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Real Time Bus Arrival Time Prediction System under Indian Traffic Condition

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***Abstract*—The estimation of bus travel time and providing accurate information about bus arrival time to passengers are important to make public transport system more user-friendly and thus enhance its competitiveness among various transportation modes. However, for the system to be effective, the information provided to passengers should be highly reliable. The model and technique used for prediction plays a major role in enhancing the accuracy and reliability of the system. The present study proposes a model based approach for accurate prediction of bus travel times for the development of a real time passenger information system under heterogeneous traffic conditions that exist in India. The proposed model considers the predicted bus travel time as the sum of the median of historical bus travel times, random variations in travel time over time, and a model evolution error. In order to capture the random variations in travel time, a model based approach with Particle filtering technique is used, wherein inputs are obtained using k-NN algorithm. The results obtained from the implementation of the above method are compared with the measured travel time data and the prediction accuracy is quantified using the Mean Absolute Percentage Error (MAPE). The Performance of the proposed method showed a clear improvement in prediction accuracy when compared with an existing model based approach using Kalman filter that was reported to be work well under similar traffic conditions.**

Keywords–bus travel time; particle filter; k-NN.

I. Introduction

Providing real-time bus arrival information could make the public transit system more user-friendly and thus enhance its competitiveness among various transportation modes. With accurate real time arrival information, transit users may efficiently schedule their trips, reduce waiting times at the stops, and thus, the quality of transit service will be enhanced. The delays or deviation from the schedule may constitute a major source of inconvenience for travellers, particularly when no advance warning is given about expected delay and its magnitude. If the transit service is not efficient enough to meet passenger's expectation, travelers tend to shift their mode to personal vehicles despite the cost. Eventually, the increased usage of personal vehicles increases congestion, which reduces the efficiency of the system as a whole. Thus, making the public transit more attractive by providing accurate prediction of bus arrival time/travel time in real time is one way to mitigate congestion.

As travel time of buses can be affected by many factors such as fluctuating travel demand, incidents, signals, bus stops, dwelling times and seasonal variations, accurate prediction of bus arrival time is challenging. Many researchers have explored several approaches for the prediction of bus arrival times such historical methods [1]-[2], statistical methods [3]-[7], machine learning techniques [8]-[11], model based methods [12]-[15] etc. Majority of these reported studies are carried out under homogenous and lane based traffic condition. These methods, which are performing well under homogenous traffic condition, may not work in the same way for traffic condition in countries like India, which is heterogeneous and less lane disciplined. Only a few studies [16]-[19] have been reported for the prediction of arrival times under such conditions. However, most of those studies have not considered the high variance nature of travel time. Hence, there is a need to develop a prediction system, which can take into account the high variability explicitly and is addressed in this study.

II. Literature Review

Various techniques have been reported to predict bus arrival times such as historic and real time approaches, statistical techniques, machine-learning techniques and model-based techniques. Historic methods [1]-[2] predict the travel time of a particular time period (trip) by averaging over several previous time periods (trips). These methods show better performance under expected traffic conditions. However, under unexpected traffic conditions, the prediction accuracy is significantly reduced. In real-time methods, travel time can be predicted for the next time period by using the value in the present time period. This method is reliable, if real-time data are continuously available and traffic conditions are normal. Any disturbance in receiving data and/or any sharp change in traffic conditions affects the performance of the method.

Statistical techniques such as time-series methods and regression techniques are very popular to predict bus travel time. Time-series methods [3]-[4] are based on the assumption that the current and future travel time patterns depends only on the historically observed data. Its accuracy greatly depends on the correspondence between the real-time and historical travel time patterns [5]. Regression techniques [6]-[7] predicts the dependent variable by using equations formed by a set of independent variables that affect travel time. These independent variables may include road conditions, traffic conditions, signals, intersections, driver characteristics, and vehicle composition. The accuracy of prediction depends on identifying and applying the suitable independent variables. Machine learning techniques such as Artificial Neural Networks [8]-[9] and Support Vector Machines [10]-[11] are commonly used to predict travel time because of their ability to solve complex non-linear relationships. However, these techniques need a large amount of data to train the system.

Model-based techniques develop models that can capture the dynamics of the system by establishing mathematical relationships between appropriate variables and a suitable estimation/prediction tool is used to predict the traffic state parameters recursively. One of the major advantages of the model based approach is that it needs only a limited amount of historical data for model calibration, making them suitable for real-time applications. Most of the model based studies [12-15] used simple linear model which are not able to capture the high variability in travel times that exist in Indian traffic condition and used classical Kalman filtering as their recursive estimation tool. However, none of these studies paid special attention to the high variability issue leading to higher prediction errors in certain sections and certain trips. Also, Kalman filtering technique suffers from the serious limitation of linearity and Gaussian assumptions. It is based on the assumption that both process and sensor noise are Gaussian distributed and it can be applied for only linear problems. As traffic system is highly non-linear and complex in nature, can follow any distribution and in those cases Kalman filter may not be a good option always to implement.

A few studies [20]-[21] have explored the use of Particle filtering technique (PF), a non-linear recursive estimation tool, for traffic state prediction problems and proposed that the performance of PF is much better than other methods, especially in highly nonlinear conditions corrupted by non-Gaussian noise. Particle filter is a technique to implement recursive Bayesian estimation using Sequential Monte Carlo methods [22]. The basic idea of particle filter is that a posterior probability density function (PDF) of state can be represented by a set of particles (random samples) with associated weights, and the estimation can be computed as the expected value of the [23] discrete PDF. Studies have also demonstrated the advantages of PF over other filters for various applications [22], [24]. Hence, the present study proposes a model based approach, which captures the high variability condition better than existing methods and uses particle filter as recursive estimation tool, which has not been explored for bus arrival time prediction system, to predict bus arrival times under high variable traffic condition.

III. METHODOLOGY

In the present study, a bus travel time prediction method was developed based on model based approach using particle filtering as a recursive estimation tool. In the proposed approach, as a first step, the entire bus route section was divided into smaller subsections of uniform length and the time taken to travel each of these subsections is considered for prediction. The proposed model considers the predicted bus travel time as the sum of the median of historical bus travel times, random variations in travel time over time, and a model evolution error [25] as shown in Eq. (I). The model considered to predict travel time of the subsection in the next instant is given below

$$T_{(t+1)} = M_{(t+1)} + X_{(t+1)} + e \tag{1}$$

where $T_{(t+1)}$ is the time taken to travel the subsection in the next instant $(t+1)$, $M_{(t+1)}$ is the median of historical travel time of the subsection for the instant $(t+1)$, $X_{(t+1)}$ is the random variation at $(t+1)^{th}$ instant travel time from the corresponding historical median travel time and e is the model evolution error. In the proposed method, bus travel time is predicted by using a combination of historical data and real time data. Using the historic data, the median of observed route travel times was obtained, which captures the primary traffic patterns. Thus the model hypothesizes the median of historical travel times as a priori estimate and hence predicting the actual travel time will be equivalent to forecasting the variations in travel time according to the current measurement. On the other hand, the real-time data was used to capture the random variations in travel time by using a model based approach with particle filtering technique. The evolution of variation of travel time from the current time instant (t) to future time instant $(t+1)$ was modeled as

$$x_{(t+1)} = x_{(t)} + w_{(t)} \tag{2}$$

where $x_{(t+1)}$ is the variation of $(t+1)^{th}$ instant travel time from the corresponding historical mean travel time, x(t) is the variation of $(t)^{th}$ instant travel time from the corresponding historical mean travel time, $w_{(t)}$ is the associated process disturbance with the $(t)^{th}$ instant. The measurement process was assumed to be governed by

$$z_{(t)} = x_{(t)} + v_{(t)} \tag{3}$$

where $z_{(t+1)}$ is the variation of $(t)^{th}$ instant travel time from the corresponding historical mean travel time, v is the measurement noise. Thus, the approach needs two sets of data input. One set of data to be used in state equation and the other in measurement equation. These two sets of data will be selected using k-NN algorithm [26] to give best input to the prediction algorithm from the real time data. The variation of these best possible inputs from the historical mean travel time were used to predict the random variation of future trip travel time from the historical median travel time. The prediction of random variation of future travel time from the historical travel time was carried out using particle filtering approach as detailed below.

Particle filtering is a technique to implement recursive Bayesian estimation using Sequential Monte Carlo methodology. The basic idea is that a posterior probability density function (PDF) of state can be represented by a set of particles with associated weights, and the estimate can be computed as the expected value of the discrete PDF [22]. It is based on point mass (particle) representations of probability densities, which can be applied to any state space model including highly nonlinear models with non-Gaussian noise densities. Initially, random samples (particles of filter) are generated using Monte Carlo methodology and are propagated and updated according to the system dynamics and measurement models.

The equivalent probabilistic state space models and the requirement for updating the information on receipt of new set of measurements are ideally suited for the Bayesian approach. In this approach, the aim is to construct the posterior PDF p($\mathbf{x}_{(t+1)}$ | $\mathbf{Z}_{(t)}$) of the state vector $x_{(t+1)}$ with the help of available information. $\mathbf{Z}_{(t)}$ represents the set of all measurements received up to and including $\mathbf{z}_{(t)}$: $Z_{(t)}= \{\mathbf{z}_{(i)}, i= 1,2,3,\ldots,t\}$. The formal recursive Bayesian estimation involves prediction and update operation.

Prediction: The posterior PDF of the state vector is propagated from time step t forward to the time step $t+1$ by using Chapman- Kolmolgorov Eq. (IV)

$$\underbrace{p(\mathbf{x}_{(t+1)} \mid \mathbf{Z}_{(t)})}_{\text{(Prior at t+1)}} = \int \underbrace{p(\mathbf{x}_{(t+1)} \mid \mathbf{x}_{(t)})}_{\text{(Dynamics)}} \underbrace{p(\mathbf{x}_{(t)} \mid \mathbf{Z}_{(t)})}_{\text{(Posterior from k)}} dx_{(t)} \tag{4}$$

Update: The prior PDF is updated to incorporate new measurements to give posterior PDF at time step t by using Bayes rule.

$$\underbrace{p(\mathbf{x}_{(t+1)} \mid \mathbf{Z}_{(t+1)})}_{\text{(Posterior at t+1)}} = \underbrace{p(\mathbf{z}_{(t+1)} \mid \mathbf{x}_{(t+1)})}_{\text{(Likelihood)}} \underbrace{p(\mathbf{x}_{(t+1)} \mid \mathbf{Z}_{(t)})}_{\text{(Posterior from k)}} / \underbrace{p(\mathbf{z}_{(t+1)} \mid \mathbf{Z}_{(t)})}_{\text{(Normalising denominator)}}, \tag{5}$$

where,

$$p(\mathbf{z}_{(t+1)} \mid \mathbf{Z}_{(t)}) = \int p(\mathbf{z}_{(t+1)} \mid \mathbf{x}_{(t+1)}) p(\mathbf{x}_{(t+1)} \mid \mathbf{Z}_{(t)}) d\mathbf{x}_{(t+1)} \tag{6}$$

The above shown prediction and update steps are analytically intractable, so it has to be resorted to approximate methods like Monte Carlo method. The aim of Monte Carlo method is to approximate the PDF by the set of random samples rather than representing as functional form. As this PDF evinces all statistical information, which may be considered as a complete solution for the estimation problem. The steps of the basic particle filter are given below.

1. The algorithm is initialized by assuming the PDF of the initial state $p(\mathbf{x}_0)$ as normal, and N particles are randomly generated using Monte Carlo simulation as $\mathbf{x}_{0,i}$ where i=1, 2, 3, 4….N.
2. Particles are updated to the next time step from the current instant using the dynamic model (Eq. (I)).
3. The predicted particles are transformed into observations using Eq. (II).
4. Weights (relative likelihood) (w_i) are calculated for the particles, which were predicted and transformed in the previous two steps with respect to the corresponding measurement received as

$$w_i = p(\mathbf{Z}_{(t)} \mid \mathbf{x}^i_{(t)}) \tag{7}$$

With the particles being assumed as normally distributed, Eq. (VII) can be represented

$$p(\mathbf{Z}_{(t)} \mid \mathbf{x}^i_{(t)}) = \frac{1}{\sqrt{2\pi \mathrm{R}^n}} e^{-(\frac{(\mathbf{Z}^i_t - \mathbf{Z}_t)^2}{2\mathrm{R}^n})} \tag{8}$$

where R^n is the measurement noise covariance, $\mathbf{Z}_t^i$ is the transformed observation, and $\mathbf{Z}_t$ is the corresponding measurement received.

5. The assigned weights are then normalized in such a way that the summation of weights is unity. That is

$$w_i = \frac{w_i}{\sum_{j=0}^{N} w_j} \tag{9}$$

6. Particles are re-sampled, that is, N new samples are obtained by sampling from the N old samples, thereby eliminating the ones with negligible weight in the old samples. The mean of the re-sampled particles is taken as the best state estimate.

The above scheme was implemented in MATLAB and the parameters of PF for implementation were selected based on trial.

IV. Data Collection and Study Stretch

Probe vehicles fitted with Global Positioning System (GPS) units are commonly used to collect data for advanced public transportation system applications, where the vehicles are being tracked continuously. In the present study, similar data were collected by using permanently fixed GPS units in Metropolitan Transport Corporation (MTC) buses in the city of Chennai, India. For the purpose of collecting data for the present study, MTC bus route 19B (shown in Fig. 1) was considered. The bus route has a route length of around 30 kms, connecting Saidapet, a major commercial area located in southern part of the city, to Kelambakkam, a sub-urban area of the city. There are 20 bus stops and 13 intersections in this route. The selected road stretch represents typical heterogeneous, lane-less Indian traffic conditions and include varying geometric characteristics, volume levels and land use characteristics such as residential, commercial and institutional areas. Also, the selected route covers both urban and rural areas throughout its stretch. In this study, the GPS data were collected every 5 seconds from 6 AM to 8 PM for 30 days. Among the 30 days' data, 23 days data were used for creating historical database. The collected GPS data included the ID of the GPS unit, time stamp, and latitude and longitude of the location at which the entry was made. Real time communication of this data was made possible through General Packet Radio Service (GPRS). The data received from each device were stored in a server using SQL database.

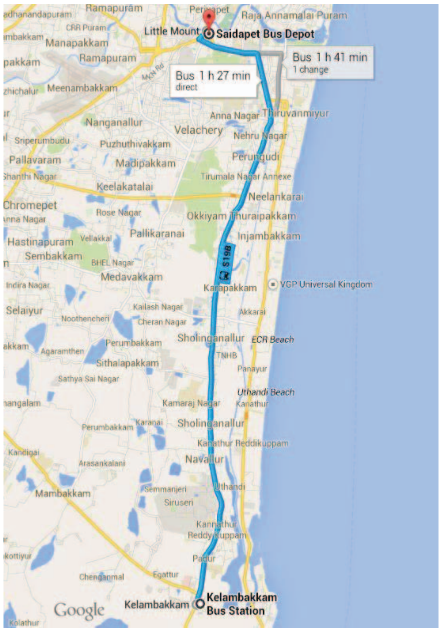

Figure 1. 19B route

V. Data Analysis

The raw data received from GPS units consist of the location details of the bus in terms of latitude and longitude at every 5 seconds. During the processing, the first step was to calculate the distance between any two consecutive entries. This was done using the Haversine formulae [27], which give the great circle distances between two points on a sphere from their latitudes and longitudes. After this process, the data consisted of the travel times and the corresponding distance between consecutive locations for all the buses. In the next stage, the entire section was divided into smaller sections each of 100 m length and the time taken to cover each subsection was calculated by using the linear interpolation technique.

VI. Results

The scheme presented in this study was used to predict travel time for each 100 m subsection. From the field, it was observed that there will be distance at least 500 m between bus stops. Hence, the final comparison was made between predicted and measured travel times for every 500 m subsections. The predicted travel time to cover a 500 m subsection was found out by adding the predicted travel time of the corresponding five 100 m travel time values obtained from the prediction algorithm. The performance of the proposed method was quantified using Mean Absolute Percentage Error (MAPE) and compared with the existing well known model based method [24].

Fig. 2 shows a sample comparison of the predicted travel times of the proposed method and existing method with the measured travel times over 500 m subsections for a sample trip in the 19B route. From Fig. 2, it can be observed that the proposed method was able to capture the variations better than the existing method. Corresponding MAPE was calculated and was found to be around 17% for the proposed method whereas the existing method had 22%, which clearly shows that performance of proposed method is better than the existing method.

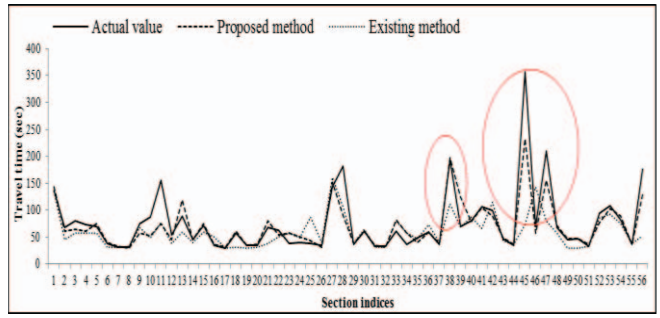

Figure 2. Sample comparison plot of actual and predicted values

The analysis was further carried out for all the trips in 19B route for a test period of one week. Fig. 3 shows the comparison of average performance among the proposed and existing methods across days in terms of MAPE. From Fig. 3, it can be observed that the proposed method is performing better than existing method with an advantage up to 6.5%.

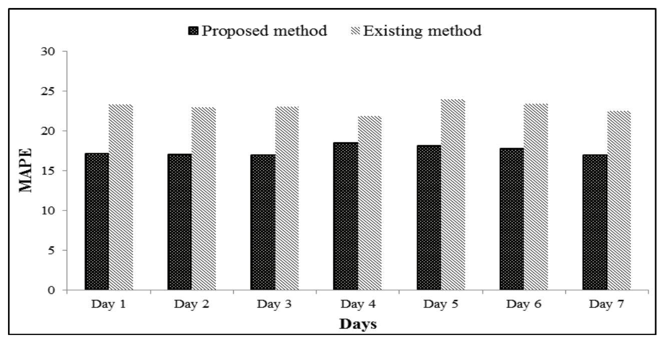

Figure 3. Comparison plot of MAPE values for proposed and existing method

VII. Conclusion

The main aim of bus arrival time prediction system is to encourage commuter's public transport, and thus help to reduce the congestion on urban roads. However, for this to happen in practice, the bus service should be made more attractive by providing reliable information about bus arrival times to passengers. The reliability of such information mainly depends on the model and prediction technique that is used. Most models formulated in the literature were not able to capture the high variability condition of heterogeneous lane less traffic condition. The present study proposed a model based prediction method that used particle filtering technique, whose inputs are obtained by k-NN algorithm, to predict bus travel times under heterogeneous traffic conditions that exist in India. The results obtained were compared with the existing spatially discretized model based approach and actual travel time obtained from the GPS fitted buses. The estimation accuracy is found to be better than the existing method with MAPE values around

17% with the accuracy of +/- 2 minutes. Also the proposed method was able to capture the high variability condition of Indian traffic. Hence, it can be concluded that proposed method can be viable one to implement for prediction of arrival times under highly variable heterogeneous traffic condition.

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