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A prediction model of bus arrival time at stops with multi-routes

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Abstract

Accurate bus arrival time is fundamental for efficient bus operation and dispatching decisions. This paper proposed a new prediction model based on support vector machine (SVM) and artificial neural network (ANN) to predict bus arrival time at an objective stop with multi-routes. The preceding bus arrival time of objective route and all other routes passing the same stop, and travel speed of the target one are three inputs of the model.

A case study was conducted with data collected in all workdays in October, 2014 in Zigong, Sichuan, China. The results of the proposed model indicate that both SVM and ANN models have high accuracy, while the ANN model is better than SVM model comparatively. The mean absolute percentage errors (MAPE) of prediction are less than 10% in most cases. By contrast, two groups with inputs changed or removed are set up to demonstrate the suitability of three inputs. No matter which method to use, SVM or ANN, the consequence of the proposed model is better than comparative groups.

Keywords: Bus arrival time prediction;Support vector machine;Artificial neural network;Multi-routes

1. Introduction

The scheduling plan of bus is critical for the operation of public transit companies. While the bus arrival time is the basis for efficient bus operation and dispatching decision. The punctuality improves the popularity of buses and

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promotes the progress of the transit metropolis. However, it is still a difficult task to predict the accurate bus arrival time due to the dynamic traffic conditions.

The bus arrival time prediction is mainly based on travel time which is derived from the prediction of traffic flow (Wu, 2012). Recently, most research works focused on predicting the arrival time of a single bus route based on the historical data. With the development of Advanced Public Transportation Systems (APTS), more data collection technologies, i.e. Globe Positioning Systems (GPS) and Automatic Passengers Counters Systems (APCS), offers various information which could generate real-time data for bus arrival time prediction. However, several bus routes may pass the same stop and the arrival time of different bus routes are affected each other. Therefore, this paper studied the routes that may have effects on the predicted bus route. The rest sections of this paper are organized as follows. The second section is the literature review of bus arrival time prediction. The third section provides a novel prediction model utilizing SVM model and ANN model. The fourth section is a case study and validation of the proposed method with bus operation data from Zigong, Sichuan, China and some conclusions are drawn finally.

2. Literature review

Due to the significance of bus arrival time prediction, many pieces of research were conducted during these years. Initially, Nam (1996) utilized stochastic queuing theory and vehicle number to predict vehicle travel time in the highway without considering intersections. Zhang and Rice (2003) took a linear model as a method to predict freeway travel time.

With the research progress of public transit, travel time prediction has been applied to bus arrival time prediction. Currently, the predicting models are classified into several types: Date Model, Time Series Model, Regression Model, Kalman Filtering Model, Artificial Neural Network, and Support Vector Machines.

Angelo (1999) used nonlinear time series models to predict bus travel time. Whereas, the poor accuracy and real-time performance make it an unsatisfactory model. Zhou (2011) came up with a dynamic model based on ahead bus arrival time using a great quantity of historical data. Patnaik (2004) obtained numbers of passengers aboard or alight from buses, distances from the station, dwelling time, station numbers and time periods using Automatic Passenger Counter to establish multivariable regression model. Regression Model assumes independence among various factors, which is impractical. Vanajakshi (2009) discussed the possibility of adopting Kalman Filtering Model to forecast the travel time, which indicated Kalman Filtering Model was obviously better than averaging method.

With the progress of machine learning technology, Artificial Neural Network Model and Support Vector Machines Model are widely used in the bus arrival time prediction. Kumar (2014) compared model based approaches and machine learning methods, which found ANN model is better than Kalman filtering with a large database. Su and Wang (2012) regarded time, weather and travel time as neurons on GA—Elman bus arrival time prediction. Lin (2014) adopted a hierarchical ANN model that is integrated with Sub-ANN models. With the purpose of verifying the feasibility of SVM in time prediction field, Yu (2006) compared SVM with ANN with three inputs: time, weather and route, which found SVM provided better results than ANN. Yao (2010) adopted attenuation factor to forecast bus travel time by Support Vector Machines. Yu (2011) predicted bus arrival times with all routes passing the same bus stop, but lost sight of differentia of objective route and other ones.

Previous research focused on the historical data and ignore other routes or mix all. There are many different routes in the same stop and the pivotal point is how to use these information. In this paper, all routes that may have effects on the predicted bus route should be considered, and real-time data from Bus Company will be utilized to predict the real-time arrival time.

3. Methodology

The prediction of bus arrival time at a certain Stop can be equaled to the prediction of bus travel time below.

$$T_{a,j} = T_{d,i} + t_{travel,ij} \tag{1}$$

Where $T_{a,j}$ denotes the arrival time of Stop j ; $T_{d,i}$ denotes the departure time of Stop i ; $t_{travel,ij}$ denotes the travel time between Stop i and Stop j .

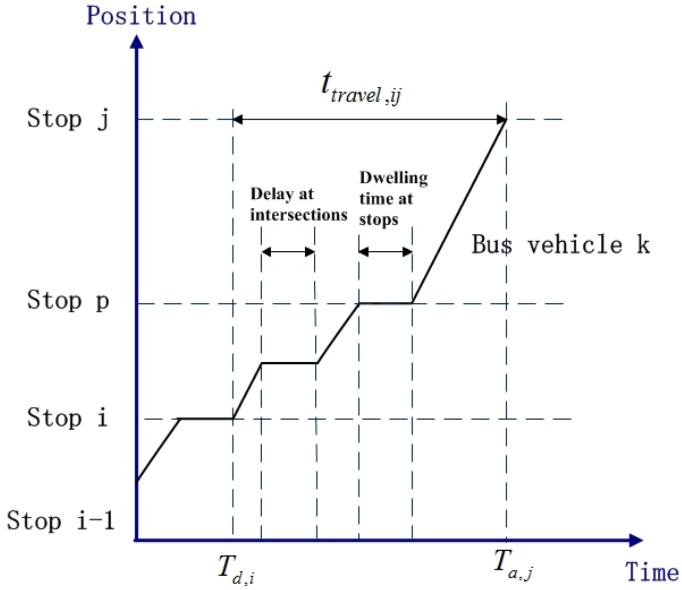

Fig. 3.1. Components of the bus travel time

There may be one or several stops between i and j . Travel time between stops can be divided into three parts according previous researches showed in Fig.3.1, including running time, dwelling time at stops and delay at intersections. In reality, there is not enough information which can be used in models referring to every part of travel time. In this paper, total travel time is viewed as an entirety.

3.1. Assumption and notations

For the purpose of computation simplicity, some definitions are given below:

- Preceding bus vehicles: bus vehicles passing the predicted stop before the objective bus;
- Objective bus vehicle: the bus vehicle whose arrival time needs to be predicted;
- Objective bus route: the bus route whose arrival time needs to be predicted;
- Different bus routes: the bus routes passing the same stops with the objective route within a certain predicted segment.

Following are the main assumptions of the model.

- Bus vehicles stop directly in bus-stops without re-stop.
- Bus vehicles are certain to stop with or without passengers boarding and alighting.
- The conditions of drivers, vehicles and stops forms of all bus routes are same.
- The highly congested situation is excluded, e.g. the saturation degree of predicted section of road is less than 1.0.
- The real-time information can be obtained and interacted between bus vehicles and the processing center.

The variables are defined as follows:

Nomenclature

N	the objective bus vehicle
L	the objective bus route
l	the different bus routes which can be regarded as one route
k_1	the number of preceding bus vehicles of the objective route
k_2	the number of preceding bus vehicles of the different routes from the objective one
i, j	index of stops, $i, j = 1, \quad , S$
$T_{d,i}^{N,L}$	the departure time from stop i of the objective bus vehicle N, route L
$T_{d,i}^{m,L}$	the departure time from stop i of bus vehicle m, route L, $m \in [1, k_1]$
$T_{d,i}^{n,l}$	the departure time from stop i of the bus vehicle n ,route l, $n \in [1, k_2]$
$h_{m,L}^{N}$	the headway between the bus vehicle N and m
$h_{n,l}^{N}$	the headway between the bus vehicle N and n
$t_{travel,ij}^{m,L}$	the travel time between stop i and stop j of bus vehicle m
$t_{travel,ij}^{n,l}$	the travel time between stop i and stop j of the bus vehicle n
$t_{travel,ij}^{L}$	the weighted travel time of preceding bus vehicles of route L
$t_{travel,ij}^{l}$	the weighted travel time of preceding bus vehicles of route l
$v_{i-1,i}^{N}$	the travel speed of objective bus vehicle N between stop i and stop $(i-1)$
$s_{i-1,i}^{N}$	the distance between stop i and stop $(i-1)$
$t_{travel,i-1,i}^{N}$	the travel time from stop i and stop $(i-1)$

3.2. Model Description

Some factors may influence the running state of bus vehicles, including road condition, bus-stop condition, intersections, drivers, and weather, etc. It is difficult to set up a model which contains all these factors because of the difficult quantization of some of them. Besides, too many factors considered will add the complexity of prediction model. In this section, three values referring to all bus routes passing the predicted stop are chosen to reflect the characteristics of bus vehicles running.

Yu (2006) suggested that the travel time of the preceding bus can be used to estimate the travel time. Preceding bus vehicles passing the several same continuous stops (the number of stops can be from one to (S-1)) can be classified into two types based on the bus routes: those with the same route as the objective bus and others not. The real time travel circumstances can be reflected by both the two types' running conditions. As a result, the two types of preceding bus vehicles' travel times with a little promotion are adopted as two input values of SVM. Time-based weighted travel time of preceding bus vehicles can improve the prediction accuracy by giving greater weights to travel times of more up-to-minute ones.

In the research of Zheng (2012), bus speed on the road link was used to reflect the travel condition, which performed well. Speed of the objective bus on the preceding segment is taken into account as the third input value.

For simplicity, the proposed model focuses on just a single bus route during particular periods, e.g. peak hours. Improvements and extensions can be realized in the practical application. The values, which reveal the bus running features under the particular condition, are listed as follows.

1. Factor 1 is the weighted travel time of preceding bus vehicles with the same route as the objective bus.

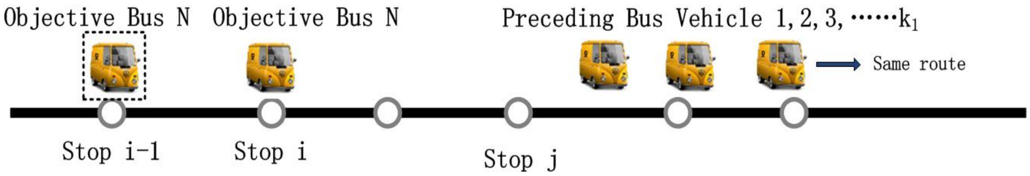

Fig. 3.2 An illustrate of factor 1 and 2

As showed in Fig. 3.2, the travel times of k_1 preceding bus vehicles will be taken into account. All k_1 vehicles belongs to the objective bus route L .

$$h_m^L = T_{d,i}^{N,L} - T_{d,i}^{m,L} \tag{2}$$

$$\frac{1}{h^L} = \sum_{m=1}^{k_1} \frac{1}{h_m^L} \tag{3}$$

$$t_{travel,ij}^L = \sum_{m=1}^{k_1} \frac{h^L}{h_m^L} \cdot t_{travel,ij}^{m,L} \tag{4}$$

Equation (2) shows the headway between a certain preceding bus vehicle m and the objective one. When the headway is shorter, the running condition of this preceding bus vehicle is more similar to that of the objective one. Owing to the maximum value of $\frac{h^L}{h_m^L}$ of the last preceding bus, the Equation (3) and (4) utilize the reciprocal value of headway to explain that it has the most influence on the weighted travel time.

2. Factor 2 is the travel speed of objective bus of the latest segment.

$$v_{i-1,i}^N = \frac{s_{i-1,i}^N}{t_{travel,i-1,i}^N} \tag{5}$$

Equation (5) denotes the average speed of objective bus. The latest segment is showed in Fig. 3.2 from stop $(i-1)$ to stop i . This value can shows the road congestion degree because of the short distance from the initial stop i of prediction.

3. Factor 3 is the weighted travel time of preceding bus vehicles with different routes from the objective bus.

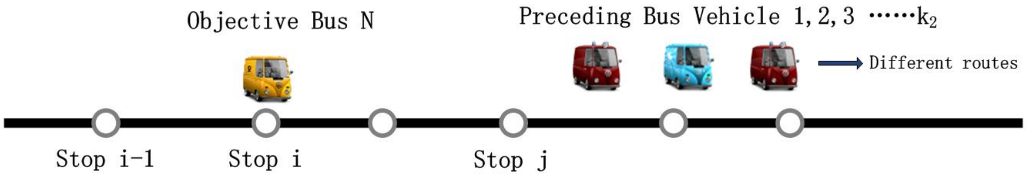

Fig. 3.3 An illustrate of factor 3

In the public transit network, several bus routes appear at a single stop. Equation (6)-(8) are similar to those of factor 1. The weighted values are applied to calculate the travel time of k_2 preceding bus vehicles with different routes. They all pass the same stops from Stop i to Stop j . In Fig. 3.3, vehicles which are not yellow are buses with different routes.

$$h_n^l = T_{d,i}^{N,L} - T_{d,i}^{n,l} \tag{6}$$

$$\frac{1}{h^l} = \sum_{n=1}^{k_2} \frac{1}{h_n^l} \tag{7}$$

$$t_{travel,ij}^{l} = \sum_{n=1}^{k_2} \frac{h^l}{h_n^l} \cdot t_{travel,ij}^{n,l} \tag{8}$$

There are several reasons for considering these non-target routes.

- These bus routes may pass several same stops and have the same route condition, which reflects the running environment. Ignorance of these non-target routes may lose quite a lot of data for prediction.
- Due to the various route designs， different bus routes may undertake different passenger demands of the same stops. Given this, integration of all routes, especially the objective one and others, may increase the prediction errors.

3.3. Support vector machine model

Support vector machine (SVM) is a machine learning model which is applied in small samples, nonlinearity, and high-dimensional pattern recognition. Different from Artificial Neural Network, it is based on mathematical method and optimization model. Various support vector machines can be produced by adopting different kernel function. There are four standard kernel functions that are linear kernel function, polynomial kernel function, radial basis function (RBF), and sigmoid kernels function. RBF kernel function is chosen here to be applied to the prediction by SVM. The expression of RBF kernel function is shown below.

$$K(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2), \gamma > 0 \tag{9}$$

Where γ is a parameter which should be determined according to your prediction needs； x_i and x_j are input values of the support vector model.

Fig. 3.4 shows the structure of the proposed model by SVM. Three input values are Factor 1, Factor 2 and Factor 3, respectively, and the output value $\hat{t}^{N}_{travel,ij}$ is the predicted travel time of objective bus from Stop i to Stop j .

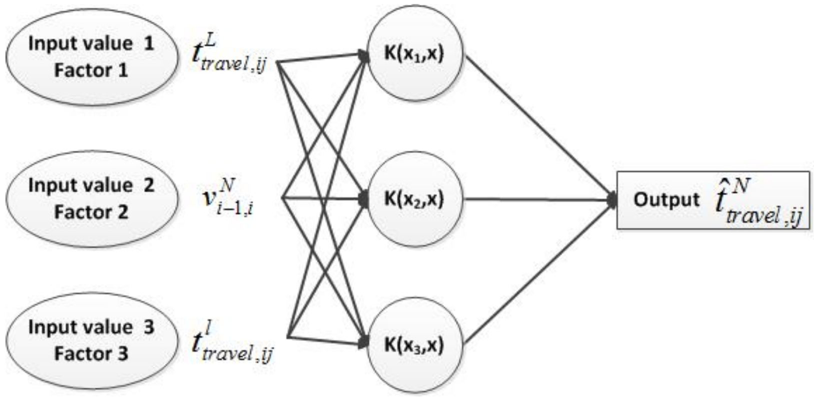

Fig. 3.4 The structure of the proposed model by SVM

3.4. Artificial neural network model

The artificial neural network model is widely used in the economic and engineering prediction. Back Propagation (BP) ANN is a multilayer feedforward network which includes three layers: input layer, hidden layer, and output layer as Fig. 3.5 shown. After determining the weights and parameters of hidden layers, the best training function is given.

Three same input values and output value as model by SVM are adopted by ANN. The number of hidden layer neural cells is set to be five. The structure of the proposed model by ANN is 3-5-1.

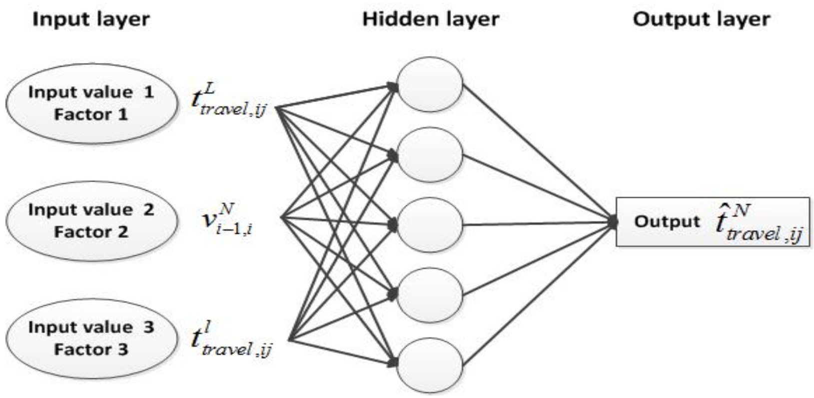

Fig. 3.5 The structure of the proposed model by ANN

The weights and thresholds between the initial neurons of BP Artificial neural network model are chosen randomly, which may lead to the local minimums. Genetic algorithm (GA) is used to optimize the BP Artificial neural network, which includes structure determination of ANN, optimization by GA and prediction by ANN. The steps of GA for finding the best weight and threshold are listed in Fig. 3.6.

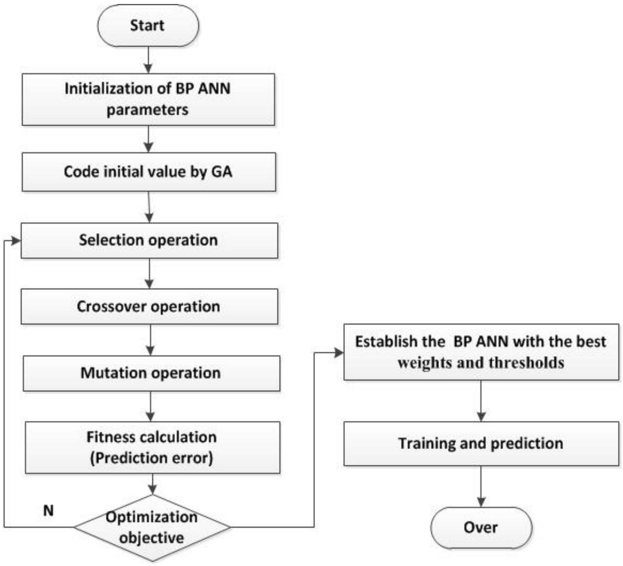

Fig. 3.6 The flow chart of ANN optimized by GA

4. Methodology

The actual bus travel and arrival time data in Zigong, Sichuan were taken as an example to demonstrate the effectiveness of the proposed model. Data of Bus Route 1 was obtained from all 16 workdays except holidays and weekends in October, 2014. Route 1 is a main route crossing the city center and suburb area. Some detail information is listed as follows:

- The operational time of Route 1 is between 5:50 a.m. and 22:00 p.m., and the average headway is about 5mins, which isn't a regular interval.
- The total length is 9.5 kilometers with 17 stops at each direction crossing the city center and suburb areas as showed in Fig. 4.1. The travel time from the first stop, Huidong bus terminal station, to the last stop, Zhangjia Dam station, is about 40mins.

4.1. Data processing

In this part, four different groups were selected because every group represents a different traffic flow and passengers demand. They are peak hours (7:30a.m.—9:30 a.m.) in the city center and suburb area, and non-peak hours (12:30p.m.—14:30 p.m.) in the city center and suburb area. We divided these collected bus arrival time data of 16 days into two parts, 400 samples for training and the rest for predicting. The characteristics of four different groups are listed in Table 4.1.

Fig. 4.1 Configuration of Route 1

Table 4.1 Characteristics of four different groups

Groups	Time	Train Sample Size	Predict Sample Size	Length	Areas
1	7:30a.m.—9:30 a.m.	400	130	2.3km	City Center(4 stops)
2	12:30p.m.—14:30 p.m.	400	170	2.3km	City Center(4 stops)
3	7:30a.m.—9:30 a.m.	400	107	1.3km	Suburb(4 stops)
4	12:30p.m.—14:30 p.m.	400	113	1.3km	Suburb(4 stops)

Note:

Four stops in the city center are Stop 5 to Stop 8 in Fig. 4.1.

Four stops in the suburb area are Stop 13 to Stop 16 in Fig. 4.1.

Considering different routes passing the same stops, Route 35 (Fig. 4.2a stop1-4) was chosen in the city center. Route 32(Fig. 4.2b stop1-4) and 38(Fig. 4.2c stop1-4) are corresponding ones in suburbs.

Fig. 4.2a Configuration of Route 35

Fig. 4.2b Configuration of Route 32 Fig. 4.2c Configuration of Route 38

Fig. 4.2 Configuration of Different Routes with Same Stops

4.2. Performance measurements

According to Eq. (1), the performance evaluation of arrival time predicted model can be conveyed to that of travel time. Two performance measures are adopted to evaluate the prediction effect of the proposed model, and respectively are Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_{travel} - \hat{t}_{travel}}{t_{travel}}\right| \times 100\% \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(t_{travel} - \hat{t}_{travel}\right)^2}{n-1}} \tag{11}$$

Where t_{travel} denotes the actual bus travel time collected by bus vehicle equipment and $\hat{t}_{travel}$ denotes the predicted bus travel time based on the proposed model, and n is the sample size for prediction.

4.3. Accuracy Analysis and Model Comparison

Accuracy Analysis

Radial basis function (RBF) kernel is used in the prediction by SVM according to the previous researches. Libsvm is an efficient software package to deal with regression and pattern recognition problems. We made use of cross-validation to determine the best cost (-c) and gamma (-g) after normalizing the data to [0, 1]. Svm-train and svm-predict help to complete training and predicting tasks in Libsvm.

Genetic Algorithms are used to optimize the BP-ANN. 3-5-1 structure (three input values, five hidden layer nodes, and one output value) is suitable for the case solved by MATLAB. One character of ANN is that the predicted results vary even if the structure and input values are same. Hence, we choose the best result of 10 tests per group in terms of the performance measure MAPE.

Three input values are prepared according to the proposed model in part 3. The parameter k_1 , which refers to the number of preceding bus vehicles of the same route in the input value 1, is set to 3. Another parameter k_2 in the input value 3 should be determined as well, e.g. . Predicted results by SVM and ANN are shown in Table 4.2.

Table 4.2 Predicted results by SVM and ANN

Group	Features	Average travel time(s)	Average Speed (km/h)	MAPE		RMSE(s)	
				SVM	ANN	SVM	ANN
G1	Peak hours, city center	826.92	10.01	11.65%	9.92%	263.59	235.40
G2	Non-peak hour, city center	463.99	17.85	9.75%	8.55%	61.01	50.53
G3	Peak hours, suburb	171.85	27.23	9.50%	10.42%	29.80	31.59
G4	Non-peak hour, suburb	149.76	31.25	8.87%	8.19%	18.63	18.26

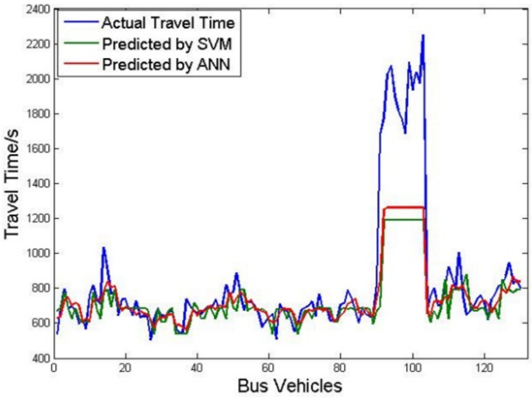

Fig. 4.3a Predicted Results of Group 1
（Peak hours, city center）

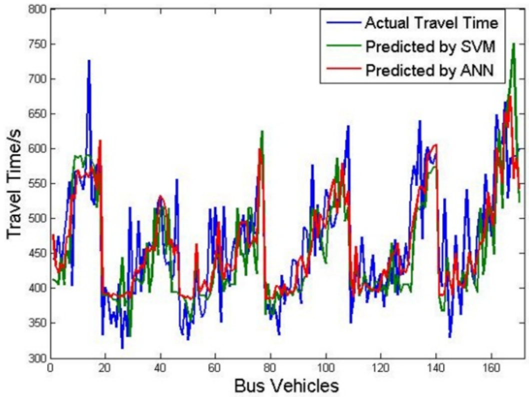

Fig. 4.3b Predicted Results of Group 2
（Non-peak hour, city center）

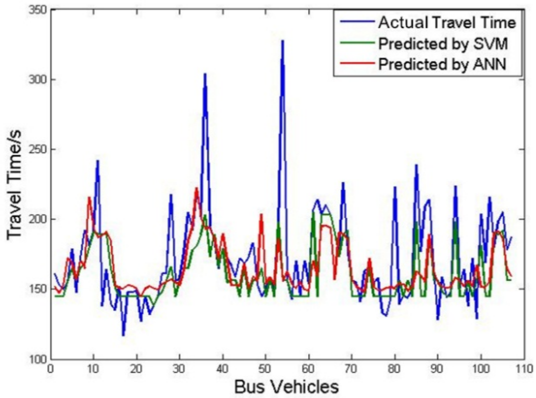

Figure 4.3c Predicted Results of Group 3
（Peak hours, suburb）

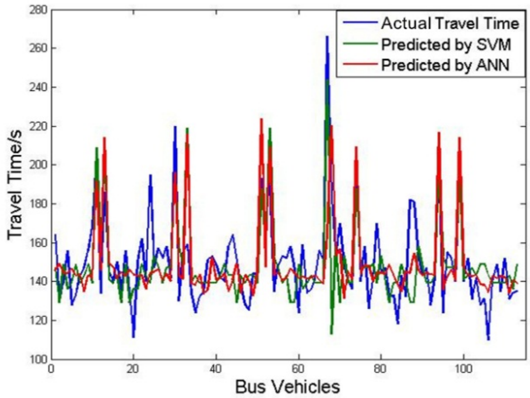

Figure 4.3d Predicted Results of Group 4
（Non-peak hour, suburb）

Fig. 4.3 Predicted Results of Different Groups

As shown in Table 4.2 and Fig. 4.3, the results predicted by ANN are better than those predicted by SVM excluding the prediction of peak hours in suburb areas. In general, the trend of predicted values is the same as the actual one, and almost all MAPE values are less than 10 %, except Group 1 by SVM and Group 3 by ANN. The value of RMSE in Group 1 is much larger than others due to the fluctuation of autual bus travel time, which shows the dispersion degree is high during the peak hours in the city center.

Model Comparison

In some previous studies, only one preceding bus vehicle of objective bus would be focused on, which leads to the randomness increase (Yu, 2011). Meanwhile, some detailed analysis on different routes with the same stops on predicted links are neglected. To verify advantages of the proposed model with three different input values, two other models with a little change are built to do some sensitivity analysis. Three scenarios with various input values are listed in Table 4.3 below.

Table 4.3 Description of three scenarios with various input values

Scenarios	Input 1	Input 2	Input 3
S0	√	√	√
S1	Changing k_1 =3 to k_1 =1	√	√
S2	√	√	×

Some explanations are given to illustrate the differences among the three scenarios.

- S0 includes all three input values as the model in part 3.
- S1 considers just one preceding bus vehicles of the objective route, which means changing the parameter k_1 from 3 to 1. Other two input values are the same as those in S0.
- S2 removes the input 3 while remaining other two input values.

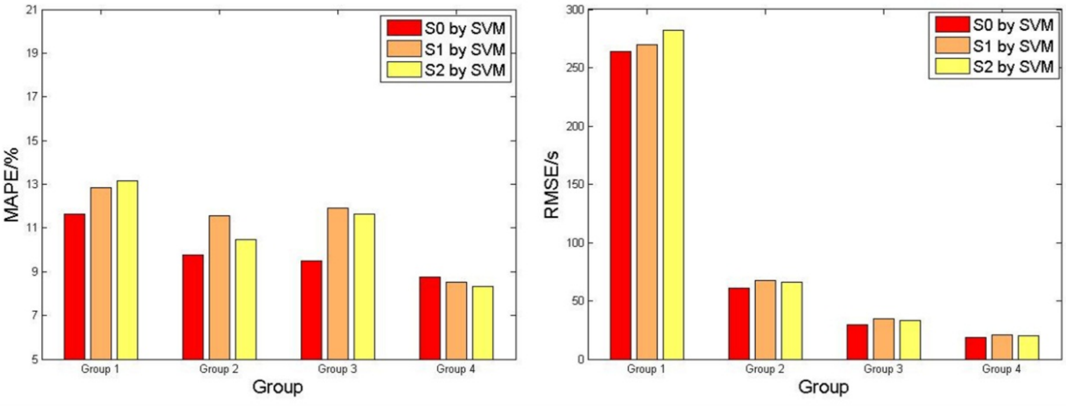

Fig. 4.4a MAPE with different input values Fig. 4.4b RMSE with different input values

Fig. 4.4 Prediction errors with different input values by SVM

Fig. 4.4 is a bar chart which describes prediction errors of three scenarios using SVM. There is a significant error reduction of S0 compared with S1 and S2 in Group 1, 2 and 3. The difference is not apparent in Group 4 due to the stability of traffic flow during the non-peak hours in suburb.

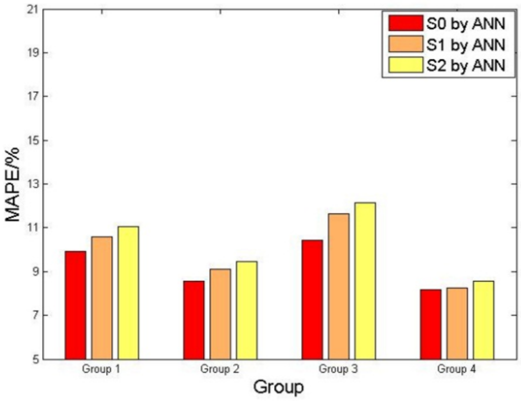

Fig. 4.5a MAPE with different input values

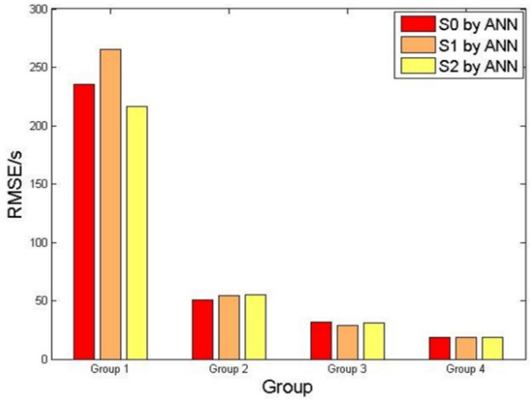

Fig. 4.5b RMSE with different input values

Fig. 4.5 Prediction errors with different input values by ANN

From Fig. 4.5a we can see that Scenario 0 results in the lowest mean absolute percentage error in any group. Some particular situation of Group 1 appearing in Fig. 4.5b suggests that there was contingency when we predicted bus travel time by ANN model. However, ignorance of different bus routes (S2) may bring out worse predicted consequence than the decrease of corresponding preceding bus vehicles numbers (S1). To sum up, similar to the prediction by SVM, Fig. 4.5 can also show some advantages of our proposed model with three different input values by ANN.

In conclusion, the two figures clearly shows that the three input values in S0 have an apparently positive influence on bus travel time prediction. Only considering one preceding bus vehicle and objective bus route may increase the prediction errors. The case study indicate that the proposed model can obtain a satisfactory result.

5. Conclusion

Accurate bus arrival time prediction can reduce the passengers' waiting time at stops and help them make a proper travel plan. Meanwhile, the prediction results can be employed as a criterion to determine when and how to conduct bus vehicles dispatching and dynamic control. Acceptance of the passengers regarding accuracy of travel time prediction can also used as an evaluation index of passenger satisfaction.

A new bus arrival time prediction model was proposed in this paper. This model considered all bus routes passing the objective stops which are related to prediction. Three factors, which had a strong influence on bus arrival time, are chosen as input values in support vector machine model and artificial neural network model. The three factors are the weighted travel time of preceding bus vehicles with the objective route $t^{L}_{travel,ij}$, the travel speed of objective bus of the latest segment $v^{N}_{i-1,i}$ and the weighted travel time of preceding bus vehicles with different routes $t^{l}_{travel,ij}$, respectively.

A case study of Route 1 in Zigong was conducted to verify the feasibility of the proposed model. The mean absolute percentage errors of SVM predicted results are 11.65%, 9.75%, 9.50%, and 8.87%, respectively in the city center during peak time and non-peak time and in the suburb area during peak time and non-peak time. Those of ANN predicted results correspondingly are 9.92%, 8.55%, 10.42%, and 8.19%. The results indicated that the proposed model can predict bus arrival time well. Two other models with inputs changed or removed were built, which demonstrated the rationality and superiority of our model.

However, improvement still is required in this study. For instance, more factors influencing the prediction of bus arrival time should be evaluated and included in the prediction model, such as weather and infrastructures (exclusive bus lanes and stops forms). Besides, this paper mainly focus on one bus route. It will be more practical and significant to improve the model to adapt the bus route network. Overcoming the large fluctuation during the peak hours in the city center to improve the predicted accuracy also need further research.

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