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Predicting bus real-time travel time basing on both GPS and RFID data

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Abstract

Instantaneous and accurate prediction of bus arrival time can help improve the quality of bus-arrival-time information service, and attract additional ridership. On the basis of bus running processes, a self-adaptive exponential smoothing algorithm is proposed to predict the bus running speed based on the short-term running speeds of taxis and buses available. And a bus travel time prediction model is proposed, in which the delay caused by the signal control and the acceleration and deceleration are considered. The research results show that there is a significant linear correlation between speeds of buses and taxis on the same link during the same time period, and the overall performance of the RFID-data-based model is superior to that of AVL-data-only-based model, regardless of whether the traffic congested or not.

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Key words: Bus transit; Arrival time prediction; RFID; AVL

1. Introduction

One important component of an advanced traveler information system (ATIS) is the bus-arrival-time information service. Dynamic at-stop real-time information plays an important role in waiting time reduction, positive psychological factors, increased willingness to pay, travel behavior adjustment, mode choice, higher customer satisfaction, and better brand effect (Dziekan & Kottenhoff, 2007).

As a basic component of bus-arrival-time, the accurate prediction/estimation of bus travel time has a significant effect on the overall performance of the prediction results of bus-arrival-time. However, bus travel time is affected by many factors, as validated in previous research. Generally speaking, those factors can be clustered into five categories: passenger factors, such as boarding, alighting time (Tétreault & A.El-Geneidy,

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2010) and passenger load (Shalaby & A.Farhan, 2004); infrastructure factors, such as number of stops (Sun & M.Hickman, 2006), number of traffic signal lights (Alfa W.B.Menzies J.Purcha & R.Mcpherson, 1988), and length of segments (Jeong & L.R.Rilent, 2005); running environment factors, such as weather (Cathey & D.J.Dailey, 2003), traffic patterns (Chen, Liu & Xia, 2004), and traffic incidents(Abkowitz & Engelstein, 1982); river behaviour factors, such as schedule recovery (Lin & Bertini, 2004); and operation and management factors, such as scheduled travel time (Chen & Xia, 2005) and control of time-check stops(Lin & Zeng, 1999).

With the development of the Advanced Public Transportation System (APTS), automatically collected vehicle location (AVL) systems have been widely implemented by large number of transit agencies in the world. In China, all transit agencies in metropolises have built operational AVL systems. In Shanghai, for example, more than 18,000 buses had been equipped with GPS-driven AVL devices in Dec 2010. The collected AVL data enables the modelling approach to estimate/predict bus travel time, like historical data based model, regression model, Kalman filter algorithm, and artificial neural network model.

However, the low sampling frequency of bus transit system cannot warrant the short-term prediction of bus travel time because the lack of real time location data during the prediction period. Besides, the accuracy of the location system cannot be warranted due to the high buildings that may block the GPS signal in the downtown area. In the urban zone of Shanghai, Radio Frequency Identification (RFID) devices are scheduled to be equipped in the near future, and buses and taxies are supposed to be equipped with the vehicle terminal. When the RFID devices are available, the running speed and travel time can be collected by the RFID data in a high frequency, which will provide supplemental data to the AVL system. Researches on bus travel time prediction with the existing AVL data and the RFID data will be of a great value to improve the timeliness and accuracy of the travel time prediction results.

The objectives of this research are to develop a short-term prediction model with input of the real-time bus location data collected by the AVL devices and the RFID data simulated by manual collected data. The input data of the model is collected in a short-term just before the time at present. The rest of the paper is organized as follows: in the next section, the bus running process was introduced and bus travel time prediction model with integrated AVL data and RFID data is proposed; next is an experiment conducted on two actual bus routes to evaluate the performance of the proposed model by comparing against the historical data based model with historical AVL data only; finally, an conclusion that the overall performance of the RFID data based model is superior to that of AVL data only based model regardless of the traffic congestion or not is got and future work needed is pointed out.

2. Model Development

The research scheme started from bus running process analysis. First, combined with existing data collection methods and RFID technologies, divide the bus route into sections properly; then analyze the main factors affecting on the travel time in one section; then propose the analytical models which can describe the complex relationship between bus travel time and the effect factors; at last measure the model performance (as shown in Figure 1).

2.1. Analysis of bus running process

The bus running process begins when the bus leaves the departure station, continues as the bus arrives at midway stops, and ends at the terminal station. The accuracy of the collected arrival and departure time at stops by the AVL system is determined by the performance of AVL devices. The section can be divided by the bus stops (bus stops not included).

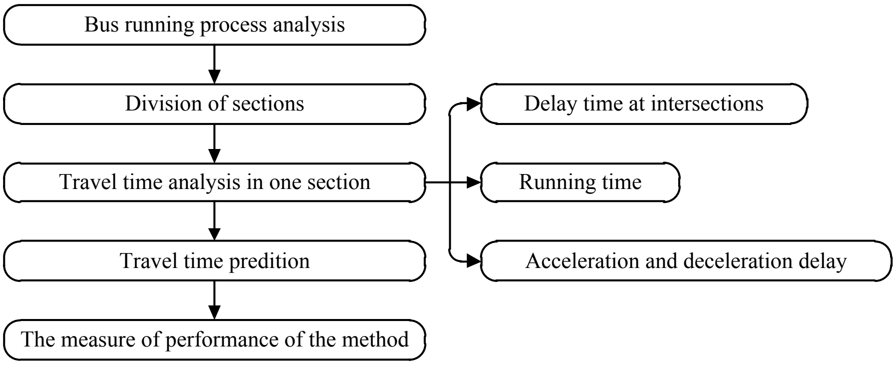


Fig.1 The research scheme

The speeds of the bus in the intersections would have an obvious change in the influence of the signal light. In the section, the bus starts at the former stop and accelerates from static to a normal running speed, then if the bus meets a red signal light at the intersections it will have a deceleration, wait and acceleration process and if the signal light is green it will go through the sections at the normal speed. Although the running process is affected by different traffic incidents, it can be described by the process of acceleration and deceleration, which mainly occur in the range of the section (see Fig.2). The travel time in one section consists of three parts (1) the running time on the road; (2) the waiting time at intersections when the bus meets the red signal light; (3) the delay during the bus accelerating or decelerating.

The running time between adjacent intersections can be recorded by the RFID devices accurately, and the parameters of the traffic signal are available in the APTS system. All of these provide conditions for the establishment of an accurate analytical model of bus travel time in one section. The running time can be predicted indirectly by the prediction of the running speed; however, due to the low sampling frequency of buses, it is more reasonable to use the speeds of buses and taxis that are available based on the RFID data to determine the running speed.

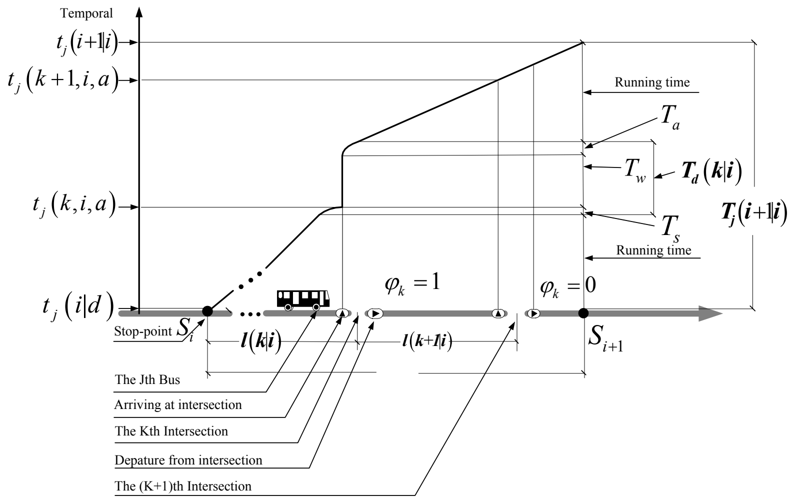


Figure. 2 Illustration of the bus running process

Due to the variation of the traffic flow, travel time prediction between two adjacent stops based on the short-term data can fits the running process well. The short-time period is determined by traffic flow properties and the schedule interval of the predicted bus and the short-time period is denoted as Δt in this research. The links in the section are divided by the intersections (as shown in Figure 2).

2.2. Bus-running-speed prediction model

As a main part of the travel time, the running time is determined by the running speed, which can be predicted through an exponential smoothing model. The model is respected to the collected running speeds of buses and taxies during the time period $\Delta\mathrm{t}$ as shown in the following equation:

$$\tau_{Vj}\left(k,i\right)=\gamma\overline{V_{oB}}+\left(1-\gamma\right)\overline{V_{eB}} \tag{1}$$

The equation (1) is calculated according to the data collected from $(t\text{-}\Delta t)$ to t. Where, t is the present time;

$\tau_{Vj}\left(k,i\right)$ is the predicted speed of the bus j on the k th link after stop i;

$\bar{V}$ is the average speed of observed vehicles;

$\bar{V}_{oB}$ is the observed average speed of the bus vehicle;

$\bar{V}_{eB}$ is the estimated average speed of the bus vehicle according to the speed of taxies whose value is given in Equation (3).

The self-adaptive exponential coefficient γ is defined in the following equation:

$$\gamma=\frac{\sigma m}{\sigma m+\mathrm{n}} \tag{2}$$

The value is calibrated according to the data collected from $(t\text{-}2\Delta t)$ to $(t\text{-}\Delta t)$. m and n is the observed number of bus vehicles and taxies. σ is a variable related to mixed traffic flow properties on the link. It can be estimated by the historical data using equation (1). Considering the fluctuation of the traffic, it is reasonable to use different values of σ in one day. The weights of bus running speed in the model are refreshed in such a way that they would increase with the increase of the number of observed bus vehicles.

According to the speed of taxies, the estimated average bus vehicle speed $\bar{V}_{eB}$ is given in the following equation:

$$\overline{V_{eB}}=f\left(\overline{V_{oC}}\right)=\alpha\overline{V_{oC}}+\beta \tag{3}$$

Where, α is the proportion;

β is the interception;

$\bar{V}_{oC}$ is the average speed of the taxis during $(t\text{-}\Delta t)$ to t.

The value of the proportion α and interception β are determined by a linear regression equation (4). The data used to estimate equation (4) is collected also from $(t\text{-}2\Delta t)$ to $(t\text{-}\Delta t)$.

$$f\left(V_{oc}\right)=V_{oB}=\alpha V_{oc}+\beta \tag{4}$$

Where $\overline{V}_{oB}$ and $\overline{V}_{oC}$ represent the observed speed of bus and taxi vehicles. The bus running speed is changing over time; thus, the model for bus vehicle speed prediction should consider the variation on time periods. Only use the data collected in from $(t\text{-}\Delta t)$ to t to predict the speed of the bus j.

2.3. Bus-arrival-time prediction model

The arrival time of the bus j at the stop $i{+}1$ is equal to the leaving time at stop i and pulsing the running time between the two stops, and the delay at intersections including the accelerating and decelerating time:

$$\tau_j\left(i+1|i\right)=t_j\left(i|d\right)+\sum_{k=1}^{K+1}\frac{l\left(k|i\right)}{\tau_{Vj}\left(k,i\right)}+\sum_{k=1}^{K}T_d\left(k|i\right) \tag{5}$$

Where, $\tau_j\left(i+1|i\right)$ is the predicted travel time of bus j from stop i to $i{+}1$ (dwell time at stops not included).

$l\left(k|i\right)$ is the length of the k th link after stop i.

$t_j\left(i|d\right)$ is the departure time of the bus j at the stop i.

$t_j\left(i|a\right)$ is the arriving time of the bus j at the stop i.

K is the number of intersections between the stop i and $i{+}1$.

$$T_d\left(k|i\right)=\left(t_G-t_j\left(k,i,a\right)+T_a+T_s-\frac{2l_0}{\tau_{Vj}\left(k,i\right)}\right)\cdot\varphi_k \tag{6}$$

Where, $T_d\left(k|i\right)$ is the delay time of the bus vehicle at the j th intersection after the stop i, which consists of the waiting time including the acceleration and deceleration time.

$t_j\left(k,i,a\right)$ is the arrival time of bus j at j th intersection after the stop i.

l_0 is the distance the bus passed when it slows down from normal running speed to static or accelerates from static to normal running speed.

T_a T is the acceleration time of the bus from static to normal running speed.

T_s is the deceleration time of the bus from normal running speed to static.

t_G is the time of the first time when the traffic light turn green after $t_j\left(k,i,a\right)$. φ_k is a 0-1 variable: if $\varphi_k{=}1$, it represents the bus j meets the red signal light and has to get a delay at the intersection k, and vice versa.

The $t_j\left(k,i,a\right)$ can be determined using the following equation:

$$t_j\left(k,i,a\right)=\begin{cases} t_j\left(i|d\right)+\dfrac{l\left(k|i\right)}{\tau_{Vj}\left(k,i\right)}+T_a-\dfrac{l_0}{\tau_{Vj}\left(k,i\right)};k=1 \\ t_j\left(k-1,i,a\right)+\dfrac{l\left(k|i\right)}{\tau_{Vj}\left(k,i\right)}+T_d\left(k-1|i\right);k\geq 2 \end{cases}$$

(7)

3. Case Study

An eastbound corridor of bus route No. 71 on Yanan Rd. and a southbound corridor of bus route No. 55 on Siping Rd in Shanghai are selected as the test routes. The traffic flow on Yanan Rd. is much higher than that on Siping Rd., especially during the morning peak. The congestion on Yanan Rd. occurs almost every day judged by the statistical data provided by the Shanghai Transportation Investment Group Company. The AVL data on both of the two bus routes are available. Considered RFID devices have not been installed at present, manual collected data by cameras is treated as the simulated RFID data. The entering and leaving time of the buses and taxies at the intersections and the signal light information were recorded by the cameras as well.

A comparison between the performance of the proposed model in this research and a historical AVL data based model is made which shows the advantage of the proposed model. According to the AVL data based model, the bus arrival time is predicted based on a statistics analysis in which the data are collected at the same time of a day, on the same day of a week. In order to have a more accurate travel time prediction according to the AVL data based model, a month of AVL data on the two routes was collected in this research.

3.1. Measure of the Models Performance

All measurement criteria subsequently developed use the difference between predicted arrival time and actual arrival time, or the prediction error:

$$\varepsilon_i = T_{Pi} - T_{Ai} \tag{8}$$

Where, T_{Pi} is the predicted arrival time; T_{Ai} is the actual arrival time;

ε_i is the prediction error of sample i.

Accuracy is the degree of closeness of the prediction value to the true value. Mean absolute error (MAE) is used to evaluate the accuracy of the model. A low MAE value indicates high accuracy:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\varepsilon_i\right| \tag{9}$$

Precision is the degree to which repeated measurements under unchanged conditions produce the same results. It can be described as the central tendency of prediction error around the true value. Mean absolute percentage error (MAPE) is the measure used to evaluate the precision of the model. A low MAPE value indicates high precision:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|\varepsilon_i\right|}{T_{Ai}} \tag{10}$$

The third measure is designed to detect its behaviour. It examines the robustness of an algorithm whether its maximum deviation within a certain range. The mathematical expression for this is the maximum of the ε_i (M). A low M value indicates good behaviour of the model:

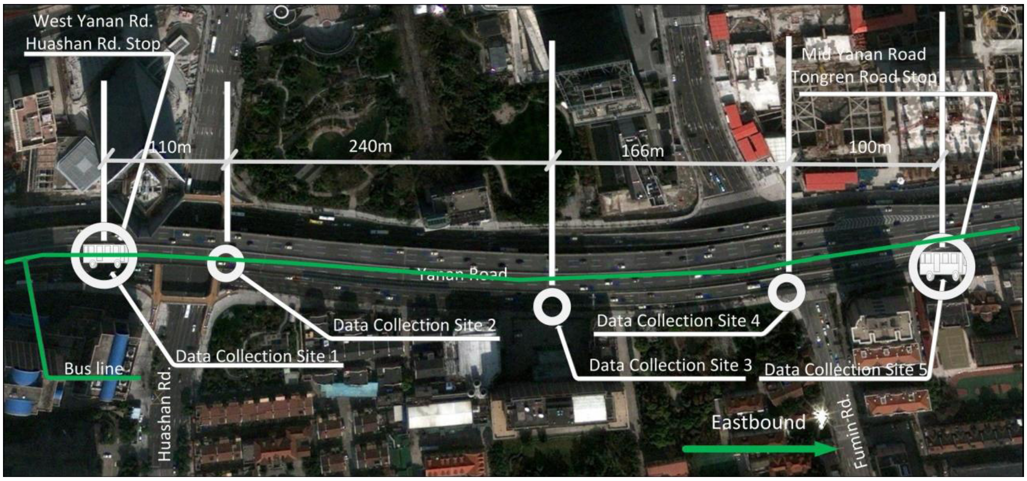
$$M = \max_i\left\{\varepsilon_i\right\} \tag{11}$$

3.2. Data Collection

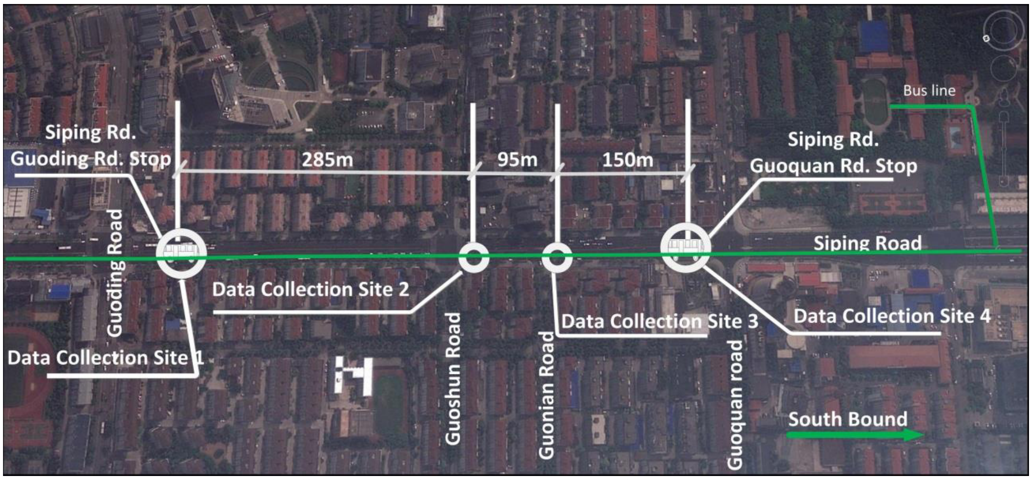
The simulated RFID data was collected on July 10th 2012, from 8:00 to 10:00 AM and from 3:00 to 5:00 PM. The scheduled headway of bus route No. 71 during the peak period ranges from 4 to 5 min. and from 6 to 7 min. during the non-peak period, for the bus route No. 55 4 min. during the peak period, and 8 min. during the non-peak period. The cameras were set up at candidate data collection sites where the vehicle license and position were collected. The changing time of the signal light and vehicles passing time between data collection sites were also collected. The simulated RFID data of Yanan Rd. was collected in the morning and that of Siping Rd. was collected in the afternoon (as shown in Figure 3).

All buses in service are equipped with AVL devices in Shanghai, and detailed information is collected and archived in real time. Bus location data are collected and uploaded under three conditions: (1) after the bus has been running for 30 s, (2) after it has covered more than 250 m within 30 s, and (3) after it arrives or leaves a stop.

At last there were a total of 4,615 records of the manual collected data whose indices are shown in Table 1, and historical AVL data from June 10th to July 10th 2012, were collected. There were a total of 8,743,709 records of the AVL data whose indices are shown in Table 2.



(a) Illustration of the data collection site of bus route No. 71



(b) Illustration of the data collection site of bus route No. 55.

Figure. 3 Illustration of the data collection site

Table. 1 Main index in manual collected data set

Variable	Description
Vehicle No.	The licensing number of the observed vehicles
Vehicle type	Types of the observed vehicles, only taxies and buses included
Time	Time collected by cameras
Position ID	The data collection site
Intersection ID	The data collection site
Red time	The time when the signal light turn into red
Green time	The time when the signal light turn into green

Table. 2 Main index in AVL data set

Variable	Description
fld_PositionID	Identification of AVL Data
fld_TerminalNo	Serial Number of GPS device, which is bound to the vehicle
fld_Time	Time collected by GPS
fld_Longitude	Longitude collected by GPS
fld_Latitude	Latitude collected by GPS
fld_Rate	Speed collected by GPS
fld_Direction	Running direction, 1 means Northbound, while 0 means Southbound
fld_PointIndex	Identification of Interest-Point
fld_StopNo	Stop Number that vehicle departs from
fld_OnLine	Status of bus, 0 means vehicle is not online, while 1 means online.
fld_Indication	Status of bus, 2 means vehicle arrives at stop, while 18 means departs from stop
fld_MileMeter	Mileage Counter, distance that vehicle has traveled on segment

The time of the bus accelerating from the static to the normal running speed and decelerating from the normal running speed to the static (T_a and T_s) and the distance passed during accelerating or decelerating l_0 can be obtained through the vehicle power and start-up performance parameters which are known. T_a and T_s have the same value which is 7.5 seconds and l_0 has the value of 55 meters in this research.

3.3. Data Processing

Considered the scheduled headway is less than 10 min. for all trips on both bus route No. 55 and bus route No. 71, take the value Δt equal to 30 min. based on the assumption that the traffic flow keeps the same level in an interval of 30 min.

The collected raw data are processed with a program. As shown in Figure 4, first the AVL data is selected, in order to obtain the arrival time and departure time of the bus vehicle at the stops. Secondly the average running time of bus and taxi vehicles between two adjacent data collection site were calculated in order to get the running speed of vehicles. Thirdly the cycle of the signal light is recorded in order to calculate the delay at intersections. At the same time, the number of bus and taxi vehicles is counted by the program.

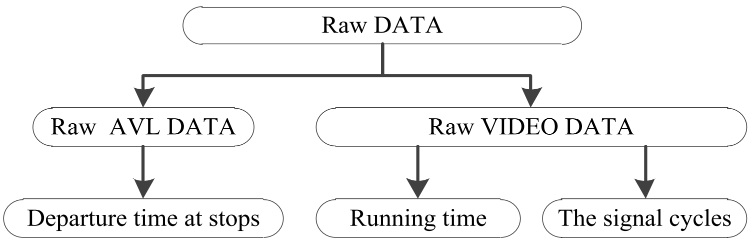
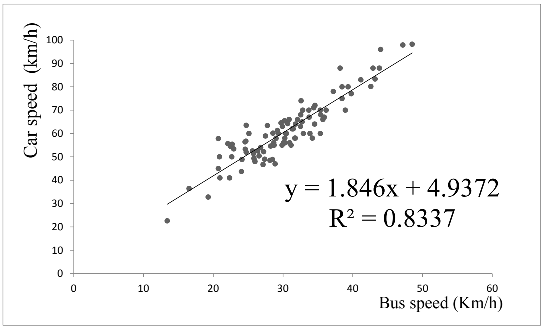


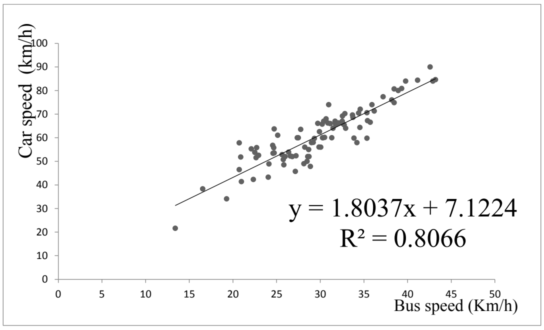
Figure. 4 The data processing flow

3.4. Results and analysis

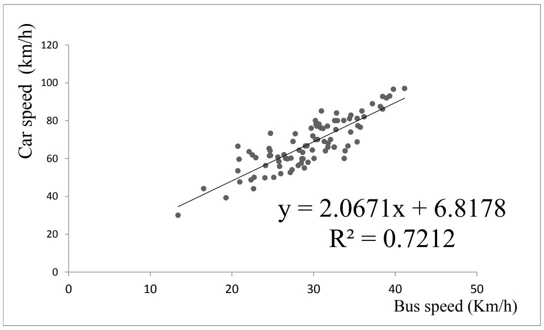
The proportion between the speeds of buses and that of taxies on different sections of the route were individually subject to linear regression with the R^2 values ranging from 0.72 to 0.83, and the regression coefficient is between 0.95 and 2.06 (as shown in Figure 5). Therefore, estimating the speeds of the buses according to the speeds of taxies is reasonable.



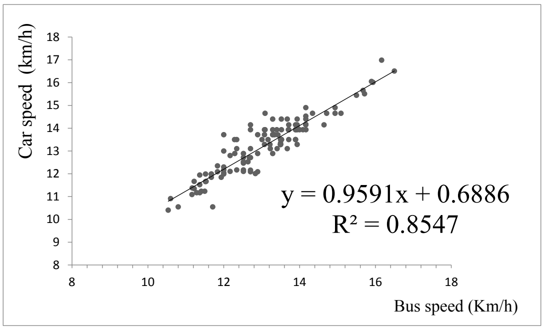
(a)SiPing Rd. Guoding Rd.-GuoshunRd.



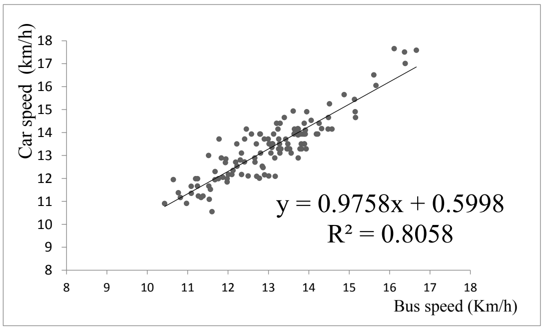
(b)SiPing Rd. Guoshun Rd.-Guonian Rd.



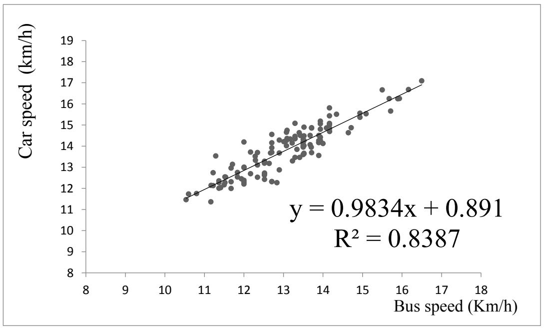
(c) SiPing Rd. Guonian Rd.-Guoquan Rd.



(d) West Yanan Rd. Huashan Rd.



(e) Mid Yanan Rd. Fumin Rd.



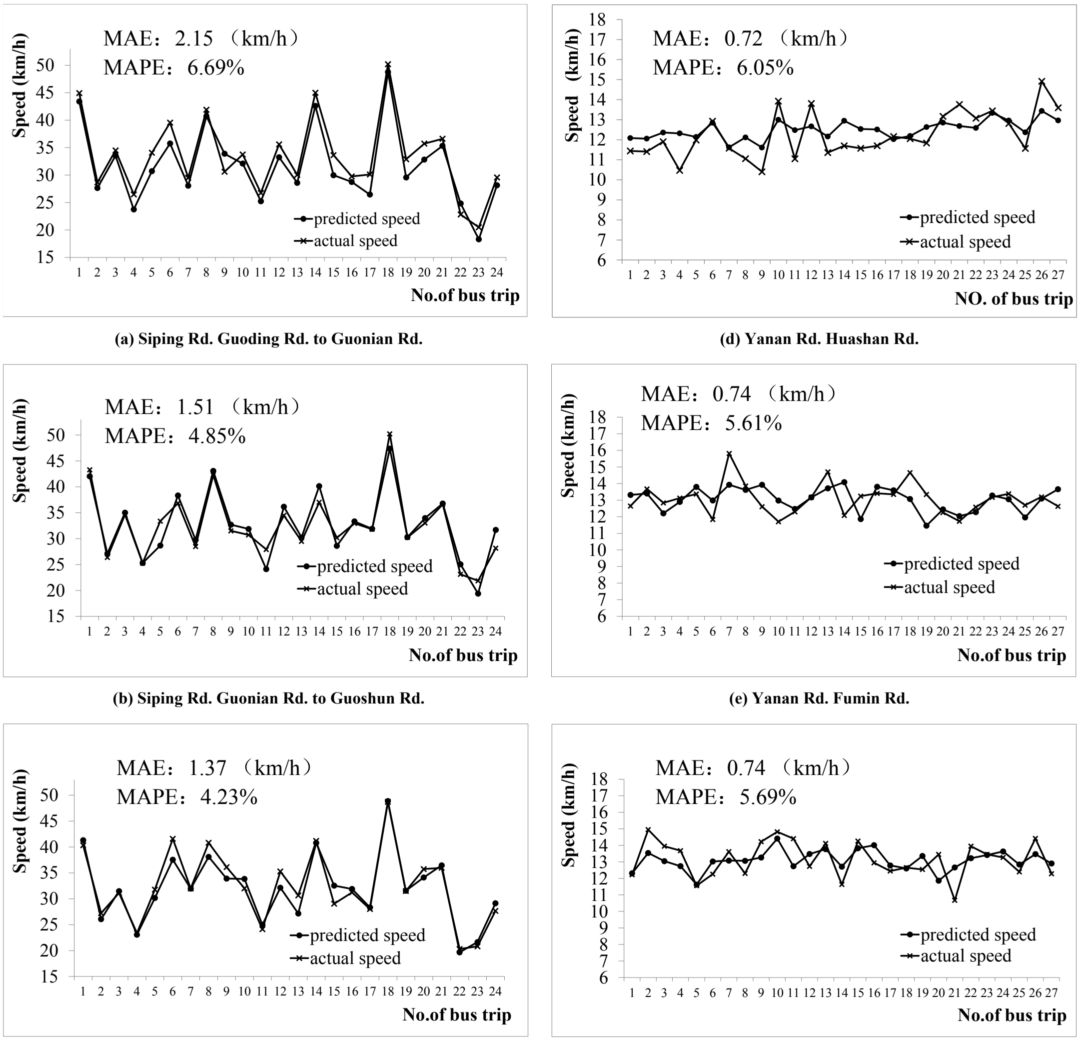
(f) Mid Yanan Rd. Tongren Rd.

Figure. 5 Speed of buses and taxies on different sections

Considered the different traffic and other conditions on the two experimental bus routes, difference between the regression coefficients is easily understood. According to the linear regression, both buses and taxies have similar speeds when the road is congested, and then the coefficient is close to 1.00; and in light or normal traffic conditions, the taxi will have a higher speed and then the coefficient is larger than 1.00.

The performance of the bus-running-speed prediction model can be measured by a comparison between the predicted speed and the actual speed (as shown in Figure 6). There is no significant difference between different bus routes. The value of the MAPE is between 4.23% and 6.69% and it is reasonable to agree that the bus-speed prediction model is precise and reliable. It shows the satisfactory performance of the bus-speed perdition model.

The experimental results show that MAE decreases and MAPE increases with the increase of the congestion degree, which means that there is an increasing uncertainty of the speed in the case of a traffic jam. The speed prediction model has a better performance in light or normal traffic conditions (see figure 6).



(a) Siping Rd. Guoding Rd. to Guonian Rd.

(d) Yanan Rd. Huashan Rd.

(b) Siping Rd. Guonian Rd. to Guoshun Rd.

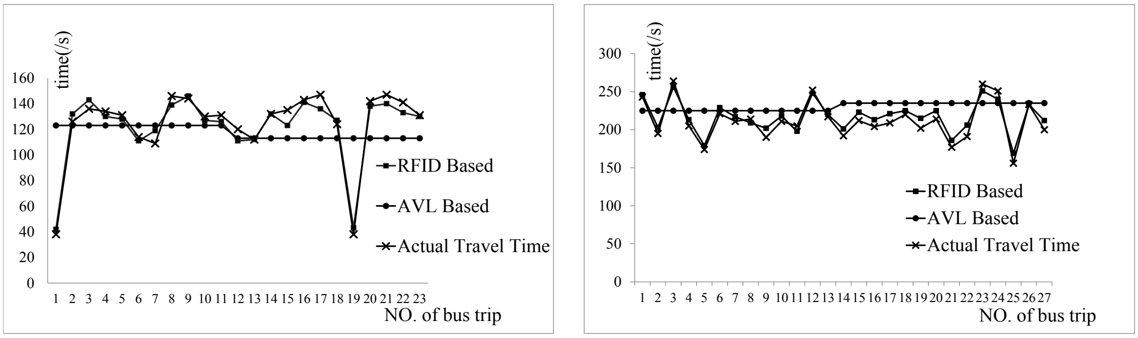
(e) Yanan Rd. Fumin Rd.

(c) Siping Rd. Guoshun Rd. to Guoquan Rd.

(f) Yanan Rd. Tongren Rd.

Figure. 6 The predicted speed and actual speed of buses on different links

Based on the bus running speed prediction model, the travel time between two adjacent stops can be determined by the equation (4). The predicted arrival time is calculated by a historical AVL data-based statistical model for the same time periods for comparison. The results of the two models and the actual arrival time is showed in Figure 7 which represents the predicted and the actual travel time between two adjacent stops. The overall MAE and MAPE and maximum of the ε_i were calculated and shown in table 3.



(a) Comparison of model for Siping Rd. **(b) Comparison of model for Yanan Rd.**

Figure. 7 The predicted time of the two models and the actual travel time

As shown in Figure 7, the result of the AVL data based model is a statistic value of the historical travel time during the same period and buses have the same predicted travel time in one interval. Therefore strictly speaking the predicted travel time is not very accurate, which does not consider the real-time traffic conditions. However the model proposed in this research significantly improved the prediction accuracy. It can works well as the traffic condition changes. According to the comparison in Table 3, the improvement in prediction errors is of great significance. According to the maximum deviation of the two models, it is reasonable to conclude that the RFID based model has a better overall performance.

Table.3 Comparison of two travel time estimation algorithms

Route	Algorithm	MAE(s)	MAPE (%)	$\lvert\varepsilon_i\rvert_{\max}$ (s)
BUS 55	AVL Based	22.17	18.99	85
	RFID Based	5.04	4.53	35
BUS 71	AVL Based	27.48	11.90	79
	RFID Based	8.26	3.89	32

4. Conclusion

Although several models have been developed using AVL data in bus-arrival-time prediction, some of them have to be recalibrated or even are inapplicable in new settings since key factors are probably different from one bus route to another. RFID data based models have the advantage of generalization under various conditions. Thus, with equipped RFID devices this kind of model will have a wide range of applications in bus travel time prediction. A linear model for the bus running speed prediction and a bus arrival time prediction model are formulated in this research, and two interesting conclusions were drawn from the results.

First, the speeds of buses and taxies have good linear relationship, and the linear regression model can predict the bus speed by utilizing the speeds of both taxies and buses, in case that bus data is unavailable. The prediction results are more accurate than using the speed of buses only, because the number of the observed taxies is larger than that of the buses. In the case of traffic congestion, buses and taxies have similar speeds; correspondingly, in light or normal traffic conditions, the taxies have higher speeds than buses.

Secondly, the overall performance of the AVL and simulated RFID data based models is superior to the historical data based model with AVL data only. An explanation is that the real-time variation of traffic condition and the delay at the intersections between two adjacent stops are considered in the proposed model. Application of this kind of model after the equipment of RFID devices will significantly improve the accuracy of travel time prediction.

Although the results are encouraging, much work still remains before a wide application of the model. Note that the value of Δt needs to be calibrated to improve the performance of the proposed prediction methods.

Acknowledgements

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