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Bus Arrival Time Prediction Using RBF Neural Networks Adjusted by Online Data

Lei Wang[a], Zhongyi Zuo[a,*], Junhao Fu[b]

[a] *School of Traffic and Transportation Engineering, Dalian Jiaotong University, No. 794 Huanghe Road, Shahekou District, Dalian 116028, P.R. China*

[b] *Navigation College, Dalian Maritime University, 1 Linghai Road, Dalian 116026, P.R. China*

Abstract

This paper proposes an approach combining historical data and real-time situation information to forecast the bus arrival time. The approach includes two phases. Firstly, Radial Basis Function Neural Networks (RBFNN) model is used to learn and approximate the nonlinear relationship in historical data in the first phase. Then, in the second phase, an online oriented method is introduced to adjust to the actual situation, which means to use the practical information to modify the predicted result of RBFNN in the first phase. Afterwards, the system designing outline is given to summarize the structure and components of the system. We did an experimental study on bus route No.21 in Dalian by deploying this system to demonstrate the validity and effectiveness of this approach. In addition, Multiple Linear Regression model, BP Neural Networks and RBFNN without online adjustment are used in contrast. Results show that the approach with RBFNN and online adjustment has a better predicting performance.

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Keywords: Intelligent Transportation; Arrival Time Prediction; RBFNN; Public Transport; System Design

1. Introduction

With the continuous development of the Intelligent Transportation System (ITS), the Advanced Public Transportation System (APTS) and Advanced Traffic Information System (ATIS) become more and more important.

* Corresponding author. Tel.: +86-15542402928; +86-(0)411-8410-5056.
E-mail address: zuozy@djtu.edu.cn.

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Bus arrival time forecasting system belongs to these systems (as shown in Fig.1.). Releasing bus arrival time information to passengers' mobile devices, helps them to plan their travel time, and to save their waiting time at bus stops. It makes more sense to attract additional passenger flow by providing bus arrival time information to improve the service quality of transit systems. Besides, operators will be able to monitor the execution of schedule, to react instantly and to evaluate the operational efficiency.

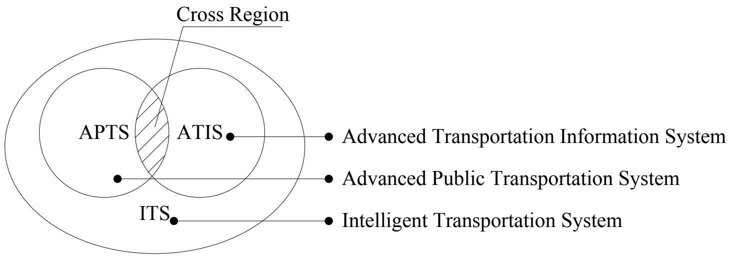


Fig. 1. Relationship among ITS, APTS and ATIS

Bus arrival time predicting method or algorithm designing was considered to be the most complicated part in the former studies. Researches on bus arrival time forecasting started by the end of 1990s which aims to extract bus operating information from vehicle monitoring systems (Lin and Zeng, 1999). With the idea of providing bus arrival information to passengers comes into our sights lately, studies focus on this domain afresh. A case study in Jinan, China was processed by Lin, et al, who proposed two artificial neural network (ANN) models to predict the real-time bus arrivals, based on historical Global Positioning System (GPS) data and automatic fare collection (AFC) system data, which illustrated ANN models are valid to bus arrival time predicting (Lin et al., 2013). Zhou, et al developed an entire system solely relies on the collaborative effort of the participating users and is independent from the bus operating companies instead of referring to GPS enabled location information from specific transit agencies (Zhou et al., 2012). Zhu et al explicitly incorporated the bus stop delays and signalized intersection delays associated with the total travel times of the buses (Zhu et al, 2011). Biagioni, et al developed an online dynamic algorithm of automatic transit tracking, mapping, and arrival time prediction by using smartphones (Biagioni et al, 2011). While Yu, et al used several methods such as support vector machine (SVM), artificial neural network (ANN), k nearest neighbours algorithm (k-NN) and linear regression (LR) as comparisons (Yu et al., 2011). A heuristic method was proposed by Yu, et al which contains two main steps, in which firstly SVM was trained to perceive the historical data and Kalman Filter was applied to import the real-time data (Yu et al., 2008).

Nowadays, the stage comes to the implementation and application of such systems from the blueprints with the gigantic development of the electronic, communication, computer software and network engineering since 21th century. Especially profiting from the popularization of smartphones, makes it possible to establish a bus arrival time forecasting system to deliver real-time bus information to both operators and passengers. On the other hand, Automobile Data Recorder and Automatic Vehicle Location (AVL) devices are equipped on bus vehicles as regular equipment, which signify that real-time location of vehicle can be available. Several cities in China have adopted bus arrival predicting systems for bus information offering online (website) or offline (electronic station board), although they can only provide an accuracy by the number of stops instead of terms of time, for example in Dalian, Xiamen and Suzhou, etc. While, can we develop a kind of system with accuracy, stability and simplification that can predict the exact time when will the next bus arrive?

In this paper, we propose an approach combining historical data and real-time situation information to forecast the bus arrival time. Firstly, Radial Basis Function Neural Networks (RBFNN) are used to learn and approximate the nonlinear relationship in historical data, so that the results can be given by the trained networks as the basic information references in the first phase. Then, in the second phase, in order to mitigate the influence from discrepancy between historical and real-time data, an online oriented method is introduced to adjust to the actual situation, which means to use the practical information to modify the predicted result of RBFNN in the first phase. Consequently, the result considered to be more dependable can be offered to transit operators, electronic station boards or passengers' smartphones. Afterwards, the system designing outline is given to summarize the structure and components of the system. We did an experimental study on bus route No.21 in Dalian by deploying this system to demonstrate the validity and effectiveness of this approach. In addition, Multiple Linear Regression model, BP Neural Networks and RBFNN without online adjustment are used in contrast. Results show that the approach with RBFNN and online adjustment has a better predicting performance.

2. Radial Basis Function Neural Networks

One ideal method to predict bus arrival time is to acquire the transformation law of vehicle operation by data mining, then to amend the mined data by bringing the real-time situation in as well. The first phase of this approach considered to be the historical data acquirement or data mining, as we assume that historical data involves comprehensive information and they are significative to imply the bus travel time in future. However data analysis and mining is a complicated and laborious work with massive data. RBFNN offer us a new way to set up a mapping among all the detectable influence factors and dependent variable.

2.1. RBF Neural Networks

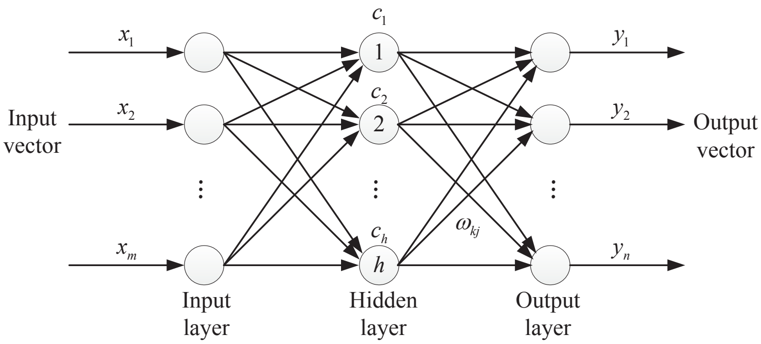


Fig. 2. Structure of RBFNN

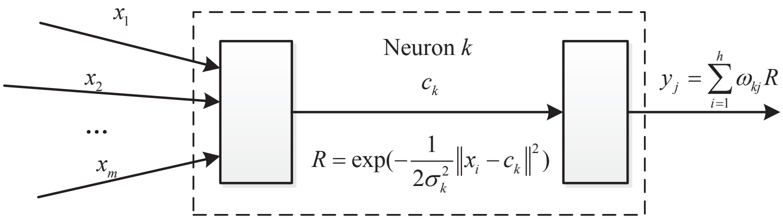


Fig. 3. Neuron Structure of RBFNN

Radial Basis Function Neural Networks are feedforward networks with RBF as activation function which can process universal approximation to any continuous function by custom accuracy. RBFNN have the structure of only three layers which are input layer, hidden layer, and the output layer (see fig.2.), while Back Propagation Neural Networks (BPNN) can possess more hidden layer. RBFNN are considered to be more effective, more accurate, faster to converge, and able to avoid problem of local extremum. The neuron structure is shown as Fig.3.

As described in reference (Park and Sandberg, 1991), RBFNN model can be concluded. The mapping method between input vector and output vector is given as

$$O = F(I) \tag{1}$$

For I is the input vector and $I=(x_1,x_2,\cdots,x_m)$; O is the output vector and $O=(y_1,y_2,\cdots,y_n)$; F is the nonlinear mapping between I and O. Suppose the number of nodes in hidden layer is h. For the input layer neuron, the only effect is to pass the signal, which means the connection weights between input layer and hidden layer are constant 1.

Using the Gaussian function as RBF, the activation function will be

$$R(x_i - c_k) = \exp(-\frac{1}{2\sigma_k^2}\|x_i - c_k\|^2) \tag{2}$$

Where $x_i \in I$, $i=1,2,\cdots,m$, $k=1,2,\cdots,h$; $\|x_i - c_k\|$ means the Euclidean norm; x_i is the input value of input node i; c_k is the centric value of basis node k in hidden layer; σ is the variance of the Gaussian function. The activation function reflects the activation condition of neuron by the discrepancy of Euclidean distance instead of linear activation functions.

So the output elements values should be

$$y_j = \sum_{i=1}^{h} \omega_{kj} \exp(-\frac{1}{2\sigma_k^2}\|x_i - c_k\|^2) \tag{3}$$

Where $y_j \in O$, $j=1,2,\cdots,n$; ω_{kj} is the connection weights between the neuron k in hidden layer and the neuron j in the output layer.

Actually, the process to train the RBFNN is to calibrate c_k, σ_k, and ω_{kj}. The learning algorithm of RBFNN can be found in reference (Lu, Sundararajan, Saratchandran, 1998).

2.2. RBFNN Used in Bus Arrival Time Forecasting

It was demonstrated by Jeong (Jeong and Rilett, 2004) that there are relationships among bus travel time, dwell time, the number of passengers getting on or off, delay, and the distance between two stops. Additionally, during the experiment, we found that the travel speed of bus reflects the congestion level of road to some extent, and the congestion situation should affect the travel time of bus, while the correlation between travel time and this factor is not clear. Linear regression shows the linear dependences are not strict, so that nonlinear relationships are supposed.

Giving the relationships assumptions between influence factors and travel time as follows:

$$D_u \propto P_u \tag{4}$$

$$T_u \propto S_u \tag{5}$$

$$T_u \propto Delay_u \tag{6}$$

$$Cong_u \to 1/V_u \tag{7}$$

$$D_u + T_u \propto P_u, S_u, Delay_u, Cong_u \tag{8}$$

So that

$$Y_u = T_u + D_u = F(S_u, P_u, Delay_u, V_u) \tag{9}$$

Where T_u is the travel time from stop u to stop $u+1$; D_u is the dwell time at stop u; S_u is the distance from stop u to stop $u+1$; P_u is the number of passengers getting on or off at stop u, usually setting $P_u = \max\{p_u^{on}, p_u^{off}\}$, where p_u^{on} represents the number of passengers getting on and p_u^{off} represents the number of passengers getting off; $Delay_u$ is the overall delay from stop u to stop $u+1$; V_u is the travel speed from stop u to stop $u+1$; $Cong_u$ is the congestion index between stop u and $u+1$; Y_u means the time interval between bus arriving at stop u and stop $u+1$.

With such kind of complicated nonlinear approximation problem, RBFNN are good enough at dealing. It is quite convenient to gather the historical data of T_u, D_u, S_u, P_u, $Delay_u$, and V_u, and consequently to organize them as samples set. Afterwards, the RBFNN model can be trained and reused.

D_u, S_u, P_u, $Delay_u$, and V_u are all statistical independent variables which can be provided by real-time bus operation data. In this phase, original data and prepared data could be offline, and once the mapping had been approximated, the mapping model can express almost entire relationship of source data, which is quite more simplified than doing analysis through enormous databases. By giving a set of these factors, we can export an result of $\hat{T}_u$, which is so called baseline data for the next phase.

3. Adjustment Model Using Online Data

Baseline data exported from the first phase is a time period parameter which actually means the travel time during stop u to stop $u+1$. When users are requesting for arrival time of a specific bus, generally the bus should be on the route in most cases than at a stop. So a conclusion can be drawn that offline prediction method cannot acquire the instant position of the bus in order to give an exact arrival time. In the second phase, we will give a method to adjust the baseline data using the online operating parameters.

3.1. Using of Kalman Filter

The instant speed of vehicle could be available to indicate the real-time operation status, which could be useful for baseline adjustment. As recording the instant speed by continuous time step, time series can be gotten. Set $v(t|t)$ as system status variable with the meaning of instant speed, and t as time point, where the length of t is determined by the time step size l, a method of instant speed prediction using Kalman Filter can be offered as following (Kalman, 1960):

Without input vector to the system, system status transforming equation and system covariance transforming iteration equation as

$$v(t|t-1) = v(t-1|t-1) \tag{10}$$

$$P(t|t-1) = P(t-1|t-1) + Q \tag{11}$$

$$v(t|t) = v(t|t-1) + Kg(t) \cdot (v_r(t) - v(t|t-1)) \tag{12}$$

$$P(t|t) = (1 - Kg(t)) \cdot P(t|t-1) \tag{13}$$

In which Kalman Gain is defined as

$$Kg(t) = \frac{P(t|t-1)}{P(t|t-1) + R} \tag{14}$$

Where, $v_r(t)$ is the observed instant speed of the bus; $P(t|t)$ stands for the calculating covariance; Q is the covariance during the system transforming; R is the observing covariance.

Combination of Baseline and Instance

We adopt a weighting arithmetic to combine the baseline data with instant speed. Firstly, turn the baseline travel time $\hat{T}_u$ to travel speed v_u by

$$v_u = S_u / \hat{T}_u \tag{15}$$

For the speed variable v_u^{aux} we call it auxiliary speed, construct the weighting method as

$$v_u^{aux} = \frac{a \cdot v(t|t) + b \cdot v_u}{a+b} \tag{16}$$

where a and b are weights; set $a = S_u^{\mathrm{f}}$ which means the length of section that has been passed through between stop u and $u+1$; set $b = S_u^{\mathrm{l}}$ which means the length of section that has not been passed through between stop u and $u+1$.

So it can be modified as

$$v_u^{aux} = \frac{S_u^{\mathrm{f}} \cdot v(t|t) + S_u^{\mathrm{l}} \cdot v_u}{S_u^{\mathrm{f}} + S_u^{\mathrm{l}}} \tag{17}$$

Where we can discover that by adopting variable weights can different dependence be given to the auxiliary speed: when the bus is more close to the stop u, v_u^{aux} depends on v_u more, while the bus is more close to the stop $u+1$, v_u^{aux} depends on $v(t|t)$ more.

Sequentially, when the bus is on the segment between stop $u0-1$ and $u0$, the predicting travel time T_{pred} from the real-time location to stop $u1$ should be given as

$$T_{\mathrm{pred}} = \frac{S_{u0-1}^{\mathrm{l}}}{v_{u0-1}^{aux}} + \sum_{u=u0}^{u1-1} \frac{S_u}{v_{u0-1}^{aux}} + \sum_{u=u0}^{u1-1} D_u \tag{18}$$

4. System Designing

In this research, we developed a set of computer software system prototype based on the bus arrival time forecasting approach proposed above. The structure of the system is shown in Fig.4. A brief introduction to each component is as follows:

- Server Scope
  - Data Collecting Server: handles the large amount of data flow from vehicle devices with database.
  - Web Server: response the query or request from users' clients or browsers and handles other basic information query requests.
  - Processing Server: using the data in database to train the model automatically and to do the online prediction for any request.
- Vehicle Scope
  - Collecting bus vehicle operating data and sending data back to the Data Collecting Server in real-time.
- User Scope
  - Several kind of interfaces are reserved to satisfy the request for the specific bus arrival time prediction information through SMS, smartphone applications, or web browsers, which are handled by Web Server.

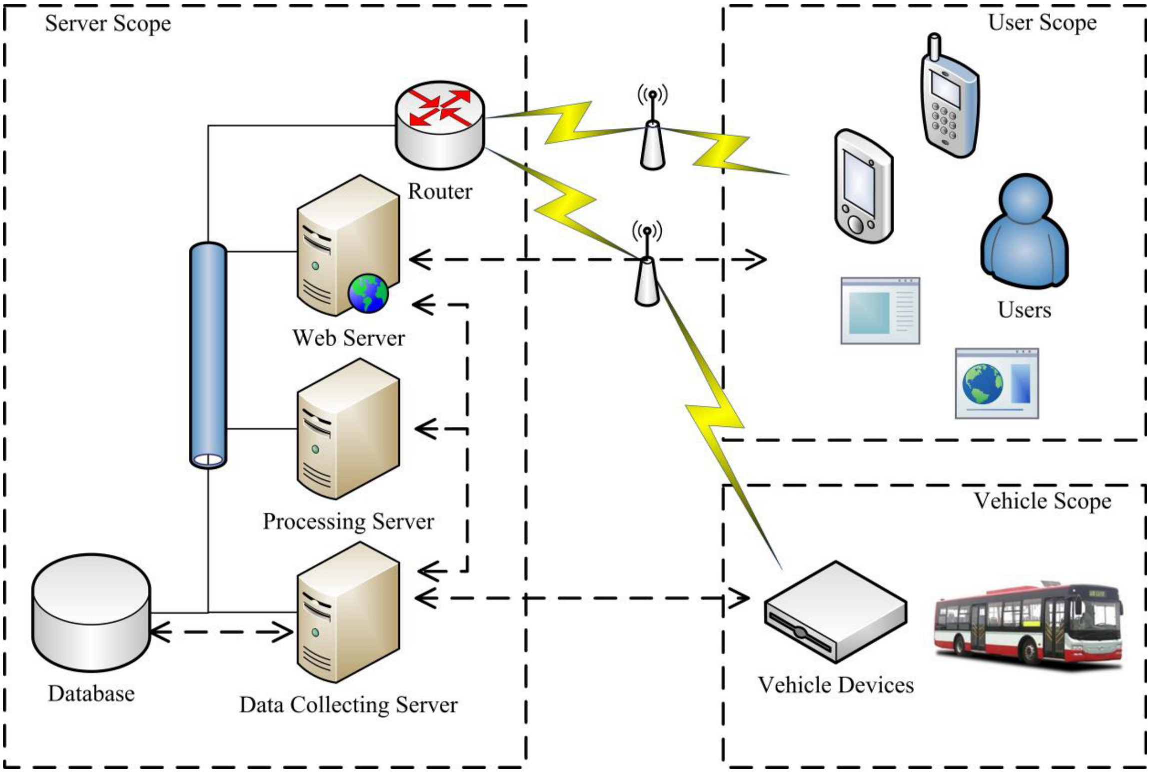


Fig. 4. System Structure Designing

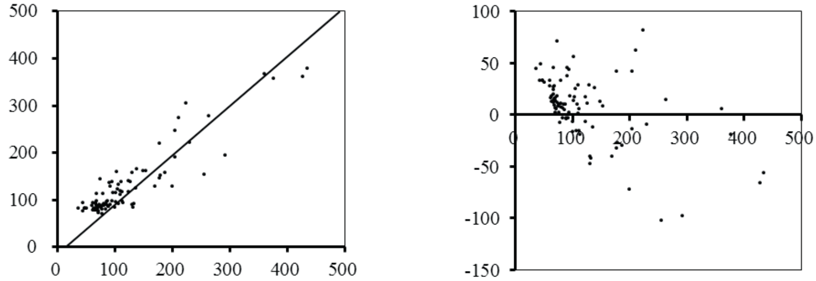
5. Experimental Study

We chose the bus No. 21 in Dalian as the experimental route to collect basic data. Because the bus operating monitoring data interface was not open to the public, we tentatively applied the vehicular devices of this system to the sample vehicles instead.

One week's data was stored and reserved in the database, which was used to train the RBFNN models. We used 3 smartphones which had installed the bus arrival time predicting and releasing software to verify the predictive effect. 90 sets of random prediction requests were processed and the results of forecast travel time were given. By recording the real operating time from the unspecified location, where the prediction requests were sent and the response of prediction results were received, to the specific stop arriving at, the effectiveness of this approach could be evaluated by residual error and relative error of each requests. The accuracy measurement of each approach is Mean Absolute Percentage Error (MAPE). Additionally, Multiple Linear Regression model, BP Neural Networks and RBFNN without online adjustment are used as comparisons.

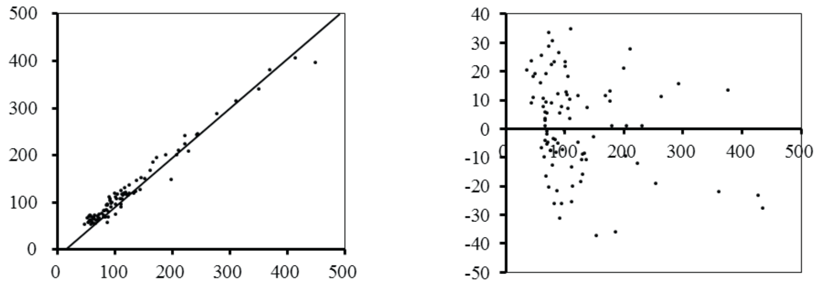
The prediction error of RBFNN without online adjustment approach is shown in Fig.5., and the prediction error of RBFNN with online adjustment approach is shown in Fig.6., in which abscissa represents observed traveling time both in (a) and (b), ordinate represents predicted traveling time in (a) and residual error in (b). Observing Fig.5.(a), we can find that points disperse from the diagonal, while points in Fig.6.(a) are much more matching with the diagonal. As shown in (b) both of Fig.5. and Fig.6., the residual errors of unadjusted RBFNN distribute from -100 to 100, while of adjusted RBFNN distribute within -50 to 50. These indicate that adjusted RBFNN model has a better accuracy than RBFNN without adjustment.

We did a contrast of MLR, BPNN, RBFNN without online adjustment, and RBFNN with online adjustment by relative error (shown in Fig.7.) and MAPE (shown in table 1.). For approaches without online adjustment, the travel time from instant position of bus to next stop was calculated by interpolation method. From an overall perspective as shown in table 1., adjusted RBFNN method has better accuracy than others. The adjusted RBFNN approach turns out to be the best option relatively by lower relative errors and MAPE.



(a) Scatter of Observed Time and Practical Time (b) Residual Error

Fig. 5. Prediction Error of RBFNN without Online Adjustment



(a) Scatter of Observed Time and Practical Time (b) Residual Error

Fig. 6. Prediction Error of RBFNN with Online Adjustment

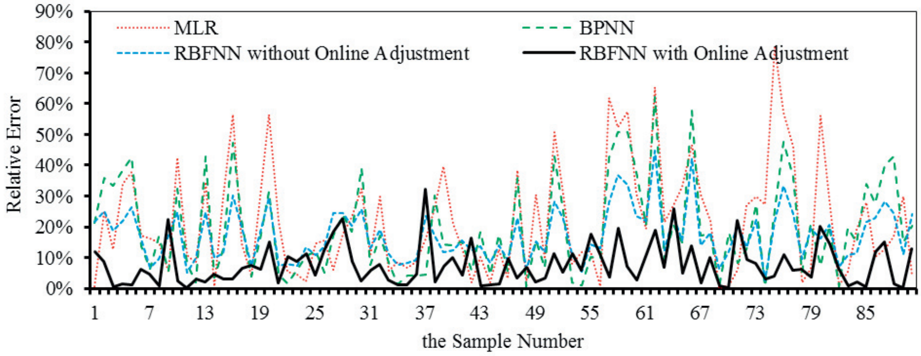


Fig. 7. Contrast among MLR, BPNN, RBFNN, and RBFNN with Online Adjustment

Table 1. Contrast of these Approaches by MAPE

	MLR	BPNN	RBFNN	Adjusted RBFNN
MAPE	22.87%	17.41%	15.98%	7.59%

6. Conclusions

This paper proposed a bus arrival time predicting approach with two phases those are RBFNN and online adjustment model. In the first phase, RBFNN model is trained by the factors of the dwell time at stop, the number of passengers getting on or off, delay, distance, and travel speed between two stops, and the baseline data can be exported. In the second phase, we developed an online filter method to import the instant speed in real-time condition to enhance the adaptability of this approach. Moreover, a structure of system designing is given for implementing the bus arrival information system. Furthermore, adjusted RBFNN by online data approach is tested by deploying this system on bus No.21 in Dalian then contrasted with other approaches, and was demonstrated to be the better method relatively.

As a part of guiding information techniques, offering and releasing accurate and reliable bus arrival time information is significantly useful of planning overall travel time and relieving the impatience when waiting for passengers. Although a new kind of forecasting approach has been proposed with an accuracy analysis in this paper, the reliability both of prediction results and bus operation status, which can tell passengers whether to trust or not, have not been studied further. Ultimately, we suppose an integrated bus information system which comprehensively includes bus arrival time prediction, bus operation monitoring, bus route and transfer information query as subsystems, which will be a useful and unique module on the urban transportation information platform.

References

Biagioni, J., Gerlich, T., Merrifield, T., & Eriksson, J. (2011). Easytracker: automatic transit tracking, mapping, and arrival time prediction using smartphones. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems* (pp. 68-81). ACM.

Jeong, R., & Rilett, R. (2004). Bus arrival time prediction using artificial neural network model. In *Intelligent Transportation Systems, 2004. Proceedings. The 7th International IEEE Conference on* (pp. 988-993). IEEE.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Journal of basic Engineering*, 82, 35-45.

Lin, Y., Yang, X., Zou, N., & Jia, L. (2013). Real-Time bus arrival time prediction: A case study for Jinan, China. *Journal of Transportation Engineering*, 139, 1133-1140.

Lin, W. H., & Zeng, J. (1999). Experimental study of real-time bus arrival time prediction with GPS data. *Transportation Research Record: Journal of the Transportation Research Board*, 1666, 101-109.

Lu Y.W., Sundararajan N., & Saratchandran P. (1998). Performance evaluation of a sequential minimal radial basis function (RBF) neural network learning algorithm. *Neural Networks, IEEE Transactions on*, 9, 308 - 318.

Park, J., & Sandberg, I. W. (1991). Universal approximation using radial-basis-function networks. *Neural Computation*, 3, 246-257.

Yu, B., Lam, W. H., & Tam, M. L. (2011). Bus arrival time prediction at bus stop with multiple routes. *Transportation Research Part C: Emerging Technologies*, 19, 1157-1170.

Yu, B., Yang, Z. Z., & Zeng, Q. C. (2008). Bus arrival time prediction model based on support vector machine and kalman filter. *China Journal of Highway and Transport*, 21, 89-90.

Zhou, P., Zheng, Y., & Li, M. (2012). How long to wait?: Predicting bus arrival time with mobile phone based participatory sensing. In *Proceedings of the 10th international conference on Mobile systems, applications, and services* (pp. 379-392). ACM.

Zhu, T., Ma, F., Ma, T., & Li, C. (2011). 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*(pp. 1-5). IEEE.