DSRC-Based Bus Trajectory Analysis and Prediction Near Signalized Intersection

Aswathi Chandrahasan, Aayush Jain, and Lelitha Vanajakshi

Abstract The current study aims to identify all possible factors influencing bus travel time near signalized intersections and predict the arrival time to stop line under the heterogeneous and lane free traffic conditions. Preliminary analysis of the bus trajectories grouped them based on uniform and non-uniform movement and whether the bus stopped or not. The prediction model is formulated considering all possible events in which a bus can get detected near an intersection, especially when the bus arrival is during the later green and early red phases. The algorithm is developed integrating the bus, traffic, and control information. Implementation and evaluation of the models developed has been carried out to understand their performance under varying conditions. Bus information is collected using the DSRC (dedication short range communication) devices. Results showed very good prediction performance with the errors reducing as the bus approached the stop line. The findings of this study can be used to predict the arrival time of the bus at the stop line, which can further be used for various applications including bus signal priority.

Keywords Bus arrival time prediction · Trajectory analysis · Signalized intersection

1 Introduction

Severe traffic congestion has become a major challenge to tackle by transportation agencies all over the world. Cities have been witnessing significant developments in the field of transportation as a consequence of rapidly growing economy, increasing levels of vehicle ownership and high expectations for superior infrastructure and services. These are more challenging in developing countries like India where uncontrolled growth of vehicle population, relatively slow infrastructure growth, and rampant encroachment of carriageway are leading to traffic snarls on a daily

A. Chandrahasan · A. Jain · L. Vanajakshi (✉)
Department of Civil Engineering, Indian Institute of Technology, Madras, India
e-mail: lelitha@civil.iitm.ac.in

A. Dhamaniya et al. (eds.), *Recent Advances in Traffic Engineering*, Lecture Notes in Civil Engineering 377, https://doi.org/10.1007/978-981-99-4464-4_8

basis. One way to address this inefficient and inadequate system is to improve the public transport system in an effective and sustainable way.

One of the major drawbacks of the public transport bus service is its unreliability. Buses face maximum delay in urban arterials near signalized intersections. Thus, if bus delay at intersections can be reduced, more people may shift to public transport from personal vehicles. This in turn will help to reduce traffic congestion because of the high occupancy of the buses than personal vehicles. Bus Signal Priority (BSP) system helps to achieve the same by detecting a bus as it approaches the intersection and providing green time to that approach so that the bus can pass the intersection without much delay. The reliability of bus services can be improved if such a BSP system is implemented accurately. This would be a more desirable and sustainable strategy than the infrastructure expansion to meet rapid traffic growth needs.

For the successful performance of the BSP system, a better understanding of the behavior of buses near intersections and in turn an accurate bus arrival time prediction to the stop line is crucial. This will help to decide how much the present green phase is to be prolonged or the current red phase is to be truncated. The present study focuses on these two aspects of understanding the behavior of bus near intersection and quick and reliable prediction of its arrival to the stop line. One major requirement for these is high-resolution, real-time data collection. The common sensors used for this purpose include intrusive sensors such as inductive loops [7], magnetometers [23], piezoelectric sensors [7], pneumatic tubes [9] and non-intrusive sensors like video cameras [3], microwave radar [6], LiDAR (Light detection and ranging) [16], ultrasonic [12], and hybrid sensor technologies [17]. Intrusive sensors are installed beneath the road surface and hence invasive to the pavement. Location-specific non-intrusive sensors though useful to detect the presence, speed, type of vehicle, lane crossing, etc., are expensive and their performance gets affected by traffic and climatic conditions. On the other hand, onboard tracking solutions like global positioning systems (GPS) help to determine the exact location of a vehicle and are more efficient under heterogeneous and less lane disciplined traffic conditions such as the one in India. A detailed literature review of data collection, data analysis, and prediction near signalized intersections is conducted to understand the gaps in this area of research.

2 Literature Review

Bus arrival time can be predicted either for a midblock section or near intersections. The studies on the prediction of bus travel time for midblock sections, especially to the next bus stop reported the use of different prediction methods such as time series analysis [4], ANN technique [11], SVR technique [21], Kalman filtering technique [20].

Most of these studies were developed for the purpose of prediction to bus stops. However, for the BSP application, the requirements are different with the prediction focusing on a small stretch of roadway near to the intersection, at high resolution, where the stochasticity is more. This means that the space span of prediction is shorter and prediction accuracy must be stricter for the same [8].

Lee et al. [13] reported a more advanced method of bus signal priority control which consisted of two parts: a high-performance online microscopic simulation model for prediction of transit travel time up to the stop line using sensor data and a priority operation model to select the best priority strategy based on the prediction results. Another related research work was reported by Tan et al. [19] using both historical and adaptive model. Automatic Vehicle Location (AVL) data and wheel speed data were taken as inputs for this study. However, this method was reported to be not suitable for heavily congested traffic.

Ekeila et al. [5] used AVL systems which are mostly installed on many transit buses for the dynamic BSP strategy. Li et al. [15] reported a predictive BSP control that predicted the arrival time of the bus until the stop line of the subject intersection by detecting the transit vehicles upstream (e.g., immediate upstream intersection of the subject intersection). Bie et al. [2] developed an analytical model using the traffic flow and time headway-based equations based on the field data. Yu et al. [22] presented an estimation algorithm based on the equations of motion for the arrival time prediction of buses to the stop line. Gang et al. [8] proposed a deep learning-based model for bus travel time prediction to the stop line. They presented a stacked auto-encoder (SAE) neural network, which is a pre-training model and included logistic regression model as the predictor. The limitation of this study is that the experimental data used was created through traffic simulations rather than being gathered in the actual world.

There are various factors which affect arrival time prediction namely, spatial and temporal factors, conditions of traffic, driving behavior, and vehicle characteristics. Travel time is correlated with characteristics of the route such as road segment, road/route length, intersections, bus stops near the intersection and turning movements. The main temporal factors considered for arrival time prediction for BSP include dwell time and intersection delay. Prediction accuracy can be enhanced by improving the dwell time and intersection delay estimates [1]. Yu et al. [22] considered bus dwell time for the estimation of arrival time. Analytical models were developed by Bie et al. [2] for the estimation of arrival time of bus up to the stop line, taking into account the bus delay at the intersection. However, the model needed detailed speed and signal settings data. For the prediction of arrival time, the average delay at intersection has also been calculated in some studies [9]. However, intersection delay modeling by an average value can sometime reduce the accuracy of bus travel time prediction models.

Traffic information such as speed, flow, density, and queue length has a direct impact on arrival time prediction. Studies based on historical data used constant average speed [9]. Adaptive average speed based on real time data was used by Yu et al. [22]. Only a few studies have considered arrival rate, discharge headway, and signal timing details for the arrival time prediction to the stop line [2].

Driving and vehicle characteristics can also contribute to variation in arrival time. Lee et al. [13] presented an arrival time prediction model which incorporated driving characteristics (i.e., aggression level) and behavior of the adjacent vehicle (lane changing and queuing at the stop line). Based on these factors, the prediction model included a set of driving rules (initialization rules, free-flow driving rules, car-following rules, lane changing rules, traffic signal reaction rules, and transit vehicle rules) using real-time traffic count and transit location information.

It can be observed that most of the above studies on bus arrival time prediction for implementation of BSP are based on traffic conditions in western countries and these studies cannot be directly implemented in India where lane discipline is not followed and too many vehicle types are sharing the road space. Hence, a research study on arrival time prediction to stop line near signalized intersection under mixed traffic conditions is needed for a successful BSP implementation under the heterogeneous and lane less traffic conditions.

3 Study Site, Data Collection, and Preliminary Analysis

3.1 Study Site

The study area selected is Tidel Park junction connecting Rajiv Gandhi IT expressway and East coast road (Fig. 1a). This is one of the nine major intersections in Rajiv Gandhi Road which is a busy arterial road in Chennai. IT-enabled service companies, industrial estates, educational institutions, and residential developments are located around this roadway. There is also a local railway line that runs parallel to this road section.

The Tidel Park intersection is a four legged one with Madhya Kailash to the north at a distance of 2.2 km, East Coast Road (ECR) to the east at a distance of 1 km, SRP tools to the south at a distance of 1.5 km and Tidel park service road to the west at a distance of 0.6 km. Since Tidel park service road is a free left road, this intersection can be taken as three legged. A six-lane roadway is in the north–south direction with three lanes in each direction having a width of 3.5 m/lane. The east bound ECR

(a) (b) (c)

Fig. 1 **a** Study Area (*Source* https://www.openstreetmap.org/), **b** OBU installed in Bus **c** RSU installed on signal pole approach is a four-lane divided carriageway. The traffic volume was observed to be around 4000 veh/hr for north bound, 3800 veh/hr for south bound, 1200 veh/hr for west bound, and 100 veh/hr for east bound.

3.2 Data Collection

Continuous information on position, speed, direction and acceleration and deceleration characteristics of buses are required for the successful implementation of BSP. This high-resolution data was guaranteed by using Dedicated Short Range Communications (DSRC) based devices. DSRC devices include On-Board Units (OBU), which communicates with Road Side Units (RSU) fixed at the intersection, when they are in the line of sight. Along with bus information, traffic and signal information are concurrently collected from video recordings.

Bus Data. For the present study, DSRC devices were used for bus detection and tracking near the intersection. The RSU is fixed at Tidel Park signal and OBUs were fixed in seven buses of route number 19 that are crossing this intersection, with OBU IDs 21, 22, 23, 25, 26, 27, and 28. When OBU installed bus comes in the vicinity (roughly around 300 m) of the RSU location, the OBU starts sending data packets to RSU and the RSU, in turn, would send that information to the server. Figure 1b&c shows OBU device installed inside a bus and the RSU that is installed at Tidel Park signal.

Data collected for five days—08/02/2022, 09/02/2022, 10/02/2022, 11/02/2022, and 14/02/2022 was used. Table 1 shows the details of the DSRC data collection period and number of trips made on each day.

Continuous information on speed, position, acceleration, or deceleration of buses was communicated till the bus leaves the intersection area. The type of movement (turning or straight) and route of each bus was obtained based on the changes observed in latitude and longitude values.

Signal and traffic data. Manual data collection using video recordings was done for signal timing details, arrival rate, and saturation discharge headway. For the proposed study, two video cameras were installed. One camera was placed facing the signal head along with vehicles crossing the stop line, to collect the signal timing details and saturation headway. Another one was installed facing the arriving vehicles

Table 1 DSRC data details

Date	DSRC Data Collection Period	No. of trips made by buses
08-02-2022	5 am to 8 pm	29
09-02-2022	6 am to 10 pm	25
10-02-2022	5.30 am to 11 pm	31
11-02-2022	5 am to 9.30 pm	36
14-02-2022	6 am to 9.30 pm	24

about 250–300 m away from signal, to collect the arrival rate of vehicles. These manually collected traffic counts were converted into Passenger Car Unit (PCU) using PCU factors suggested in IRC 106 [10].

3.3 Data Cleaning and Preliminary Analysis

Duplicate values were removed from raw data as part of data cleaning. After that, check for outliers was done on the basis of speed thresholds, i.e., speed cannot be less than zero km/h and the upper threshold was taken as the 95th percentile speed.

Next level data cleaning was done using Quantum Geographic Information System (QGIS) software. By importing latitude and longitude values into QGIS, a dynamic display of bus position was created. By analyzing the routes of buses in QGIS software, the trips which do not pass through the study area were identified. Such trips were removed, and remaining trips were selected for the bus arrival time prediction to the stop line. Table 2 shows the details of the final data set used.

As part of the preliminary analysis, using the information of continuous positions of buses with timestamp, bus trajectories were created. Then trajectories of each bus were plotted in tableau software. The trajectories were found to be falling into the following two groups: Uniform trajectories, and non-uniform trajectories with/without stopping.

Figure 2 shows sample trajectories falling under these groups. Prediction was done separately for each of these groups.

Table 2 Final data set

Description	Date of data collection				
	08/02/2022	09/02/2022	10/02/2022	11/02/2022	14/02/2022
Total number of trips after preliminary data cleaning	29	25	31	36	24
Number of trips available in signal video data	17	20	21	19	13
Number of trips which shows error in QGIS	5	7	8	3	3
Remaining number of trips for implementation	12	13	13	16	10
Number of trips from Madhya Kailash	1	2	1	4	3
Number of trips from Thiruvanmiyur	1	0	0	1	1
Number of trips from SRP Tools	10	11	12	11	6

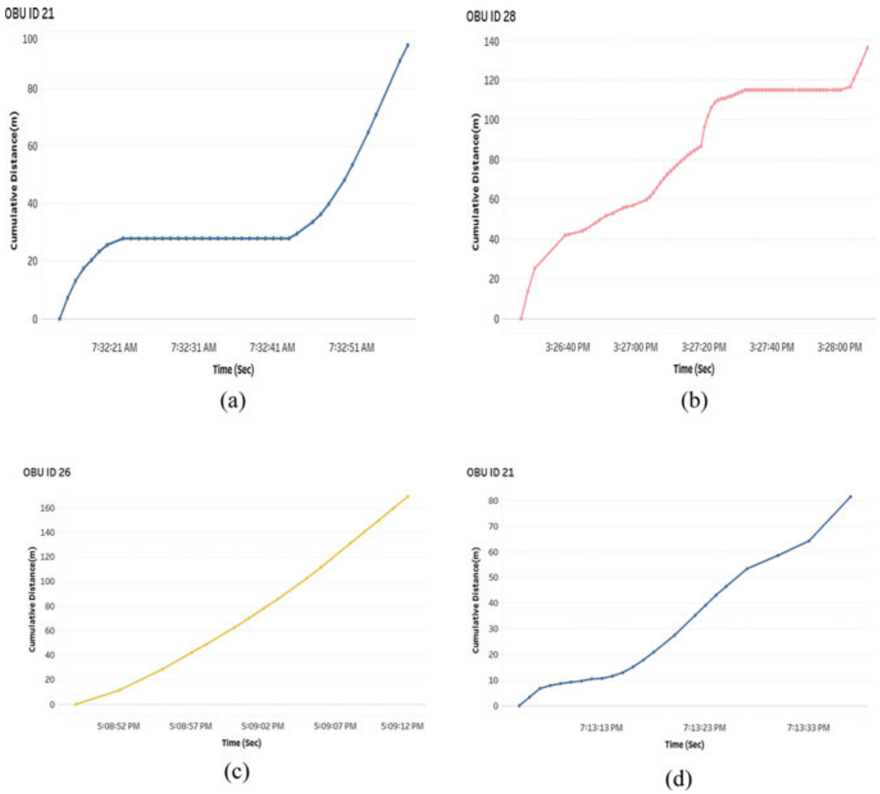

Fig. 2 Sample trajectories of the identified groups **a** Uniform trajectory with stopping, **b** Non-uniform trajectory with stopping, **c** Uniform trajectory without stopping, **d** Non-uniform trajectory without stopping

4 Bus Travel Time Prediction Model

The prediction model assumes that the intersection is under-saturated such that queuing vehicles clear within the cycle without any residual queue. The model splits the travel time into three parts from the advanced detection position to stop line, as travel time from detection point to the end of queue, waiting time in the queue, and time for discharging of queued vehicles in front of the bus. A model proposed in Bie et al. [2] was used as the base model for the present study. An advantage of this model is that it takes into account all possible outcomes, especially when the bus arrives in the later green light and early red-light stages. Modifications were made to this base model to take into account the heterogeneous traffic conditions and the lane free movement in the study area.

4.1 Model Formulation

Suppose the signal has n phases and current green phase is k. Let the bus placing the priority request is on phase j. Let G denotes green time, Y denotes yellow time, and R denotes red time. Based on the signal operating status when a bus is detected, the model is classified into different categories as discussed below.

Priority phase as current green phase ($k = j$). In this category, when the bus is detected first, phase *j* is having green time or in other words, the bus is detected during the green signal. The main concern in this situation is whether the bus can arrive at the stop line before the end of current green signal. If bus can reach stop line within available residual green time, bus need not make a stop and anterior queue length determines its arrival time to stop line. If it cannot reach within the given residual green time, it needs to make a stop and wait for green signal in the next cycle. Free-flow travel time from the current position to the stop line determined as in Eq. (1) can be used to check whether the given residual green time is sufficient to cross.

$$T_f = \frac{D}{V_f}, \tag{1}$$

where D = Distance between the current location of the bus and stop line in m, and V_f = Free-flow speed in m/s. This V_f is taken as 95th percentile speed of buses in that link.

When free-flow travel time is more than residual green time ($Tf > Gr$), bus cannot pass the stop line in the current cycle. For this case, bus arrival time T from the current position to the stop line, including waiting time for green in next cycle and anterior queue length to discharge, can be obtained as shown in Eq. (2).

$$T = G_r + Y + \overline{R_c} + R_n + N\bar{t} + \varphi, \tag{2}$$

where T = Predicted arrival time of the bus in seconds;

Gr = Residual green time of phase j in seconds;

Y = Yellow time of phase j in seconds;

$\overline{R_c}$ = Red time in current cycle after detection point in seconds;

Rn = Red time in next cycle before start of green time in seconds;

$\bar{t}$ = Saturation discharge headway in seconds per PCU;

φ = Time interval between front end of the bus and rear end of adjacent anterior vehicle in seconds (it is nearly a constant number when vehicles are discharging at saturation flow rate and can be obtained by field survey);

N = Queue length in front of the bus up to the stop line.

Since no residual queue is left at the end of each cycle and vehicles at the intersection arrive randomly, N can be expressed as

$$N = \left(T_f - G_r\right)q, \tag{3}$$

where q is the average vehicle arrival rate of phase j in PCU/second, and ($Tf - Gr$) is elapsed red time of phase j in seconds.

When free-flow travel time is less than residual green time ($Tf \le Gr$), bus need not stop before reaching the stop line since sufficient residual green time is available. The key issue for this case is whether the bus can move forward without being hampered by the queue length. Intuitively, if the queue is short, the bus can arrive at the stop line freely. Otherwise, it has to alter its speed. Therefore, it is necessary to determine the critical number of anterior vehicles that could affect the bus. However, for the bus to arrive at the stop line freely, the number of anterior queue vehicles should be such that.

$$N_c = \frac{T_f}{\bar{t}}, \tag{4}$$

where Nc = critical number of queue vehicles in front of the bus,

Tf = free-flow travel time from the current position to the stop line in seconds and $\bar{t}$ = saturation discharge headway in Seconds/PCU.

Since the bus is coming during the green time, vehicles in front of it are discharging. Hence, actual anterior queue length up to the stop line can be calculated as

$$N = \left[R_p + R_c^{'} + G_e\right]q - \left[\frac{G_e}{\bar{t}}\right], \tag{5}$$

where R_p = Red time in the previous cycle after end of green time in seconds;

R'_c = Red time in the current cycle before detection in seconds;

G_e = Elapsed green time in the current cycle in seconds.

The number of vehicles that arrived since red light of phase j started is the first term of the Eq. (5) and the second term is the number of vehicles that have been released since the green light started. To avoid negative N, the above equation can be modified as.

$$N = \max\{\left[R_p + R_c^{'} + G_e\right]q - \left[\frac{G_e}{\bar{t}}\right], 0\}. \tag{6}$$

If $N \le Nc$, the bus arrival time $T = Tf$. Otherwise, arrival time will be affected by queue length and arrival time can be updated as

$$T = N\bar{t} + \varphi. \tag{7}$$

Priority phase as red phase ($k \neq j$). In this case, phase j has red time when the bus places a priority request or in other words, bus is detected during the red indication. Since the signal is not a fixed time one, the timings in adjacent cycles are different making the waiting time for the green varying. If bus is placing a priority request after the green time of phase j in the current cycle, it needs to wait for the green signal in the next cycle. However, if bus is placing priority request before the green time of phase j in current cycle, it can wait for its right of way in the current cycle itself. It can be noted that the waiting time for the latter case will be less compared to the former.

Priority phase before the current green phase ($k > j$). In this case, the green time of phase j has ended in the current cycle and bus needs to wait for the green in the next cycle. Since bus is coming during the red time, there will be two types of vehicles in front of the bus—vehicles which already formed the queue during the red time and vehicles which are moving in front of the bus to join the end of queue. Out of these, the number of vehicles in front of the bus which already formed the queue during the elapsed red time can be calculated as.

$$N_1 = R_e q, \tag{8}$$

where R_e = Elapsed red time in seconds.

Travel time needed from current bus location to the end of this queue is.

$$T_f' = \frac{D - (N_1 \times \overline{L})}{V_f}, \tag{9}$$

where $\overline{L}$ = average vehicle length in meters. During this time interval, vehicles will be moving in front of the bus to join the end of queue. Number of such vehicles will be

$$N_2 = T_f' q. \tag{10}$$

Thus, the total number of vehicles in queue in front of the bus will be

$$N = N_1 + N_2 = \mathrm{Re} \cdot q + \left(\frac{D - (\mathrm{Re} \times q \times \overline{L})}{V_f} \right) q. \tag{11}$$

Sometimes, the second term in Eq. (11) can be negative and in such cases, it may indicate that bus made a lane change. In such cases when $D < (R_e q \overline{L})$, the anterior queue length is updated as shown in Eq. (12).

$$N = \left(\frac{D}{V_f} \right) q = T_f q. \tag{12}$$

Finally, the time for bus to reach stop line is

$$T = \overline{R}c + R_n + N\bar{t} + \varphi, \tag{13}$$

where R_n = Red time in the next cycle before the starting of green.

Priority phase after the current green phase ($k < j$). In this case, green time of phase j has not started in the current cycle and the bus has to wait for its right of way in the current cycle itself.

Queue length calculation in this case is similar to that of case $k > j$. The number of vehicles which already formed queue in front of the bus is

$$N_1 = \left(R_p + R_e\right)q, \tag{14}$$

where R_p = Red time in the previous cycle after the end of green time in seconds;

R_e = Elapsed red time seconds.

In this case, the bus travel time from the current position to the end of queue is calculated as in Eq. (9) and number of vehicles arriving to join the queue is calculated as in Eq. (10). Thus, the total number of vehicles in queue in front of the bus is

$$N = (R_P + R_e)q + \left(\frac{D - \left[\left(R_p + R_e\right) \times q \times \overline{L}\right]}{V_f}\right)q \tag{15}$$

Here also when $D < (\left(R_p + R_e\right)q\overline{L})$, anterior queue length is updated as in Eq. (12).

Then, the time for bus to reach stop line can be obtained by substituting queue length value in.

$$T = \overline{R_c} + N\bar{t} + \varphi. \tag{16}$$

If queue length value obtained in any of the above-mentioned cases is closer to zero, the arrival time to stop line can be updated as $T_{f,}$ irrespective of the signal in which the bus is detected.

The overall methodology for arrival time prediction model is given in Fig. 3.

5 Implementation and Evaluation

Evaluation of the model was done by comparing the actual arrival time, with the predicted arrival time at different distances from the stop line. Madhya Kailash to Tidel Park approach was selected for implementation and evaluation. The phase plan of the selected signal is shown in Fig. 4. Since the priority phase is the 3rd phase in the phase plan, case c (waiting time > threshold value) does not exist. Trajectories are classified into case a, b, and d by comparing bus detected time with actual signal time.

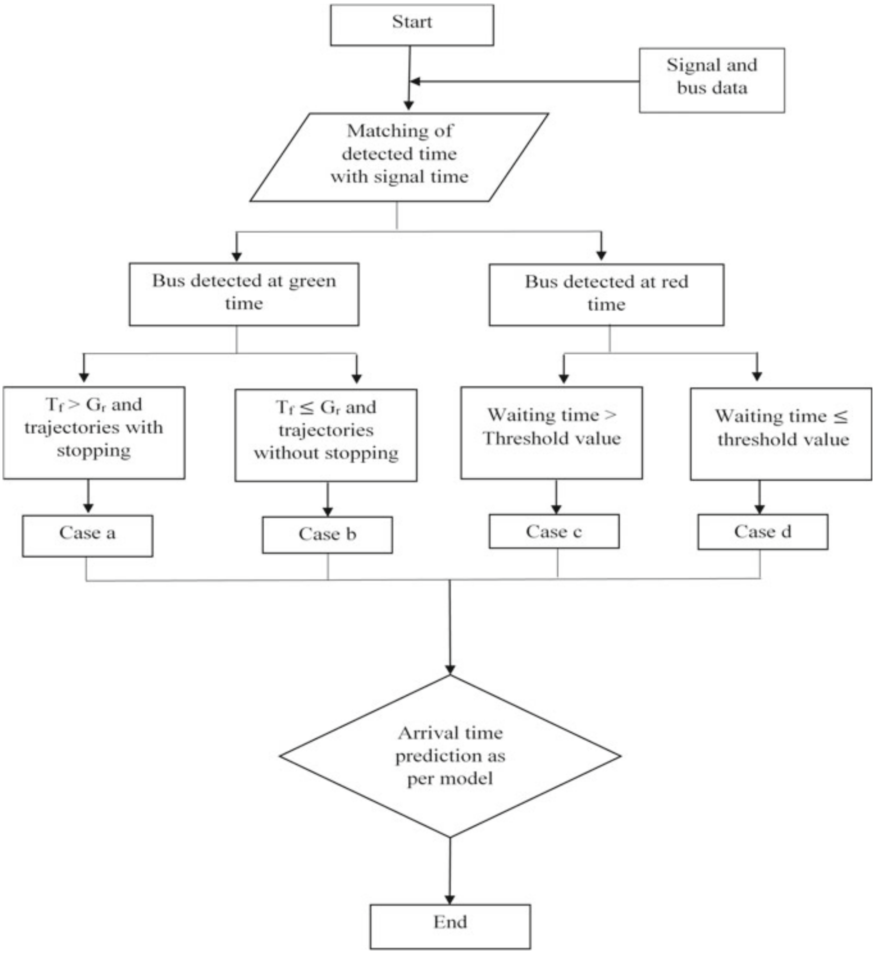

Fig. 3 Methodology for arrival time prediction model

Performance evaluation was done at 300, 250, 200, 150, and 100 m away from the stop line to see how prediction varies as the bus comes closer to the stop line. Thus, five detection points were there for each trajectory. From the detection time at mentioned distances and comparing it with signal time, bus trajectories were classified as per the model and 3.63% were found to fall in case a, 40% in case b and 56.36% in case *d*. As the bus is moving after the first detection, the signal status may change. Hence, the same trajectory may show different cases at different positions. Table 3 shows sample classification details of OBU 21 detected on 11/02/2022 at different distances from stop line. It can be seen that the status was *d* when the bus was first detected, which changed to b as it was traveling.

Performance of the developed analytical model was checked by observing the error between actual and predicted arrival times for each individual bus at 300 m,

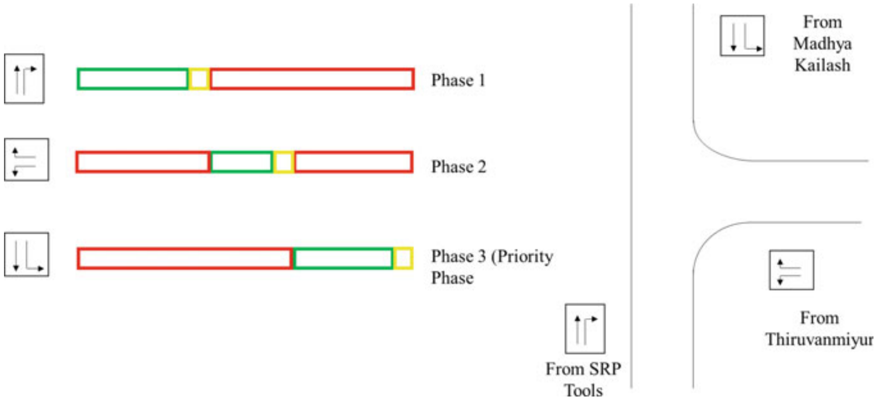

Fig. 4 Phase diagram for the study area

Table 3 Classification details of OBU 21 at different distances

Detected time	Distance from current position to stop line D (m)	Free-Flow speed V_f (m/s)	Free-flow travel time T_f (s)	Signal status at detected time	Residual green time G_r (s)	Category
10:52:22	300	15.06	19.92	Red	–	Case d
10:52:33	250	15.06	16.60	Green	66	Case b
10:52:40	200	15.06	13.28	Green	59	Case b
10:52:46	150	15.06	9.96	Green	53	Case b
10:52:55	100	15.06	6.64	Green	44	Case b

250 m, 200 m, 150 m, and 100 m away from stop line. Then the variation of this error with distance from the stop line (Fig. 5) was analyzed to understand the prediction accuracy.

Average errors were analyzed next by considering all *11* trajectories together at different distances from the stop line. Figure 6 shows average error values along with maximum and minimum error value observed for varying distances from the stop line. From Fig. 6, it can be observed that error value is decreasing as the distance from the stop line decreased.

Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were calculated to quantify the errors for all predictions from each category using Eqs. (17) and (18) respectively [18].

$$MAE = \frac{1}{n}\sum |x_o - x_p|, \tag{17}$$

$$MAPE = \frac{1}{n}\sum\left[\frac{|x_o - x_p|}{x_o}\right]100, \tag{18}$$

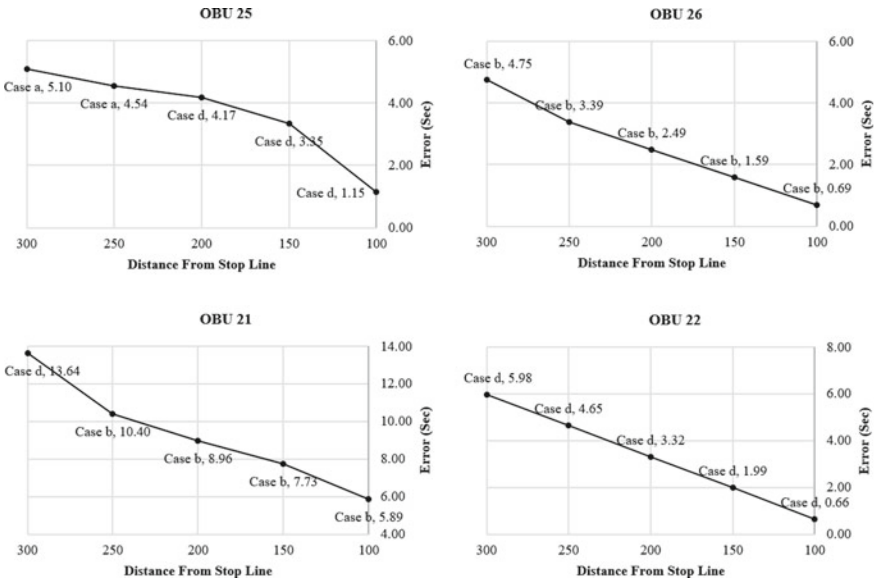

Fig. 5 Variation of the error for each bus coming on 11/02/22 with distance from the stop line

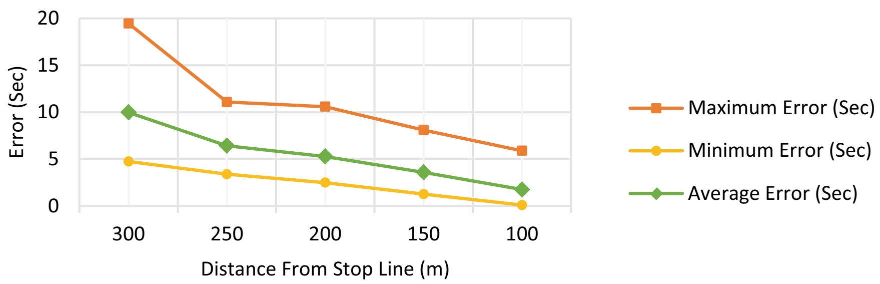

Fig. 6 Plot of maximum, minimum, and average error values at different distances from the stop line

where n is the number of observations; x_o is the observed value; and x_p is the predicted value.

Figure 7 shows the variation of MAE and MAPE values for all predictions from each category (case a, case b, and case d). It can be seen that the MAE is below 5 s for cases a and d. MAPE also shows acceptable range (Lewis et al., 1986) of values for all cases. A higher MAPE value can be observed for case b compared to other categories since its arrival time prediction was mainly based on the constant free-flow speed value, which is an assumption that needs verification.

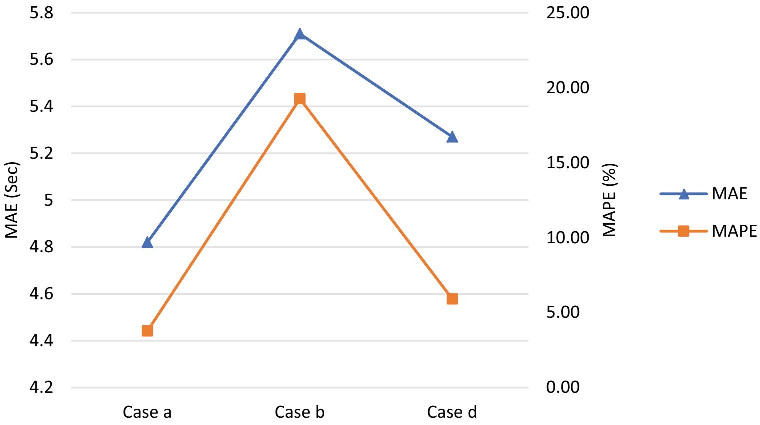

Fig. 7 MAE and MAPE for cases a, b and d

6 Summary and Conclusions

The goal of the present study was to accurately predict the time of arrival of buses, which are detected in the vicinity of an intersection, to the stop line, that can be used for the development of an efficient BSP solution. The bus data were collected using DSRC-based OBU and RSU devices. On the other hand, traffic data were collected from video recordings and signal timings by manual observation.

Preliminary analysis of the data showed different types of trajectories, which were grouped based on uniform and non-uniform movement and whether the bus stopped or not. Analytical models were developed for each group separately considering the signal timings and queue condition. Performance evaluations were conducted for each group at different distances from the stop line. It was found that the errors reduce as the bus comes closer to the stop line. MAPE values calculated for all scenarios of the model were within 20%, indicating good performance of the model (Lewis et al., 1986).

As future extension, the queue length calculation can be done by incorporating actual speeds, which will capture the deceleration and acceleration characteristics of the bus, instead of a constant free-flow speed value.

Acknowledgements The authors acknowledge the support of the Ministry of Information Technology, Government of India, for this study as part of the funded project through Project Number CE/19-20/331/MEIT/008253. The authors also acknowledge the "Connected Intelligent Urban Transportation Lab," funded by the Ministry of Human Resource Development, Government of India, through project number CEMHRD008432.

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