda	20.9	34	44	537
5	Narol to Naroda	15.0	24	19	1565
6	RTO to Hatkesar	21.8	30	29	777
7	RTO-Anjali-RTO	24.1	38	31	334
8	RTO to Maninagar	18.0	26	44	503
9	Science City to SPR road	20.8	30	38	374
10	Town Hall to SPR road	10.9	18	28	325

has many limitations. To this end, whole BRT route road coordinates were extracted and divided into 25m length grids (1-dimensional gridding) and a number is assigned to each grid (see Fig. 4). Next, each GPS point logged was assigned the nearest grid number. Now to separate upstream and downstream trips, estimating the trip end based on grid number gradient creates many false alarm and miss detections. The fluctuations in the GPS data when the bus stops can cause such false alarms and a data set with continuous downstream (without upstream logs) can miss the trip end points. To overcome this problem, data was separated based on time difference initially. Next, adaptive smoothing was used to ignore grid number gradient changes when the bus stops. Subsequently, the upstream trips and downstream trips for all selected routes were separated.

4.2. Methodology

The travel time variability of a BRT service depends mainly on interfering traffic volume variability at intersections, bus bunching and bus dwell time at the bus stops. Identifying each of their dynamic impact on the total variation is necessary for travel time predictions and bus scheduling. The following method is proposed which is also shown in the flowchart. Initially, create a high-resolution velocity profile along all the selected routes. Also generate the velocity variation level at each grid and analyse the travel time characteristics across all routes across hours and days of the week. Further, estimate the delay contribution of each type of lane. To estimate the variation spread across a BRT route, segment the route efficiently and estimate the variation of each grid. Finally, to characterize each intersection, cluster and group them according to their travel time profile.

4.2.1: Average velocity estimation

GPS data was separated based on hour of the day and after which each group was divided according to the grid number. Further, using the speed information of each of those logs, average velocity can be directly calculated. However, this approach can be biased due to 2 reasons. Firstly, the recorded speed (v_{GPS}) in the GPS data is instantaneous and quantized to 5km/hr. intervals. To overcome this issue, relative velocity v_{rel} as calculated at each point based on location and time information of successive logs: $v_{rel} = (x_{l+1} - x_l)/(t_{l+1} - t_l)$ where $x_{l+1}, x_l, t_{l+1}, t_l$ are location and time stamp of successive logs $l, l+1$ However, as the time difference between the successive logs is not

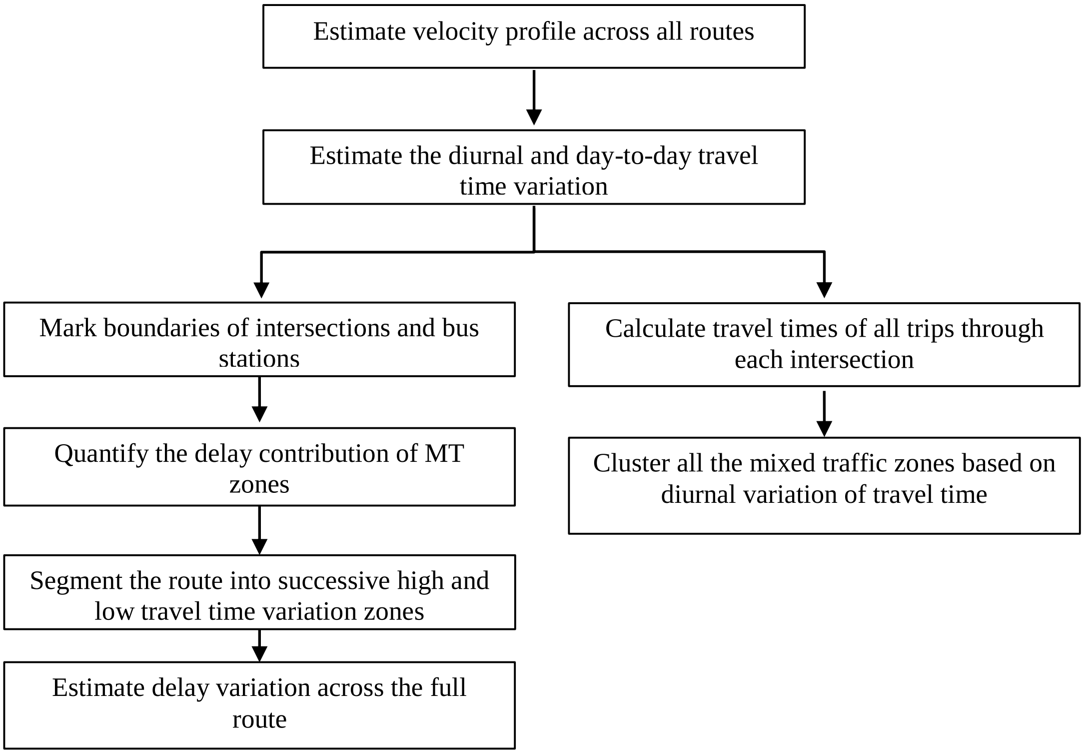

Fig. 3. Methodology to investigate mixed traffic zone effects on BRT.

consistent, another hybrid speed variable v_f :

$$v_f = \begin{cases} 0.5(v_{GPS} + v_{rel}) & t_{i+1} - t_i < 20 \\ v_{GPS} & t_{i+1} - t_i > 20 \end{cases} \tag{1}$$

is used a velocity for each log. Secondly, every time a bus stops for a longer time, zero speed will be attributed multiple

Fig. 4. BRT route gridding along with grid number labelling.

Fig. 5. Grid selection for delay quantification: Red box is the marked intersection and dotted squares represent selected grids based on velocity.

times to the same grid. The issue was addressed in the following way. Consider that in a trip, $\{v_k\}_{(k=l)}^{L} = 0$ such that $\{x_k, y_k\}_{(k=l)}^{L} = constant$ where v_k is speed at location $\{x_k, y_k\}$ and L is the number of successive logs. This whole set was replaced by a single log with velocity $v = s_{L+1,l} / t_{L+1,l}$ where $s_{L+1,l}$ is distance between $(L+1)^{th}$ record and l^{th} record, $t_{L+1,l}$ is time taken between $(L+1)^{th}$ record and l^{th} record. The average velocity at each grid was calculated according to:

$$V_{ave_i} = median(\{V_{ij}\}_{j=1}^{K}), \quad (2)$$

where v_{ave_i} is average velocity at grid i and $\{v_{f_{ij}}\}_{j=1}^{K}$ is the hybrid velocity v_f of K GPS records with grid number.

However, this filtered data was used only during velocity profile estimation. But for time travel analysis, unfiltered data was used.

4.2.2 *Average travel time*

Many of the trips had missing logs during the starting and initial stage of the trip. Such trips had travel times calculated and corrected using the estimated velocity profiles separately for upstream and downstream trips across different times of a day and different days of a week.

4.2.3. Delay Quantification

Bus slowing occurs either at a bus station, intersection or a non-dedicated lane. To estimate the delay at all such different zones, their corresponding grid numbers were recorded manually. When a bus arrives at an intersection, it waits within the dedicated lane until a gap exists for it to cross. Further, some buses must wait way beyond intersection stop line margins and bus stations due to bus bunching. To acknowledge this affect, grids having velocity less than 18 kmph were identified initially (see Fig. 5 for our method which selects the affected grids considered due to intersections). Subsequently, the identified grids were assigned to the manually categorized intersections set or bus station set. Next, the velocity profile during the peak hour was used to calculate average time spent at each grid according to $t_i = d / v_{fi}$ where v_{fi} is average velocity at grid i. Next, the delay proportions are calculated summing the time spent at respective categories.

4.2.4. Spatial distribution of delay variation

Many studies attempted to estimate the travel time variation and proposed indices to quantify the variation. However, the contribution of different zones to the total variation has not been studied well especially for BRT. Generally, the grids before and after slow velocity areas are prone to have high velocity variation. However, directly

Fig. 6. Variable-length route segmentation for delay variation estimation: Green segment: includes dedicated lane; Red segment: includes intersection and bus stop.

summing the variation of each grid contributes to larger variation. This is because of the correlation between adjacent grids. To this extent, a heuristic segmentation was carried out in the following way. The idea is to divide the grid into high and low speed zones. A BRT, normally has successive zones with different characteristics such as bus station, intersection, and a dedicated lane. As a result, segmenting was carried out such that each part consisted either an intersection together with a bus station or only a BRT dedicated lane (can be seen in Fig. 6). In affect, such segmentation separates the zones with high and low variations and reduces the correlation between adjacent grids. This method asserts that correlation between successive segments is very less. Next the time spent by each trip in each segment is calculated from the time difference of GPS logs. After segmentation, the travel time and variation for each segment was calculated.

4.2.5. MT zones clustering

MT zones run throughout the bus route. Their effect on BRT delay especially depends on the level of interference with the non-BRT vehicles. The diurnal travel time variation is one factor which can clearly show the impact of the non-BRT vehicles. The travel time variation can be mainly categorized into 5 types (shown in Fig. 7). To categorize the intersections depending on one of these types, the travel time at each intersection was grouped into 5 intervals-06:00-08:30, 08:30-12:00, 12:00-17:00, 17:00-20:30 and 20:30-2330. As a result, each intersection segment crossing time has 5 elements corresponding to each time zone. Next the intersections were clustered and visualized using T-SNE (t-distributed stochastic neighbour embedding) clustering algorithm.

T-SNE:

T-SNE is a nonlinear dimensionality reduction technique well-suited for embedding high-dimensional data for visualization in a low-dimensional zones of two or three dimensions. Specifically, it models each high-dimensional object by a two- or three-dimensional point in such a way that similar objects are modelled by nearby points and dissimilar objects are modelled by distant points with high probability. local structure of the high-dimensional data is captured, while revealing global structure such as the presence of clusters.

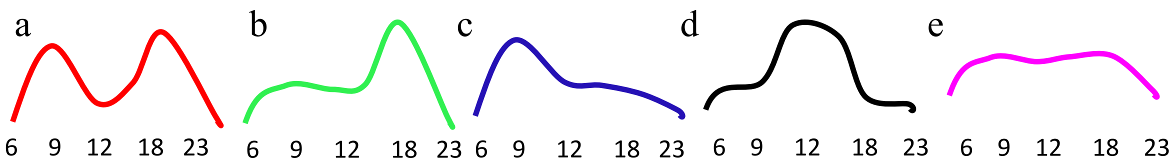

Fig. 7. Different patterns of travel time variation in a day. (a) Longer trips during morning and evening, (b) Longer trips during evening, (c) Longer trips during morning, (d) Longer trips during afternoon and (e) No specific peak hours.

Fig. 8. Estimated velocity profile along route.

5. Results and Discussion

After trip separation, the number of routes extracted along with the number of bus stations and MT lanes is tabulated in Table 1. Using the average grid method, the velocity profile was obtained as shown in the Fig. 8. Clearly, velocity at the MT lanes marked in red is low. Further, using such profiles, travel times were calculated for all the trips throughout the day. The travel times for the route 3 is shown in the Fig. 9(a). It can be observed that there are two busy time segments-morning and evening peak hours. To analyse and compare the day to day patterns, data with the similar traffic characteristics need to be considered. In this regard, travel time averages considering only the peak hours were calculated and shown in the Fig. 9(b). Clearly, almost all the routes had longer travel times occurring from Tuesday to Friday.

To understand how critical, the MT zones affect the travel times, their corresponding delay proportions must be estimated. The distance proportions of MT zones, bus stations and dedicated zones were determined initially (see Fig. 10(a)). Next, the time spent at each of the category for all the 10 routes was estimated which can be seen in 10(b). Though the distance proportions of the bus stops and MT zones together is less than 25% along all the routes, it can be seen that the time spent at bus stops and MT zones contribute about 50% of the time. Figure shows the effect of bus stations for route 4 and 7 with the time spent at MT zones being more than 25%. Especially, for route number 7, BRT, on an average, to travel through intersections of length 3 km, it takes 19 minutes. The average velocity of each of the categories shown in Fig. 10(c) also strengthens this inference. These proportions also drive the exposure to vehicle exhausts contributing to poor air quality.

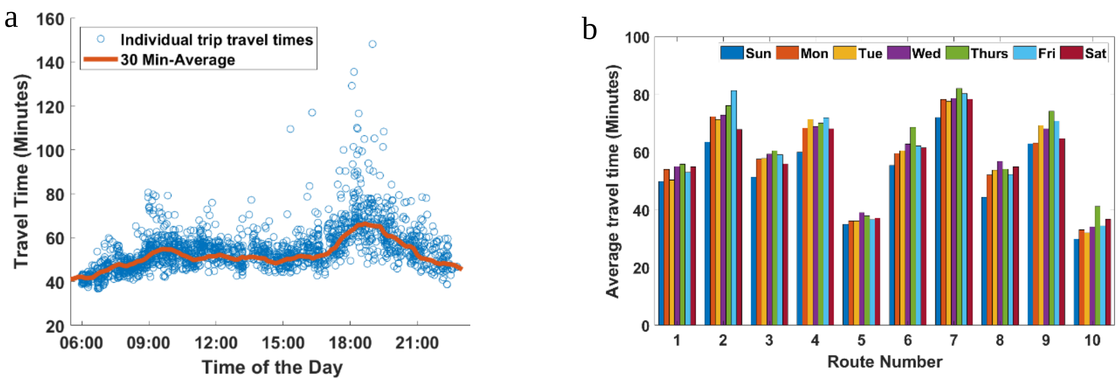

Fig. 9. (a) Estimated travel time along route 3 throughout the day; (b) Calculated day-to-day travel times for all routes.

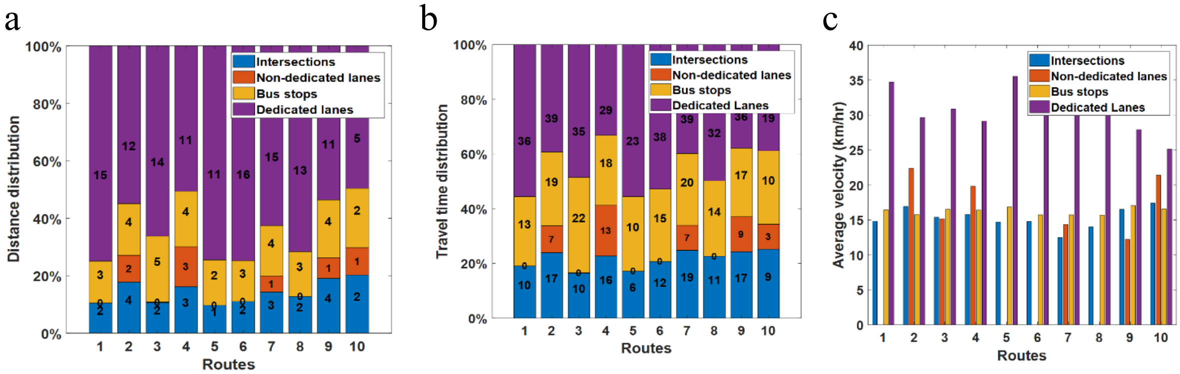

Fig. 10. (a) Distance proportions of all lane types; (b) Delay proportions of all lane types and (c) Average velocity of all lane types.

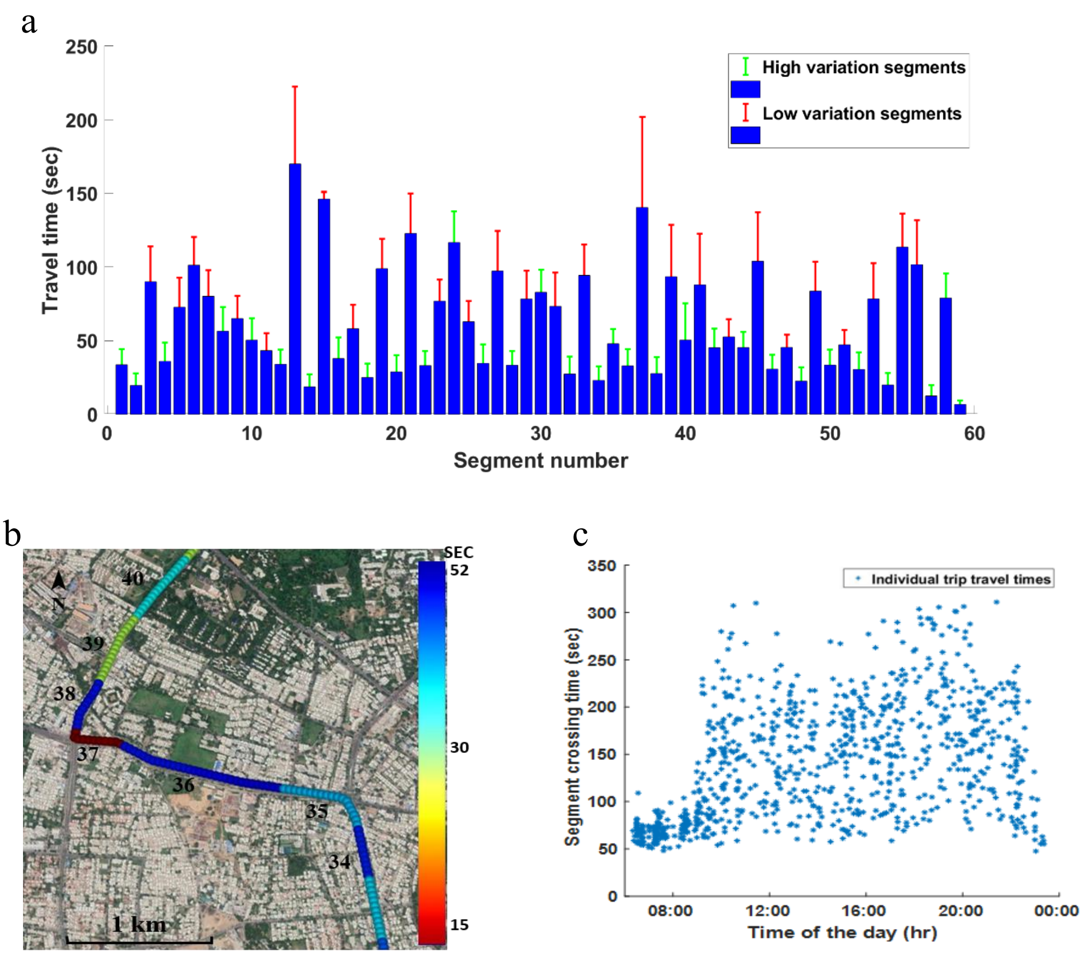

Fig. 11. (a) Statistics of delay variation profile of the segmented grid; (b) Variation profile superimposed on google earth; (c) Diurnal variation of segment crossing time at Shivranjani.

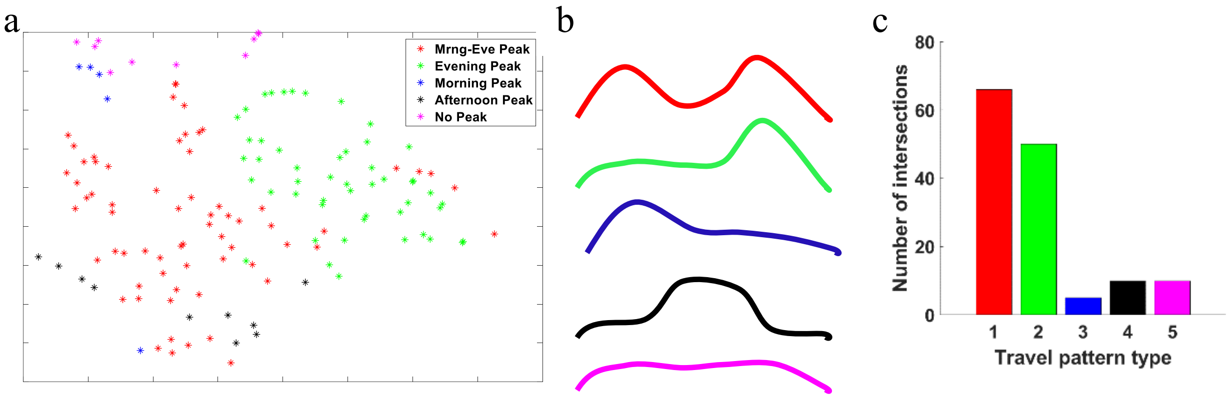

Fig. 12. (a) MT zones clustering based on travel time profile (b) types of travel time profile (c) Total intersections with of each type.

Spatial attribution of travel time variation is not straight forward due to correlation between adjacent grids. As our approach of segmentation minimizes such correlation, it can be helpful for accurate travel time predictions. Route number 6 which has 30 intersections and 23 bus stops was selected for demonstrating this method. The route was segmented into high and low variation zones resulting in 58 segments. The mean and standard deviation of each zone was calculated as shown in Fig. 11(a). The high variation zones in the figure are marked in red and the low variation zones were marked in green. Segments 13 and 37 had the larger mean and standard deviation due to their traffic volume at intersections and the bus frequency at the bus stations. Further, segments travel time variation profile of the whole route is superimposed on to google earth as shown in Fig. 11(b). Segment 37 has busiest intersection near Shivranjani junction whose travel time profile throughout the day is shown in Fig. 11(c).

MT zones have different characteristics which alter their respective dynamic travel time patterns. To inspect each of their patterns, the travel time vector for all the 146 MT zones were selected. Each intersection had a value corresponding to one of the 5 time slots detailed in section. All the intersections were clustered based on their diurnal travel time profile and the data was visualized using t-SNE. This clustering is shown in Fig. 12(a). Most of the intersections are successfully clustered according their characteristics. Some intersections with travel pattern type of afternoon peak and no peaks were also observed (see Fig. 12c). No peak patterns occurred mostly due to less non-BRT interference.

7. Conclusion

The punctuality of BRTS operation can be improved by identifying the reason of delay in detail. In this paper, the authors attempted to understand the affect of mixed traffic zones on BRT. From raw GPS data, trips were separated and travel time analysis along all the routes at different time frames with different characteristics was analysed. It was observed that the time spent by the BRTS bus at MT lanes contribute about 25 % of the travel time. Further, BRT route was divided into successive variable length segments and variation profile of each segment's travel time was estimated. Finally, all the intersections were clustered based on their diurnal variation of travel time patterns. Future work will attempt to use the segmented delay variation estimates for accurately predicting the total travel time.

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