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A SURVEY ON APPLICATION OF ARTIFICIAL INTELLIGENCE FOR BUS ARRIVAL TIME PREDICTION

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ABSTRACT

With the intention of satisfying mobility requirements for trustworthy, healthy and secure transport, there are more considerations on the establishment of intelligent transport systems (ITS) currently. Advanced traveller information systems (ATIS), as a part of ITS, is to provide travel time information as precisely as possible. Basically, there are reasons leading to delay in bus arrival time, e.g. traffic jam, ridership distribution, and climate situation. Consequently, these issues impress on growing travellers waiting time, postponement in timetable, rise in transit's expense and private vehicles' uses, dissatisfaction of passengers and reduction of passengers, providing of precise transit travel time information are significant since it will result in further transit passages and upsurge the acquiescence of passengers. In this paper, we first explore the importance of arrival time for passengers and present a new taxonomy of bus arrival prediction models, and then review some recent works. Finally, summary of the main technologies illustrate big picture of the studies.

Keywords: *Bus Travel Time Prediction, Intelligent Transportation Systems (ITS), Advanced Traveller Transportation Systems (AITS), Kalman filtering, machine learning, statistical methods, ANN*

1. INTRODUCTION

In the 21st century, as we are faced with the extreme expansion of modern society and urbanization, transport has been one of the pillars of civilization [1,2]. Transport or transportation is the movement of people, animals and goods from one location to another. Transport is important since it enables trade between peoples, which in turn establishes civilizations. IBM research [3] in over 50 developed and developing world cities reveals that most people strive for cleaner, less congested cities and improved traffic flow, primarily through increased use of enhanced public mass transit systems.

Generally, passenger transport may be public or private. In fact, in developed countries still most of the people use private vehicles. Also, in developing countries the level of vehicle ownership is rising at a faster rate [3,4]. However, to come up such problems is that we need to make people interest to use public transport by offering enhanced services.

So far, different solutions for encouragement of people to use public transportation systems (i.e., buses) have been forwarded. One of them is providing travelers with reliable travel information by means of Advanced Public Transport System (APTS) and Advanced Traveler Information System (ATIS), which are the primary key components in Intelligent Transportation Systems (ITS) [5,6]. APTS/ATIS applications has the ability of making people more interested to change from private vehicles to public transport by providing convenient service [7]. One such ATIS application includes pre-trip and real-time passenger information systems, arrival time notification systems. While bus services play an essential role in the provision of public transport, a diminution in travel-time erraticism consequences to cuts passengers' anxiety and stress caused by uncertainty in decision making about departure time and route choice [8].

As has been explained on [9], a precise travel time prediction is valuable for both travelers and logistic operators, while its aid outcomes in evading congested route to lessen transport outlays and upsurge facility excellence. For traffic managers, travel time information is a significant index of traffic system operation. Especially, travel-time data is critical for pre-trip and en route information which is highly informative to drivers and travelers

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to have smart choice or design better schedules [10]. According to Mazloumi [11,8], buses are contingent on environments' situation; to provide precise forecasts of bus travel times, there is a wide range of determinants that must be considered, such as passenger demand, weather conditions, road condition, and most significantly, traffic flow at signalized intersections. These issues influence on public transportation system efficiency consequential in, growing passengers waiting time, worsening of schedule adherence, irregular intermodal transfers, raising operation's cost, traffic delays, etc. [12]. Figure 1 demonstrates the major demand and capacity which impact directly on public transport efficiency.

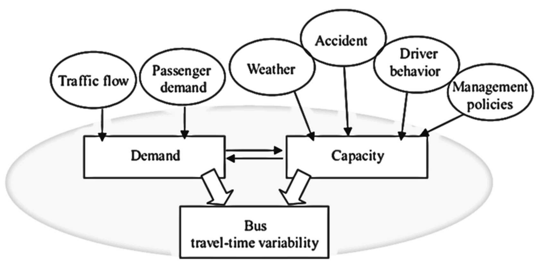

Figure 1. Demand And Capacity Related Determinants Of Bus Travel-Time Variability [11]

After a brief introduction on the importance of the bus arrival time for advance public transportation systems, this paper intend to represent the diversity of the approaches taken to resolve the difficulties related to bus schedule. The rest of the paper is structured as follows: Section 2, an overview of bus arrival time prediction models is addressed. Section 3, a table consist of overview showed as conclusion.

2. TAXONOMY OF BUS TRAVEL TIME PREDICTION MODELS

In previous researches, a variety of studies have been focused to address the bus arrival time prediction drawback. A number of approaches had been proposed for travel time prediction over the years; these existing methodologies have been categorized into five mostly wide types used of prediction models: (a) historical data based models, (b) statistical models, (c) Kalman filtering model, (d) machine learning models, and (e) hybrid models. Obviously, there are a variety of classifications for bus arrival time prediction models which were introduced in other studies. For instance, Lee [9] grouped them into four categories: regression method, time series estimation method, hybrid of data fusion or combinative model and artificial intelligence method like neural network; Sun [13] stated them into three types of prediction models: models based on historical data, multi-linear regression models, and artificial neural network models; Jin in [14] refers these methods mainly included nonparametric statistical methods, time series model, neural-network models and others; the most similar to our aforementioned categories can be found in [7] that Zhu explained the methods such as historic and real-time approaches, machine learning techniques (Artificial Neural Network (ANN), support vector machines), model based approaches (Kalman filtering) and statistical methods (regression analysis, time-series) for the Prediction of bus arrival time. However, we will pursue our five categories in the discussion presented on the next subsections.

2.1. Historical Data Based Models

Commonly, a bus arrival time prediction algorithm is based on static and dynamic information. Static information, donates to Historical Data here, provides from bus schedule information, recurrent traffic circumstances and average dwell time. While, dynamic information, donates to real-time models here, includes: real-time bus location data, delay at bus stops, and current traffic circumstances [15]. In this type of prediction models, it gives the current and future bus travel time from the historical travel time of the same bus of the previous journeys on the same time period. Historical approach predicts the travel time at a particular time as the average travel time for the same period over different days. The results of these models are satisfiable under expected circumstances, but the precision of these models in unexpected congestion and delay situations, is seriously decreased [16]. The real-time approach predicts the next time interval travel time to be the same as the present travel time [7].

In these models, we are faced with a cyclical traffic patterns and the ratio of the historical travel time on a specific route to the current travel time stated in real-time will repeat again. The procedure needs an extensive set of historical information and it is not easy to establish the system in a new setting [17]. In real-time models, the almost recently observed journey travel times will remain the same in the future. There is a requirement to provide a precise auto bus arrival time estimation system by real-time data based on diverse traffic circumstances. Padmanaban et al [16] proposed a method that uses real-time data from diverse traffic circumstances and plus consideration of delays for estimation. It fundamentally was found the future

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travel time to be the equal as the current one. This proposed method is not incompetent when data is unavailability of (i.e. loss in reception, equipment failure, etc.) [16]. Chen et al developed a prediction algorithm that combined these two approaches. Primarily, from a historical database, an estimated travel time was obtained. It was adjusted as real-time location data are obtained [18].

Lin and Zeng in [19], used GPS-based bus location data, and other information as input data, including bus schedule information, bus delay patterns, and bus stop type information (a time-check stop vs. a regular stop) However, they did not consider the effect of traffic congestion and dwell time at bus stations. Also they found that treating time-check stops and regular stops differently would make a big difference in the performance of the algorithm. Kidwell [20] presented an algorithm for predicting bus arrival times based on real-time vehicle location. The algorithm worked by dividing each route into zones and recording the time that each bus passed through each zone. Predictions were based on the most recent observation of a bus passing through each zone. However, this algorithm was not suitable for large cities where both travel time and dwell time could be subjects to large variations.

On the whole, these models are reliable only when the traffic pattern in the area of interest is relatively stable. One of their main limitations is that it requires an extensive set of historical data, which may not be available in practice, especially when the traffic pattern varies significantly over time.

2.2. Statistical Models

According to Karlaftis [21], Glymour claims that "statistics is the mathematics of collecting, organizing and interpreting numerical data, particularly when these data concern the analysis of population characteristics by inference from sampling" [22]. Statistics have solid and widely accepted mathematical foundations and can provide insights on the mechanisms creating the data. However, they frequently fail when dealing with complex and highly nonlinear data (curse of dimensionality) [21]. Bus arrival time is also impressed by several factors including driver behavior, carriage way width, intersections, signals and etc. and 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.

2.2.1. Time series model

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 [23]. Variation in historical data or changes in the relationship between historical data and real-time data could significantly cause inaccuracy in the prediction results [24], and the problem in these methods usually back to its short time delay if the prediction model is in the real time [25] , [26]. D' Angelo used a non-linear time series model to predict a corridor travel time on a highway [27]. 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.

2.2.2. Regression models

This approach is applying mathematical models to predict the expected travel times between stops and then the expected bus arrival times at individual stops. Regression models use multiple independent variables (regressors) to clarify a single dependent variable using a linear or non-linear relationship. This model is usually provided by regressing travel times against a set of independent variables, such as traffic circumstances, passenger, number of bus stops, and climate situation. Regression models are conventional approaches for predicting travel time [28]. Regression models predict a dependent variable with a mathematical function formed by a set of independent variables. To make a regression model, the dependent variables require being independent. This obligation confines the applicability of the regression model to the transportation systems because variables in transportation systems are highly inter-correlated [23]. Patnaik in [29] developed a set of regression models to estimate bus arrival times with collected

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data by automatic passenger counters (APC) embedded on buses. The attained results demonstrated that the proposed models could be employed to predict bus arrival times based on different situations. However, this method is dependable only in case such equations could be provided, that it might not be probable for any application environments where in the most system variables, they are characteristically correlated. Kwon et al. [30] proposed the linear regression method and tree-based methods to estimate travel time on freeways based on the flow and occupancy data (measured by loop detectors).

2.3. Kalman Filtering Model

Kalman filtering models [31,6,32] have been used extensively in travel time estimation research. As Kalman [33] argues the basic function of Kalman filtering model is to provide prediction of the present status in the system, nonetheless it correspondingly works as the basis for estimation future values or for mending prediction of variables in former times. [17] used Kalman filtering techniques to forecast auto travel time. The Kalman filtering model has the potential to adapt to traffic fluctuation with time-dependent parameters [34]. These models are effective in predicting travel time one or two time periods ahead, but they deteriorate with multiple time steps [32]. Park and Rilett compared artificial neural network (ANN) models with other prediction models including Kalman filtering techniques to predict freeway link travel time. In contrast with, the average mean absolute percentage error (MAPE) of ANN altered from 8.7 to 16.1 for 1 and 5 time periods respectively , while in Kalman filtering, it altered from 5.7 to 20.1 [32]. Bae and Kachroo [35] prescribed Kalman filter model to estimate arterial travel time for buses with equipped buses to AVL[1] as probe vehicles. Cathey and Dailey proposed a method which had three components namely tracker, filter and predictor [36].The Kalman filter applied in the filter section. In [6], they predict bus arrival time on Indian traffic circumstances by using GPS[2] data installed on buses. Their method was using a model-based algorithm and the estimation was relying on Kalman filtering method. Shalaby and Farhan collected data by AVL and APC[3] for the prediction of bus arrival time [37]. They employed Kalman filter for estimation of bus running time and passenger dwell time in an integrated framework and compared the results with a historical model, a regression model. Nanthawichit et al. [38] applied a macroscopic traffic flow model along with Kalman filtering algorithm to forecast travel time with combination of detector data and probe vehicle data. There are further studies that can be found in combination Kalman filtering with other models and we discuss later on hybrid models.

2.4. Machine Learning Models

Machine learning (ML) is studying how the computer to simulate or to realize the study behavior of human being. Figure 2 illustrates the basic structure of ML. The environment provides certain information to the learning section in system, and the learning section reviews knowledge library with consideration such this information. 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 [39,40]. 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 [41]. 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 methods are presented under these categories.

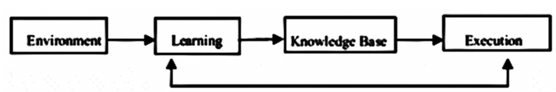

Figure 2. Learning System Basic Structure [40]

2.4.1. Artificial neural network model

ANNs emulate the learning process of the human brain [32]. They are good at pattern recognition, prediction, classification, etc. ANNs have two stages, training and testing. During the training stage, inductive learning principles are used to learn patterns from a training set data. There are two types of learning processes used: unsupervised and supervised learning. In unsupervised learning, the network attempts to classify the training set data into different groups based on input patterns. In supervised learning, the desired output from output layer neurons is known, and the network adjusts the weight of connections between neurons to produce the desired output. During this process, the error in the output is propagated back from one layer to the previous layer by adjusting the weights of the

[1] Automatic Vehicle Location
[2] Global Positioning System
[3] Automatic Passenger Counter

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connections. This is called the back-propagation method, which is the most frequently used technique in transportation applications. The learning process of ANNs can be continuous so that the models can adapt to changes in environmental characteristics. In other words, ANN models can be considered dynamic prediction models because they can be updated and modified using new online data.

Due to their ability to solve complex non-linear relationships, artificial neural network models (ANNs) have been developed for transportation since the early 1990s [42]. ANN models had better results than those of existing link travel time techniques, including a Kalman filtering model, an exponential smoothing model, a historical profile, and a real-time profile [32] In addition, ANN model showed better performance than historical average and autoregressive integrated moving average (ARIMA) models to predict short-term traffic flow. While other models are dependent on cyclical traffic data patterns or need independence between dependent and independent variables, ANNs do not require that variables are uncorrelated and/or that they have a cyclic pattern.

2.4.2. Support vector machines

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. Since support vector machines 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. In [12], the authors developed Support Vector Machine (SVM) as a new learning machine algorithm to predict the bus arrival time. They pointed out that unlike the traditional ANN, SVM is not amenable to the over-fitting problem, and it could be trained through a linear optimization process. However, they [12] indicated that when SVM is applied for solving large-size problems, a large amount of computation time will be involved. In addition, the methods for selecting input variables and identifying the parameters should be further researched.

2.5. 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 [43].The issue in SSNN is that the model requires large data set for offline training. Van Lint [44]mixed linear regression model and locally weighted linear regression model in a Bayesian framework to enhance forecast precision and reliability. Although their meth od may produce larger prediction errors weather each sub-model in the model layer is biased. Jeong and R.Rilett [45] proposed a travel time prediction model with consideration schedule adherence and dwell times. 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 [46] developed a multiple linear regression model and an ANN model on heterogeneous Indian traffic circumstances with limited dataset for bus travel time prediction. Park and Lee [47] claims Bayesian model and neural network model can be good combination to estimate for urban arterial link travel times. Chen and Chien [48]compared link-based and path-based travel time prediction models using Kalman filtering algorithm with simulated data. Chu et al. [49] 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. Kuchipudi and Chien [50]proposed a hybrid model with combination of path-based and link-based models on real data and under different traffic conditions. In [51] , [52], reported a short term transit vehicle arrival times prediction algorithm by combination of real-time AVL with historical data source in Seattle, Washington. They used a Kalman filter model to track a vehicle location and statistical estimation for prediction of bus arrival time purpose.

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3. CONCLUSIONS

In the previous section, an overall review highlighted some efforts which have been made up to now for prediction bus arrival travel. Besides, there were other may many more studies that we could not explain all them here. However, it is worth mentioning them in a glance that we prepared in the following. Predicting transit arrival/travel times has been the focus for many existing studies. Table 1 summarizes existing studies with respect to author, year of published,

Table 1. Overview of bus arrival time prediction techniques

Author	Year	Model / Architecture	Data Source	Considered Feature(s)
Zhu et al. [7]	2011	Historical data	GPS and FCD	Traffic flow, signal delay and dwell time
Chien et al. [17]	2003	Hybrid	RST	Real time data , and previous time interval data, Kalman filter and Historic data used
Lin [19]	1999	Historical data	GPS	bus schedule, bus delay patterns
Kidwell [20]	2001	Historical data	GPS	dividing each route to zones
Chien [23]	2002	Machine learning	CORSIM	ANN , link-based and stop-based data
Sun [28]	2003	Statistical	AVI	Local linear regression ,Result compared with K-NN
Patnaik [29]	2004	Statistical	APC	Regression, number of stops, dwell times, number of passengers, & weather
Park et al. [32]	1999	Machine learning	AVI	Correlation analysis between neighboring links, feed forward ANN, one hidden layer
Vanajakshi [53]	2007	Hybrid	AVI	Comparison with ANN, SVR1 used with radial basis kernel function (RBF)
Lee et al. [9]	2009	Hybrid	LBS	real-time and historical data, data mining technique used, knowledge base
Shalaby et al [37]	2003	Kalman filter	AVL and APC	dwell times, route divides into multi-link
Sun et al. [13]	2007	Hybrid	GPS	Route Linearization, finite state machine
Wu et al. [10]	2004	Hybrid	Loop detector	Using regression combination (SVR), RBF as kernel function
Bin et al. [12]	2007	Machine learning	GPS (not clear)	SVM ,Estimation of traffic congestion, RBF
Yu et al. [54]	2011	Machine learning	AVI	SVM, multiple routes, comparison with ANN, k-NN and linear regression (LR)
Yu et al. [5]	2009	Hybrid	GPS	Linear regression , Historical data
Fei et al. [55]	2011	Machine learning	Loop detectors	Bayesian, Historical data for traffic in conjunction
Padmanaban et al. [16]	2009	Hybrid	GPS	dwell time , heterogeneous traffic conditions, Kalman filtering, Historic data
Zhang et al. [56]	2009	Hybrid	GPS (not clear)	Real time data, Historic data

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Table 2. Overview Of Bus Arrival Time Prediction Techniques

Author	Year	Model / Architecture	Data Source	Considered Feature(s)
Lin et al. [15]	2002	Machine learning	GPS (not clear)	Markov chain,
Jeong [45]	2004	Machine learning	DGPS[1]	ANN, fourteen different learning functions, dwell time and schedule adherence

prediction model, data source, and considered features (consist of important details in article).

REFRENCES:

[1] B. Drilo, D. Saric, and R. Filjar, "The role of telecommunications in development of new-generation Intelligent Transport Systems," in *1st International Conference on Wireless VITAE* , Aalborg , 2009, pp. 125 - 127.

[2] Na Zeng, Ke-jing Qin, and Jun Li, "Intelligent transport management system for urban traffic hubs based on an integration of multiple technologies," in *IEEE 17Th International Conference on Industrial Engineering and Engineering Management* , Xiamen, 2010 , pp. 1178 - 1183.

[3] Jamie Houghton, John Reiners, and Colin Lim, "Intelligent Transport System:How cities can improve mobility," IBM Institute for Business Value, USA, 2009.

[4] Kum Kum Dewan and Ahmad Israr, "A Step To Reduce Congestion.," *Engineering Letters*, vol. 1, no. 14, pp. 61-66, 2007.

[5] Bo YU, Bin YU, Jing LU, and Zhongzhen YANG, "An Adaptive Bus Arrival Time Prediction Model," in *Proceedings of the Eastern Asia Society for Transportation Studies*, vol. 7, 2009.

[6] L. Vanajakshi, S. SUBRAMANIAN, and R. SIVANANDAN, "Travel time prediction under heterogeneous traffic conditions using global positioning system data from buses," *Intelligent Transport Systems, IET*, vol. 3, no. 1, pp. 1-9, March 2009.

[7] Tongyu Zhu, Fajin Ma, Tao Ma, and Congcong Li, "The Prediction of Bus Arrival Time Using Global Positioning System Data And Dynamic Traffic Information," in *Wireless and Mobile Networking Conference (WMNC), 2011 4th Joint IFIP*, Beijing, China , 2011, pp. 1-5.

[8] EHSAN MAZLOUMI, GEOFF ROSE, GRAHAM CURRIE, and MAJID SARVI, "An Integrated Framework to Predict Bus Travel Time and Its Variability Using Traffic Flow Data," *Journal of Intelligent Transportation Systems*, vol. 15, no. 2, pp. 75-90, 2011.

[9] Wei-Hsun Lee, Shian-Shyong Tseng, and Sheng-Han Tsai, "A knowledge based real-time travel time prediction system for urban network," *Expert Systems with Applications 36*, vol. 36, no. 3, pp. 4239–4247, 2009.

[10] Chia-Chen Wei, Da-Chun Su, Ming-Hua Chang, and Jan-Ming Ho, "Travel Time Prediction With Support Vector Regression," in *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS*, vol. 5, 2004, pp. 1438-1442.

[11] Ehsan Mazloumi, Graham Currie, and and Geoffrey Rose, "Using GPS Data to Gain Insight into Public Transport Travel Time Variability," *Journal of Transportation Engineering* , vol. 136, no. 7, July 2010.

[12] Yu Bin, Yang Zhongzhena, and Yao Baozhena, "Bus Arrival Time Prediction Using Support Vector Machines," *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, vol. 10, no. 4, pp. 151-158, 2007.

[13] Dihua Sun et al., "Predicting Bus Arrival Time on the Basis of Global Positioning System Data," *Journal of the Transportation Research Board ,Transportation Research Record 2034*, pp. 62–72, 2007.

[14] Xuexiang Jin, Yi Zhang, and Danya Yao, "Simultaneously Prediction of Network Traffic Flow Based on PCA-SVR," in *ISNN 07 Proceedings of the 4th international symposium on Neural Networks*, vol. 4492, 2007, pp. 1022-1031.

[15] Wei-Hua tin and Robert L Bertini, "Modeling schedule recovery processes in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

transit operations for bus arrival time prediction," in *The IEEE 5th International Conference on Intelligent Transportation Systems*, 2002, pp. 857-862.

[16] R. P. s. Padmanaban, Lelitha Vanajakshi, and Shankar C. Subramanian, "Estimation of Bus Travel TimeIncorporatingDwellTimefor APTS Applications," in *IEEE Intelligent Vehicles Symposium*, vol. IV, 2009, pp. 955-959.

[17] S.I.J. Chien and C.M. Kuchipudi, "Dynamic travel time prediction with real time and historical data," in *Annual Meeting 81st*, Washington, 2003.

[18] M, S. I Chen and X. Liu Chien, "Application of APC/AVL Archived," in *Annual Meeting of the Transportation Research Board*, Washington D.C., 2003.

[19] W-H LIN and J Zeng, "Experimental Study on Real-Time Bus Arrival Time Prediction with GPS Data," *In Transportation Research Record: Journal of the Tranportation Research Board , No. 1666*, pp. 101–109, 1999.

[20] Brendan Kidwell, "Predicting Transit Vehicle Arrival Times," GeoGraphics Laboratory , Bridgewater State College, Bridgewater, Mass., 2001.

[21] M.G. Karlaftis and E.I. Vlahogianni, "Statistical methods versus neural networks in transportation research: Differences, similarities and some insights," *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 3, pp. 387–399, 2001.

[22] C. Glymour, D. Madigan, D. Pregibon, and P Smyth, "Statistical themes and lessons for data mining. Data Mining and Knowledge Discovery," *Data Mining and Knowledge Discovery*, vol. 1, no. 1, pp. 11–28, 1997.

[23] S. I Chien, J., Y. Ding, and C. Wei, "Dynamic Bus Arrival Time Prediction with Artificial Neural Networks," *Transportation Engineering* , pp. 429-438, 2002.

[24] B. L. Smith and M.J. Demetsky, "Short-term traffic flow prediction: Neural network approach," *Tr ansportation Research Record*, vol. 1453, pp. 98–104, 1995.

[25] Y. J. Stephanedes, E. Kwon, and P. Michalopoulos, "Online diversion prediction for dynamic control and vehicle guidance," *Transportation Research Record*, vol. 1287, pp. 11–19, 1990.

[26] S. A. DeLurgio, "Forecasting Principles and Applications," New York: McGraw-Hill., 1998.

[27] M. P. D'Angelo, H. M. Al-Deek, and M. C. Wang, "Travel Time Prediction for Freeway Corridors78," in *78th Annual Meeting of the Transportation Research Board*, Washington D.C., 1999.

[28] H. Sun, H. Liu, and B. Ran, "Short term traffic forecasting using the local linear regression model," in *82nd Annual Meeting*, Washington, 2003.

[29] J. Patnaik, S. Chien, and A. Bladikas, "Estimation of Bus Arrival Times Using APC Data," *Journal of Public Transportation*, vol. 7, no. 1, pp. 1–20, 2004.

[30] J. Kwon, B. Coifman, and P. Bickel, "Day-to-Day Travel Time Trends and Travel Time Prediction from Loop Detector Data," *Transportation Research Record*, vol. 1717, pp. 120-129, 2000.

[31] Chen M, Liu X B, and Xia J X, "A dynamic bus arrival time prediction model based on APC data," *ComputerAided Civil and Infrastructure Engineering* , vol. 19, pp. 364-376, 2004.

[32] D., Park and L. R. Rilett, "Forecasting Freeway Link Travel Times with a Multilayer Feedforward Neural Network," *Computer-Aided Civil and Infrastructure Engineering*, pp. 357-367, 1999.

[33] Kalman R.E., "A new approach to linear filtering and prediction problems," *Transactions of the ASME–Journal of Basic Engineering*, vol. 82, no. D, pp. 35–45, 1960.

[34] Amer Shalaby and Ali Farhan, "Prediction Model of Bus Arrival and Departure Times Using AVL and APC Data," *Public Transportation*, 2004.

[35] S. Bae and P. Kachroo, "Proactive Travel Time Predictions under Interrupted Flow," in *IEEE Conference on Vehicle Navigation and Information Systems*, vol. Seattle, Washington, 1995, pp. 179-186.

[36] CATHEY F.W. and DAILEY D.J.:, "A prescription for transit arrival departure prediction using automatic vehicle location," *Transp. Res. C, Emerg. Technol*, vol. 11, pp. 241–264, 2003.

[37] Amer Shalaby and Ali Farhan, "Bus Travel

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Time Prediction Model for Dynamic Operations Control and Passenger Information Systems," in *Paper submitted for presentation at the TRB 82*, Washington D.C, 2003.

[38] C. Nanthawichit, T. Nakatsuji, and H. Suzuki, "Application of probe-vehicle data for real-time traffic-state estimation and short-term travel-time," *Transportation Research Record* , vol. 2987, pp. 49–59, 2003.

[39] Yaochu Jin and Bernhard Sendhoff, "Pareto-Based Multiobjective Machine Learning: An Overview and Case Studies," *EEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART C: APPLICATIONS AND REVIEWS*, vol. 38, no. 3, pp. 397-415, May 2008.

[40] Ming Xue and Changjun Zhu, "A Study and Application on Machine Learning of Artificial Intellligence," in *International Joint Conference on Artificial Intelligence*, Changchun, China , 2009, pp. 272-274.

[41] Recknagel F, "Applications of machine learning to ecological modelling," *Ecological Modelling*, vol. 146, no. 1, pp. 303-310, December 2001.

[42] G., Chang and C. Su, "Predicting Intersection Queue with Neural Network Models," *Transportation Research*, vol. 3, no. 3, pp. 175-191, 1995.

[43] H. Liu, H. van Zuylen, H. van Lint, and M Salomons, "Predicting urban arterial travel time with state-space neural networks and Kalman filters," *Transportation Research Record* , vol. 1968, pp. 99–108, 2006.

[44] J.W.C. van Lint, S.P. Hoogendoorn, and H.J.: van Zuylen, "Accurate freeway travel time prediction with state-space neural networks under missing data," *Transportation*, vol. 13, no. 5, pp. 347–369 , 2005.

[45] R. Jeong and R Rilett, "Bus Arrival Time Prediction Using Artificial Neural Network Model ," in *The 7th International IEEE Conference on Intelligent Transportation Systems*, 2004, pp. 988- 993.

[46] Y. Ramakrishna, P. Ramakrishna, V. Laxshmanan, and R. Sivanandan, "Bus travel time prediction using GPS data," in *Proceedings of the Map India* , 2006.

[47] Taehyung Park and Sangkeon Lee, "A Bayesian Approach for Estimating Link Travel Time on Urban Arterial Road Network," *Springer ICCSA* , *LNCS* , vol. 3043, pp. 1017–1025, 2004.

[48] M. Chen and S. Chien, "Dynamic freeway travel-time prediction with probe vehicle data, link based versus path based," *Transportation Research Record*, pp. 157–161, 2001.

[49] L.Y. Chu, J.S. Oh, and W. Recker, "Adaptive kalman filter based freeway travel time estimation," in *in the 84th TRB Annual Meeting*, Washington, DC, 2005.

[50] C.M. Kuchipudi and S. Chien, "Development of a hybrid model for dynamic travel-time prediction," *Transportation Research Record* , vol. 1855, pp. 22–31, 2003.

[51] Jiann-Shiou Yang, "Travel time prediction using the GPS test vehicle and Kalman," in *In American Control Conference*, vol. 3, Portland, Oregon , USA, 2005, pp. 2128 - 2133.

[52] Z. Wall and D. J. Dailey, "An Algorithm for Predicting the Arrival Time of Mass Transit Vehicles Using Automatic Vehicle Location Data," in *78th Annual Meeting of the Transportation Research Board*, Washington D.C, 1999.

[53] Lelitha Vanajakshi and Laurence R. Rilett, "Support Vector Machine Technique for the Short Term Prediction of Travel Time," in *Proceedings of the IEEE Intelligent Vehicles Symposium*, Istanbul, Turkey, 2007, pp. 13-15.

[54] Bin Yu, William H.K. Lam, and Mei Lam Tam, "Bus arrival time prediction at bus stop with multiple routes," *Transportation Research Part C : Emerging Technologies*, vol. 19, no. 6, pp. 1157-1170, December 2011.

[55] Xiang Fei, Chung-Cheng Lu, and Ke Liu, "A bayesian dynamic linear model approach for real-time short-term freeway travel time prediction," *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 6, pp. 1306–1318, 2011.

[56] Jian Zhang, Ling Yan, Yin Han, and Jing-jing Zhang, "Study on the Prediction Model of Bus Arrival Time ," in *International Conference on Management and Service Science,MASS*, Shanghai, China , 2009, pp. 1 - 3.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[57] H Akaike, "Canonical Correlations Analysis of Time Series and the Use of an Information Criterion," in *Advances and Case Studies in System Identification*, R. Mehra and D.G. Lainiotis, Ed. New York: Academic Press, 1976.

[58] Peng Chen, Zhao Lu, and Junzhong Gu, "Vehicle Travel Time Prediction Algorithm Based on Historical Data and Shared Location," in *Fifth International Joint Conference on INC, IMS and IDC*, Shanghai, China , 2009, pp. 1632-1637.

[59] R.P.S. Padmanaban, K. Divakar, L. Vanajakshi, and S.C. Subramanian, "Development of a real-time bus arrival prediction system for Indian traffic conditions," *Intelligent Transport Systems, IET*, vol. 4, no. 3, pp. 189-200, 2010.

[60] Alberto J. Santiago, James E. Clark, and Henry C. Lieu, *CORSIM USER MANUAL VERSION 1.01*.: Federal Highway Administration, 1996.

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