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Urban Bus Arrival Time Prediction: A Review of Computational Models

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Abstract: ***Traffic flow in major urban roads is affected by several factors. It is often interrupted by stochastic conditions, such as traffic lights, road conditions, number of vehicles on the road, time of travel, weather conditions, driving style of vehicles. The provision of timely and accurate travel time information of transit vehicles is valuable for both operators and passengers, especially when dispatching is based on estimation of potential passengers waiting along the route rather than the predefined time schedule. Operators manage their dispatches in real time, and passengers can form travel preferences dynamically. Arrival time estimation for time scheduled public transport busses have been studied by many researchers using various paradigms. However, dynamic prediction on some type of transit vehicles, which do not follow any dispatch time schedule, or stop station constrains introduces extra complexities.***

In this paper, a survey on the recent studies using historical data, statistical methods, Kalman Filters and Artificial Neural Networks (ANN) have been applied to GPS data collected from transit vehicles, are collected with an emphasis on their model and architecture.

Index Terms: ***Bus Travel Time Prediction, Intelligent Transportation Systems (ITS), Advanced Traveller Transportation Systems (AITS), Kalman Filtering, Machine Learning, Artificial Neural Networks (ANN).***

I. INTRODUCTION

A robust prediction of bus arrival times has been gaining more importance in designing an effective trip planning in the ever increasing traffic conditions with and increasing computing and communication means. Availability of Vehicle Location Information (VLI), as a part of Advanced Travel Information (ATIS) helps increasing accuracy of the arrival time prediction. There might be various factors effecting bus arrival times.

Such a list can easily be augmented by many factors such as traffic conditions, weather conditions, passenger count, signaling, traffic accidents and driving times.

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II. A TAXONOMY OF THE BUS TRAVEL TIME PREDICTION MODELS

A. Models based on the Historical Data

This type of prediction model gives the current and future bus travel time from the historical travel time of previous journeys on the same time period. The current traffic condition is assumed to remain stationary. Williams and Hoel pointed out that the phenomenon that traffic conditions follow nominally consistent daily and weekly patterns leads to an expectation that historical averages of the conditions at a particular time and day of the week will provide a reasonable forecast of future conditions at the same time of day and day of the week [42]. Therefore, these models are reliable only when the traffic pattern in the area of interest is relatively stable, e.g. rural areas.

1) Using Average Travel Time

These models use the historical average travel time directly or in combination with other inputs in some way to give bus arrival time. In most researches they were developed for comparison purpose [13] [26] [28] [38]. And in almost all those researches they were outperformed by the respective proposed main algorithms. However, they were also shown to outperform some of the models, e.g. multilinear regression models [13] [26]. Chung and Shalab developed an expected time of arrival (ETA) statistical model using explanatory variables [7]. The proposed model predicted arrival time from the input of two categories: the last several days' historical data and the current day's operational conditions. An operational strategy was additionally incorporated into the model to reduce the risk that an overestimated arrival time can result in missing the bus. In developing the model, the most notable constraint was the size of historical data to calibrate the model. Unlike transit vehicles, school buses have one run per route per day and their schedules are revised every school year. That necessitated that the ETA model should be based on a method applicable to the relatively small size of historical data. Because the buses were conventionally operated along fixed routes and stops and according to published schedules, their ETA model assumed that the travel time between two stops can be explained by the historical trends of bus travel times and other independent correlated variables. For the operational conditions, the study incorporated schedule adherence and weather condition but did not consider for dwell time due to stable demand.

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The authors evaluated the performance of the model using data collected from real-world operations of school buses on which a global positioning system-based automatic vehicle location (AVL) system was installed. It was mentioned that the proposed model consistently showed lower levels of prediction error than moving average and regression approaches. With the operational strategy, the model provided a sufficiently reliable service in which approximately 99 travel times can also be combined with real-time travel time information to develop a dynamic travel time prediction algorithm [4].

2) Using Average Speed

These type of models use the average speed of vehicles over certain links to predict travel times. They are specially applicable to predict travel time using data collected by GPS technology as the distance taken over links can be calculated using the position information.

Commonly, these models make use of map matching techniques, which can be established on a Geographic Information System (GIS) Software to estimate the vehicle position and travel times. Weigang et al developed a model to estimate bus arrival times at bus stops using GPS information [41]. The model consisted of a main algorithm calculating the estimated arrival time and two sub algorithms to determine the position and the speed of the bus on the road.

First, the bus route is divided into a number of short, straight lines, sub routes then these lines were modeled as first-degree equation in a plane. When the GPS equipment in the bus transmits its position, speed and other related information to the control center, it is unlikely that this position would coincide with any point on the straight line graphs. Thus, the actual position was mapped to a point on the graph to get the position of the bus.

Second, when using the speed information from the GPS, the arrival time at the stop point will be infinite if the vehicle is stationary. In order to solve this problem, they made use of historical bus travel speed along the route segment and current speed of the bus derived from the GPS data. With the improved method and empirical calibration, the results from the developed model were found to be satisfactory in the implementation and experiment. They found the mean error between output results from system and the actual position of bus is less than 8 reduced by increasing the number of lines representing the bus route. The same kind of model has later been developed by Sun et al with slight modification [31]. The proposed prediction algorithm combined real-time location data from global positioning system receivers with average speeds of individual route segments, taking into account historical travel speed as well as temporal and spatial variations of traffic conditions. Recalling the estimated average speed to a station, proposed by Weigang et al [41], would depend primarily on its historical average speed along the route as the bus is far away from the station, Sun et al argued that the current speed of a bus is usually a more important factor influencing how fast the bus will travel over the distance to the station of interest [31]. Their algorithm basically included of two components. The first component consisted of real-time bus tracking model with the purpose of processing the GPS data, projecting them onto the electronic map and then obtaining the distance to each bus station. The second component was a bus arrival time prediction model used to estimate the time to downstream bus station in real time on the basis of the output of the first component and various other factors.

The system was implemented as a finite state machine to ensure its regularity, stability, and robustness under a wide range of operating conditions. A case study on a real bus route was conducted to evaluate the performance of the proposed system in terms of prediction accuracy. The results indicated that the proposed system was capable of achieving satisfactory accuracy in predicting bus arrival times and perfect performance in predicting travel direction. However, it was observed that their model less performed during peak hour than of peak hours. This is due to the variation in traffic condition and thus speed increases as the level of congestion increases. The performance of the algorithm was also compared with the algorithm proposed by Weigang et al in terms of prediction accuracy and showed an improvement [41]. Generally, historical data based models require an extensive set of historical data, which may not be available in practice, especially when the traffic pattern varies significantly. These models are not suitable for large cities where both travel time and dwell time experience large variations. Their accuracy largely rely on the similarity between the real time and historic traffic patterns.

B. Statistical Models

Bus arrival time is impressed by several factors including driver behavior, carriage way width, intersections, signals and etc. Those factors are used as independent variables in many studies. The precision in these methods depends to all the dependent variables that they are recognized and incorporated in the model, which is a tough procedure [16].

The most literatures about time series model and regression model have been published before 1990s. However, recently, new studies worked on combination of these models with others that we discuss them in hybrid models.

1) Time Series Models

Time series models depend on the data which is from historical time periods and forecast the future time periods. In this model, it is assumed that a pattern or mixture of patterns

happens occasionally over time and these patterns can be provided by mathematical functions and for this purpose historical data can be used. Time series models assume that the historical traffic patterns will remain the same in the future. In the time series models, its precision highly depends on a function of the correspondence between the real-time and historical traffic patterns [5]. Variation in historical data or changes in the relationship between historical data and real-time data could significantly cause inaccuracy in the prediction results [29], and the problem in these methods usually back to its short time delay if the prediction model is in the real time [30] [10] .

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D' Angelo used a non-linear time series model to predict a corridor travel time on a highway [9]. He compared two cases: the first model used only speed data as a variable, while the second model used speed, occupancy, and volume data to predict travel time. It was found out that the single variable model using speed was better than the multivariable prediction model.

2) Regression Models

Regression models predict and explain a dependent variable with a mathematical function formed by a set of independent variables [5]. Unlike historical data based prediction models, these are able to work satisfactorily under unstable traffic condition.

Regression models usually measure the simultaneous effects of various factors, which are independent between one and another, affecting the dependent variable. Patnaik et al proposed a set of multilinear regression models to estimate bus arrival times using the data collected by automatic passenger counter (APC) [25]. They used distance, number of stops, dwell times, boarding and alighting passengers and weather descriptors as independent variables. They indicated that the models could be used to estimate bus arrival time at downstream stops. However, this approach is reliable when such equations can be established. Jeong [13] and Ramakrishna et al [26] also developed multilinear regression models using different sets of inputs. Both studies indicated that regression models are outperformed by other models. One great advantage of multilinear regression model is that it reveals which inputs are less or more important for prediction.

For example, Patnaik et al discovered that weather was not an important input for their model [25]. Also Ramakrishna et al found out that bus stop dwell times from the origin of the route to the current bus stop in minutes and intersection delays from the origin of the route to the current bus stop in minutes are less important inputs [26].

In general, the applicability of the regression models is limited because variables in transportation systems are highly inter-correlated [5].

C. Kalman Filtering Model

Kalman Filters have been used extensively for predicting bus arrival time [3] [38] [39] [5] [44] and many more. The basic function of the model is to provide estimates of the current state of the system. But it also serves as the basis for predicting future values or for improving estimates of variables at earlier times, i.e., it has the capacity to filter noise [16] [20] [33]. Yang [44], Wall and Dailey [39] presented a short term transit vehicle arrival times prediction algorithm by combining real-time AVL data with an historical data source in Seattle, Washington. Their algorithm consists of two components: tracking and prediction. They used a Kalman filter model to track a vehicle location and statistical estimation for prediction of bus arrival time purpose.

As has been tried to mention above, the model relied on the real-time location data and historical statistics of the remaining time to arrival. That is, it assumed that other variables possibly influencing the arrival time as mentioned on [35] were implicitly included in the statistics. Therefore, they did not explicitly deal with dwell time as an independent variable. It was mentioned in the literature that some empirical results had shown that the proposed algorithm was flexible enough to function in adverse conditions and was able to produce predictions that could be useful to the rider. It was found that they could predict bus arrival time with an error less than 12 percent.

The algorithm was implemented as a web application finally to provide the predicted arrival times to users. Shalaby and Farhan developed a bus travel time prediction model using the Kalman filtering technique [28]. They used downtown Toronto data collected with four buses equipped with AVL and automatic passenger counter (APC). They used five-weekday data in May 2001. Four days of data were used for learning and developing models, and one-day data were used for testing. They developed two Kalman filtering algorithms to predict running times and dwell times separately. However, when they developed a historical average model, a regression model, and a time lag recurrent neural network model, they included dwell times in link travel time. They defined a link as the distance between two time check point stops and each link included between 2 and 8 bus stops. Consequently, they predicted dwell time only at time check points, not at every stop. To develop a dynamic, real-time model, they updated the predicted time of bus arrival and departure at time check points. Of the 27 stops on the route, their model was updated at only the six time check points. They claimed that Kalman filtering techniques outperformed the historical models, regression models, and time lag recurrent neural network models in terms of accuracy, demonstrating the dynamic ability to update itself based on new data that reflected the changing characteristics of the transit-operating environment. Chien and Kuchipudi developed a travel time prediction model for vehicles with real-time data and historic data [4]. Here also Kalman filtering algorithm was employed for travel time prediction because of its ability to continuously update the state variable with changing observation. Their study, however, concentrated on a comparison of the path-based and link-based travel time values. Results revealed that during peak hours, the historic path based data used for travel time prediction were better than link based data due to smaller travel time variance and larger sample size. The advantage of using historic data over the link-based model is procurable, allowing prediction at any given time, but at the expense of prediction accuracy under congestion situations. Yang focused on the traffic characteristics after special events (e.g. conventions, concerts, football match) and predicted the travel time after graduation ceremony using recursive discrete time Kalman filtering as a case study [44]. GPS equipped test vehicles were used for data collection and the predicted travel times at a given instant of time was determined from observed and predicted travel times at the previous time instant. The performance of the model was quantified using mean absolute relative error. The prediction error was found to be around 17.6 with given the fact of many uncertainties (e.g. weather, traffic condition, signal timing) associated with such event.

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Vanajakshi et al developed an algorithm based on Kalman filtering algorithm under heterogeneous traffic conditions on urban roadways in the city of Chennai, India [38]. Their motivation was that they believed most studies used data collected from homogeneous lane-disciplined traffic, either directly from the field or indirectly through simulation models. The unique feature of their algorithm is that the discretization had been performed over space rather than over time unlike the aforementioned Kalman filtering models. It was mentioned that this feature could be used in reflecting the effects of events such as accidents that had taken place in the previous subsection of the route on the travel time predicted for the given subsection. The results obtained from the overall study were promising. Their algorithm outperformed the average approach over 7 days out of 10 days. In general, Kalman filtering algorithms give promising results on providing a dynamic travel time estimation which other most models lack.

D. Machine Learning Models

Machine learning (ML), is a branch of artificial intelligence, is about the construction and study of systems that can learn from data. ML methods contain of two stages, i.e., choosing a candidate model, and next, prediction the parameters of the model through learning process on existing data [15]. ML methods have certain benefits with respect to statistical methods: dealing with complex relationships between predictors that can come up within a huge volume of information; processing non-linear relationships between predictors; processing complicated and noisy data [27]. These models can be used for prediction of travel time, without implicitly addressing the traffic processes. Results obtained for one location are normally not transferable to the next, because of location specific circumstances, e.g., geometry or traffic control. Artificial Neural Network (ANN) and Support Vector Machine (SVM) models are presented under these categories.

1) Artificial Neural Network Models

ANNs have been recently gaining popularity in predicting bus arrival time because of their ability to solve complex non-linear relationships [3] [26] [13] [5] [23]. ANNs, motivated by emulating the intelligent data processing ability of human brains, are constructed with multiple layers of processing units, named artificial neurons. The neurons contain activation functions (linear or nonlinear) and are highly interconnected with one another by synaptic weights.

Information can be processed in a forward or feedback direction through fully or partially connected topologies. Meanwhile, the synaptic weights can be adjusted to map the input-output relationship for the analyzed system automatically through a learning process [12]. Unlike the aforementioned models, ANNs can be developed without specifying the form of the function, while the restrictions on the multi collinearity of the explanatory variables can be neglected. Chien et al developed an enhanced Artificial Neural Network model to predict dynamic bus arrival time [5]. The so called Back-Propagation algorithm was used. Their motivation was that due to long learning process of ANN, it is usually hard to apply ANNs on-line. Consequently, an adjustment factor to modify travel time prediction with new input of real-time data was developed. They generated traffic volume and passenger demand that AVL cannot collect, using Corridor Simulation model (CORSIM) to use them as inputs. For an actual implementation they assumed they could obtain similar data from APC and AVL systems. Therefore, APC needs to be deployed in addition to AVL systems if their model is to be implemented practically. In the study, dwell time and scheduled data were not considered. They checked the performance of their model using simulation result. They claimed their model can accurately perform well for both single and multiple stops. On another study, Chen et al developed a methodology for predicting bus arrival time using data collected by APC [3]. Their model consisted of an ANN model to predict bus travel time between time points and a Kalman filter based dynamic algorithm to adjust the predicted arrival time using bus location information. The ANN was trained with four input variables, day-of-week, time-of-day, weather and segment; and produced a baseline estimate of the travel time. The dynamic algorithm then combined the most recent information on bus location with the baseline estimate to predict arrival times at downstream time points. The algorithm not only explicitly considered variables influencing the travel time but also updated it using the real-time APC data. The authors indicated that their model was powerful in modeling variations in bus-arrival times along the service route. It was observed that the dynamic algorithm performed better than the corresponding ANN model because it incorporated the latest bus-arrival information into the prediction. The ANN model also performed better than the timetable. Jeong and Rilett also proposed an ANN model for predicting bus arrival times and demonstrated its superior performance as compared with the historical data based and multilinear regression models [14]. Historical data based model gave superior results, as compared to the multiple linear regression. The authors have tested 12 training and 14 learning functions and the best functions were chosen for the prediction purpose.

The advantage of their models was that traffic congestion, schedule adherence and dwell times at stops were considered as inputs for the prediction. Ramakrishna et al developed a Multiple Linear Regression (MLR) model and an ANN model for prediction of bus travel times using GPS-based data [26]. These models were applied to a case study bus route in Chennai city, India. It was indicated that ANN model performed better than Multiple Linear Regression model. In general, ANN models have the ability to capture the complex non-linear relationship between travel time and the independent variables. These models have been proved to be effective for the provision of satisfactory bus arrival time information. They could be very useful in prediction when it is difficult or even impossible to mathematically formulate the relationship between the input and output. Though the learning and testing process is inherently delicate and is slow to converge to the optimal solution [12], it is still possible to do an off-line training and adapting ANNs to real-time condition if the inputs are chosen carefully.

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2) Support Vector Machine Models

Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. While other machine learning techniques, such as ANN, have been extensively studied, the reported applications of SVM in the field of transportation engineering are very few. SVM and support vector regression (SVR) have demonstrated their success in time-series analysis and statistical learning [8]. Since SVM have greater generalization ability and guarantee global minima for given training data, it is believed that support vector regression will perform well for time series analysis. Bin et al 2006 proposed SVM as a new neural network algorithm to predict the bus arrival time [1]. They pointed out that unlike the traditional ANN, SVM is not amenable to the overfitting problem, and it could be trained through a linear optimization process. This study predicted the arrival time based on the travel time of a current segment and the latest travel time of the next segment. The authors built separate models according to the time-of-day and weather conditions. The developed model was tested using off-line data of a transit route and exhibited advantages over an ANN based model methods. These models have been developed for prediction of travel time on highways, e.g. [8]. They compared their proposed SVR predictor to other baseline predictors, the results showed that the SVR predictor can reduce significantly both relative mean errors and root mean squared errors of predicted travel times. However, Bin et al indicated that when SVM is applied for solving large size problems, a large amount of computation time will be involved [1]. In addition, the methods for selecting input variables and identifying the parameters should be further researched.

3) Hybrid Models

Several researchers suggested hybrid frameworks that integrated two or more models for travel time prediction. Liu et al proposed a hybrid model based on State Space Neural Networks (SSNN) and the Extended Kalman filter (EKF) as trainer [49].The issue in SSNN is that the model requires large data set for offline training. Van Lint et al mixed linear regression model and locally weighted linear regression model in a Bayesian framework to enhance forecast precision and reliability [36]. Jeong and R.Rilett proposed a travel time prediction model with consideration schedule adherence and dwell times [14]. Also they compared a historical data based model, Regression Models, and ANN Models. As result, they found that ANN Models outperformed the historical data based model and the regression models in the case of estimation precision. Ramakrishna et al developed a multiple linear regression model and an ANN model on heterogeneous Indian traffic circumstances with limited dataset for bus travel time prediction [26]. Park and Lee claims Bayesian model and neural network model can be good combination to estimate for urban arterial link travel times [23]. Chen and Chien compared link-based and path-based travel time prediction models using Kalman filtering algorithm with simulated data [2]. Chu et al considered the model system noises and developed an adaptive Kalman filtering-based travel time prediction method that fuses both point detector data and probe vehicle data [6]. Kuchipudi and Chien proposed a hybrid model with combination of path-based and link-based models on real data and under different traffic conditions [18]. Yang reported a short term transit vehicle arrival times prediction algorithm by combination of real-time AVL with historical data source in Seattle, Washington [44]. They used a Kalman filter model to track a vehicle location and statistical estimation for prediction of bus arrival time purpose.

III. CONCLUSIONS

Due to complex nature of the data, generally a single method or algorithm has not achieved any robust, and feasible results. However there is an increasing trend to utilize hybrid algorithms to improve the prediction accuracy.

From this review, it could be concluded that, no single method could produce robust predictions due to the nature of the environment, and actors. While machine learning algorithms produce better results, and robustness, because of the methods applied here, they generalize in a large data set, which reduce accuracy in case of short periods from the actual prediction time. For the future we propose a model, which classifies conditions as innumerable states. For example a combination of traffic accident, with rainy weather would produce better prediction when we limit our data set, to similar conditions. In case of insufficient information about the conditions, some positive data could be used most representative neural network dataset. In such bounded fragments, regression or time series further application of Kalman filters, would isolate, any other dynamic factors, while improving accuracy.

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