Real-Time Bus Arrival Time Prediction: Case Study for Jinan, China

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Abstract: Providing real-time bus arrival information can help to improve the service quality of a transit system and enhance its competitiveness among other transportation modes. Taking the city of Jinan, China, as an example, this study proposes 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. Also, to contend with the difficulty in capturing the traffic fluctuations over different time periods and account for the impact of signalized intersections, this study also subdivides the collected dataset into a bunch of clusters. Sub-ANN models are then developed for each cluster and further integrated into a hierarchical ANN model. To validate the proposed models, six scenarios with respect to different time periods and route lengths are tested. The results reveal that both proposed ANN models can outperform the Kalman filter model. Particularly, with several selected performance indices, it has been found that the hierarchical ANN model clearly outperforms the other two models in most scenarios. **DOI: 10.1061/(ASCE)TE.1943-5436.0000589.** *© 2013 American Society of Civil Engineers.*

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Introduction

To contend with increasing transportation demand, public transit systems have been recognized as one of the most effective modes to relieve traffic congestion. In an advanced transit system, providing bus arrival time information can help to improve service quality, attract more riders, and thus enhance its competitiveness among other transportation modes. However, the existing bus information systems (BIS) in most Chinese cities, such as Jinan, can only offer bus location information (e.g., the coming bus is 2 stations away). Therefore, to offer passengers a direct perception of bus arrivals, a reliable prediction model for bus arrival time is essential. Over the past decades, many efforts have been devoted to this field, which can be divided into five categories: (1) historical average models (Lin and Zeng 1999; Chien and Kuchipudi 2003; Jeong and Rilent 2005; Sun and Hickman 2006; Sun et al. 2007; Chen et al. 2012); (2) regression models (Alfa et al. 1988; Tétreault and El-Geneidy 2010); (3) artificial neural networks (ANN) models (Park and Rilett 1999; Chien et al. 2002); (4) Kalman filter (KF) models (Wall and Dailey 1999; Cathey and Dailey 2003; Chen et al. 2004; Shalaby and Farhan 2004; Chen et al. 2005; Vanajakshi et al. 2008; Padmanabanl et al. 2010); (5) other methods: Markov chains (Lin and Bertini 2004; Yeon et al. 2008), the k-nearest neighbor model (Chu et al. 2007), and support vector machine based on multiple bus routes (Yu et al. 2011).

Particularly, Shalaby and Farhan (2004) established the KF model to predict bus arrival time based on link travel time and the number of waiting passengers, which are collected by an automatic vehicle location (AVL) system and an automatic passenger counter (APC) system. With the AVL information, Vanajakshi et al. (2008) predicted bus arrival time under mixed traffic flows with a KF model considering the flow dispersion. Chien et al. (2003) studied travel time data collected by an automatic fare collection (AFC) system, and established segment-based and stop-based KF models for short-term arrival prediction. Park and Rilett (1999) concluded that the ANN model can provide better performance than some link-based models, such as KF models, exponential smoothing models, and historical profiles. Jeong and Rilett (2004) later proposed an ANN model to predict bus dwelling time at bus stops with AVL data, and Chien et al. (2002) suggested link-based ANN and stop-based ANN models for bus arrival time prediction, taking the historical arrival time, travel speed, traffic flows, and delays as inputs. Bladikas et al. (2009) analyzed impacts of different weather conditions on bus travel time variance. Moreover, Yu et al. (2011) conducted observation surveys to collect bus travel time data to develop support vector machine (SVM) models for multiple routes, which are more accurate than those single-route models if the overlapped rate of bus routes is very high.

Due to the high uncertainty of bus travel time in a congested network, the ANN model, which is based on the fundamental theory of neural network, has been proved as one of the most efficient methods for bus arrival predictions. This study selects the city of Jinan as an example for this model's implementation. Jinan, the capital city of Shandong Province with a population over 6 million, has more than 180 bus routes, six bus rapid transit (BRT) routes, and over 4200 bus vehicles. Particularly, some unique operational characteristics in Jinan are found: non-fixed daily schedule, incomplete data, high departure frequency, short station spacing, and congested road network. Also, buses are equipped with both an in-vehicle global positioning system (GPS) and an AFC system.

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The GPS-based AVL system can provide dynamic bus location information, and the AFC system would collect partial bus dwelling information when passengers swipe their cards (Li et al. 2011). In this study, GPS data are selected as the major data resource and AFC data are used to fill gaps when GPS data are missing.

To facilitate the performance of ANN models, how to select the input variables is an important issue. Based on the collected field data, this paper analyzes the potential impact factor of bus travel time, selects the candidate variables, and then proposes an ANN model. However, our data analysis reveals that bus travel time significantly fluctuated over different time periods. Also, the existence of signalized intersections can greatly increase delays. Therefore, to improve prediction accuracy, the whole dataset is subdivided into a bunch of clusters according to the data collection time and the predefined delay level. Following that, the sub-ANN (SANN) model is then developed for each data cluster, and further integrated as a hierarchical ANN (HANN) model. In this study, about 80% of the field data is used to calibrate the parameters of the ANN models and 20% is utilized for model evaluation and validation.

This paper is organized as follows: in the next section, an introduction of the data collection site is given and several corresponding challenge issues are concluded; following that, a set of input variables are selected and two ANN models are developed. Next, this study presents a case study with six different scenarios in Jinan, and several key findings are summarized in the conclusion section.

Data Collection and Analysis

The data were collected on route 63 from November 1 to November 30th, 2010. Fig. 1 illustrates the bus stop distribution along the study route with bus stops numbered in balloons, and some operational characteristics are

- The length of the selected route is about 8.1 km;
- There are about 15 stops marked by numbers 1 to 15 on each direction;
- The bus operation time is from 6:00 a.m. to 9:00 p.m.; and
- The departure headway is around four minutes during peak hours and about 10 minutes during non-peak hours.

Two types of data are collected: GPS data and AFC data, and the GPS data are used as our major resource. Since GPS data may be lost sometimes during the data transmission process, the AFC data will be used to fill the gap when the GPS data is not available based on the following principles:

- Bus arrival time at stops could be estimated by the card swiping time of the first boarding passenger minus the summation of door-opening time and average passenger boarding time; and
- Bus departure time from stops could be estimated by the card swiping time of the last passenger plus door-closing time and average passenger moving time from a ticket machine to a seat (half vehicle length divided by the average pedestrian walking speed).

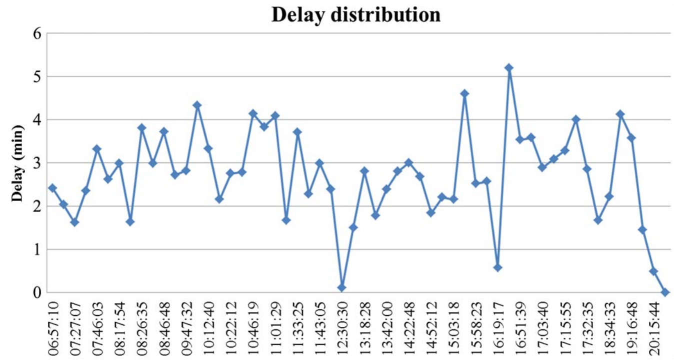

Fig. 2. Time-dependent bus delay of route 63 from stop 3 to stop 10

Fig. 2 shows the delay distribution of one segment (from stop 3 to stop 10) on route 63, from 6:57 a.m. to 08:50 p.m. on November 28, 2010. Particularly, bus delays can be approximately computed using the following equation:

$$\text{Bus delay} = \text{Actual travel time} - \text{Free flow travel time} - \text{Average bus dwelling time} \quad (1)$$

where the average bus dwelling time is an approximate value obtained from historical data. Under the low-traffic demand pattern, the delay can drop to zero, while it can sharply reach up to four minutes during peak hours. Therefore, it would be difficult to capture the trend of bus delay using a well-defined mathematic model. To better understand the prediction background, this study carefully takes the following characteristics into account.

1. Since only some passengers may swipe a bus card to pay for tickets, the AFC system, which is only used to collect bus fares, is unable to offer reliable information for bus dwelling time at stops. Also, the update interval of GPS (e.g., 30 s in Jinan) would limit the estimation accuracy. Hence, it is not appropriate to select bus dwelling as one of the input variables in the ANN models;
2. The network is intensive, revealed by the short distance between bus stops. Also, multiple bus routes may be overlapped on one single arterial;

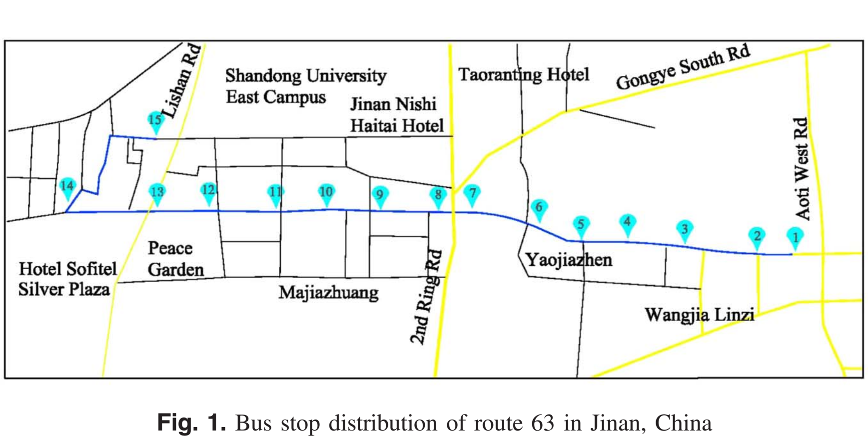

Fig. 1. Bus stop distribution of route 63 in Jinan, China

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3. To satisfy the large passenger demand, the transit system is operated under a high departure frequency ($6 \sim 30$ buses per hour), which consequently requires a quick-response prediction model;
4. The departure schedule is changed over time. For the concern of the demand variation, most transit agencies cannot provide a fixed timetable to passengers. Instead, the responsive agencies may adjust the schedule according to the information frequently observed by on-site surveyors.

In conclusion, those characteristics can lead to high uncertainty regarding bus arrival time. Based on the data analysis, several methods could be candidates for prediction, including time series model, KF model, regression model, and ANN model. The accuracy of the time series model relies highly on the stability of historical traffic patterns, and a significant variation of historical data can cause inaccurate predictions. Linear or nonlinear regression models could measure the simultaneous influence of various factors affecting the dependent variables via correlation and significance tests. However, the inputs of a regression model are required to be independent variables so it may limit its application to a transit system containing various highly intercorrelated variables. The KF model is only effective for one time step ahead prediction, and the results will deteriorate when the prediction time window increases. In contrast, the ANN model is a promising approach to describe complex systems having significant intercorrelated factors. Consequently, the neural network technique is selected in this paper.

Model Development

Candidate Variables

Based on the aforementioned discussions, the bus dwelling time at stops cannot be accurately estimated with the available data. Therefore, instead of using dwelling time directly, this study selects bus travel time (the sum of running time and dwelling time) and bus headway as the major input variables. Bus travel time and headway could be computed by the following equations:

$$tt_{i,j}(k) = a_j(k) - d_i(k) \qquad i < j \leq N, \qquad k \leq K \tag{2}$$

$$h_i(k) = a_i(k) - a_i(k-1) \qquad i < j \leq N, \qquad k \leq K \tag{3}$$

where $a_i(k)$ represents the arrival time of bus k at stop i; $d_i(k)$ is the departure time of bus k from stop i; $tt_{i,j}(k)$ denotes the travel time of bus k between stop i and j; and $h_i(k)$ denotes the actual headway between bus k and downstream bus k-1 at stop i; N is the number of bus stops; and K denotes the number of bus vehicles.

In response to different levels of passenger demand, the transit system could be operated with two types of strategies: schedule-based and headway-based. A schedule-based strategy is normally used in low demand routes. For those bus routes with high passenger demand, many cities (e.g., Jinan) utilize the headway-based operation strategy, in which buses are dispatched from depots based on proper time-space headways, instead of on a fixed scheduled timetable. Consequently, in the headway-based transit system, the actual bus headway is an essential variable which directly affects bus arrival time. Fig. 3 presents daily headway distributions in weekdays and weekends. As shown in Fig. 3(a), the actual headways fluctuated significantly over different times of day on weekdays. However, Fig. 3(b) reveals a more-stable headway distribution over the weekend.

Fig. 4 shows the average travel time and the corresponding variance over different times of day (a.m.-peak hours (7:00–9:00), p.m.-peak hours (5:00–7:00), and off-peak hours) and different

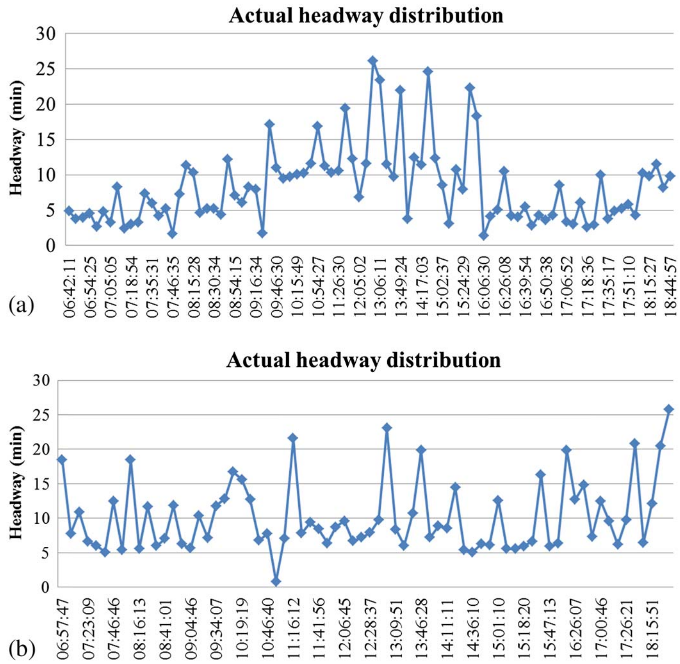

Fig. 3. Actual headway distribution of bus route 63 at stop 8: (a) actual headway distribution on weekdays; (b) actual headway distribution on weekends (x-axes are time)

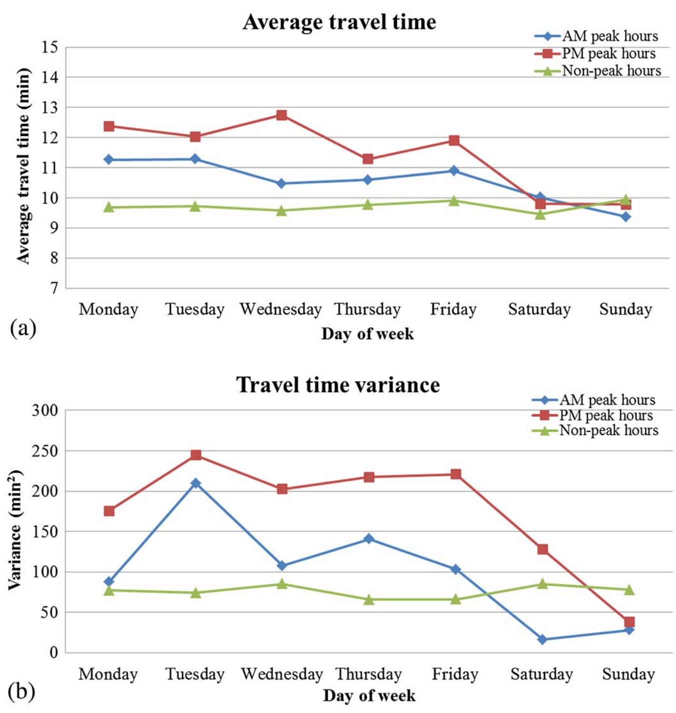

Fig. 4. Statistic of travel time from stop 3 to stop 10

days of week (Monday–Sunday). From this figure, one can observe large variations in travel times during weekdays (Monday–Friday), and a much smaller variation during the weekends. To account for this phenomenon, this study defines a set of time indices to identify the prediction time periods. Specifically, four different time periods are distinguished: weekday a.m. peak hours, weekday p.m. peak hours, weekday off-peak hours, and weekend all-day.

Also, in real world applications, traffic signals at intersections can greatly impact bus travel time. To better understand the

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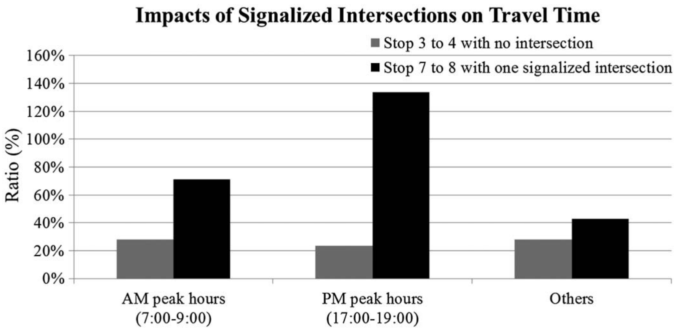

Fig. 5. Impact of signalized intersection on travel time

influences of signalized intersections, this study selects two route segments for comparisons: (1) stop 3 to stop 4 without intersections; and (2) stop 7 to stop 8 with one signalized intersection. Fig. 5 shows the comparisons of bus delay between these two segments, using the data collected on weekdays (November 24, 2010, to November 11, 2010). Obviously, the delay of segments 3–4 is apparently less than the one of segment 7–8, especially during the p.m. peak hours. For the convenience of modeling, this study defines a delay ratio as

$$\text{Delay ratio} = \frac{\text{Bus delay}}{\text{Free flow travel time} + \text{Average bus dwelling time}} \quad (4)$$

where the bus delay can be calculated by Eq. (1). Based on the calculated delay ratios, a set of indices are defined to represent the experienced delay levels

- Level 1-the ratio is less than 0.25;
- Level 2-the ratio ranges [0.25, 0.5);
- Level 3-the ratio ranges [0.5, 0.75); and
- Level 4-the ratio is greater than or equal to 0.75.

In summary, the selected input variables for the bus arrival prediction are listed in Table 1.

Table 1. Summary of Input Variables

Variables	Description	Data source
$a_i(k)$	Arrival time at stop i	GPS and AFC
$d_i(k)$	Departure time of bus k from stop i where $k \geq 1$, $i \geq 1$	GPS and AFC
$tt_{i,j}(k\text{-}1)$	Travel time of bus k-1 between stop i and j	GPS and AFC
$tt_{i,j}(k\text{-}2)$	Travel time of bus k-2 between stop i and j	GPS and AFC
$tt_{i,j}(k\text{-}3)$	Travel time of bus k-3 between stop i and j	GPS and AFC
$h_i(k)$	Headway of bus k at stop i	GPS and AFC
$h_i(k\text{-}1)$	Headway of bus k-1 at stop i	GPS and AFC
$h_i(k\text{-}2)$	Headway of bus k-2 at stop i	GPS and AFC
$h_i(k\text{-}3)$	Headway of bus k-3 at stop i	GPS and AFC
tt	Time index (indicate the time of day and day of week)	Computed data
td	Index of the delay level	Computed data

Since greater numbers of input variables can lead to longer computation times, it is inappropriate to include all the available historical data in the ANN model. Hence, to balance prediction accuracy and computation efficiency, this study only selects the historical travel time of the last three preceding buses that passed the target bus stop several minutes before to be used as the model inputs. These three related variables, $tt_{i,j}(k\text{-}1)$, $tt_{i,j}(k\text{-}2)$, and $tt_{i,j}(k\text{-}3)$, can be found in Table 1.

ANN Model

Due to the complex relations between bus arrival time and the candidate variables mentioned in the preceding subsection, a basic ANN model is first developed for bus travel time prediction. And the bus arrival time at the downstream stop could be easily computed by the sum of predicted travel time and departure time from the upstream stop. In this study, an ANN architecture with typical three layers (the input layer, hidden layer, and output layer) is adopted (Kalaputapu and Demetsky 1995; Hagan et al. 1996). The back-propagation algorithm is applied to optimize weights of the hidden layer with the objective of minimizing the prediction errors (Chien et al. 2002), and the transfer function is a sigmoid nonlinear function. Multiple numbers of hidden neurons (10, 13, 15, 16, 18, and 20) are tested, and the best number 16 is selected for our case.

The estimated travel time for bus k between stop i and j is given as

$$\overline{tt}_{i,j,tt,td}(k) = f_{tt,td}(i,j) \sim f_{tt,td}[a_i(k), tt_{i,j}(k - MT), h_i(k - MH), tt, td] \quad (5)$$

where $f(\bullet)$ stands for the ANN function; and $tt_{i,j}(k - MT)$ and $h_i(k - MH)$ indicate the historical bus travel time and headway from stop i to stop j, respectively.

HANN Model

Given the data analysis, the bus travel time varied over different time periods. Therefore, it is not appropriate to put all the collected data together and form a single prediction model (i.e., the ANN model). A better alternative is to separate the problem according to the prediction time. Following this principle, the dataset is subdivided into four groups with respect to weekday a.m. peak hours, weekday p.m.-peak hours weekday off-peak hours, and weekends. Different segments may experience different delays caused by intersections, and the dataset is further subdivided based on the defined delay level. With the separation of data, a set of SANN models are developed, each of which corresponds to one divided data cluster.

In order to facilitate the predication model, those developed SANN models are further integrated as a HANN model. For the convenience of this discussion, a set of binary variables are introduced

$$b_{i,j,tt,td} = \begin{cases} 1 & \text{if } tt = u, td = v, u \leq TT, v \leq TD \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where u and v denote the type of time of day and the level index of the delay ratio in Fig. 5, respectively. TT is the total number of time types, and TD is the total number of the delay levels.

According to Eqs. (5) and (6), the HANN model can be formulated as follows:

$$\overline{tt}_{i,j,tt,td}(k) = \sum_{u=1}^{TT} \sum_{v=1}^{TD} b_{i,j,tt,td} f_{tt,td}(i,j) \quad (7)$$

With Eqs. (2) and (7), the predicted arrival time of bus k at stop j from the current stop i can be computed using the following equation:

$$\bar{a}_j(k) = d_i(k) + \overline{tt}_{i,j,tt,td}(k) \quad (8)$$

The flow chart of solution program is shown in Fig. 6.

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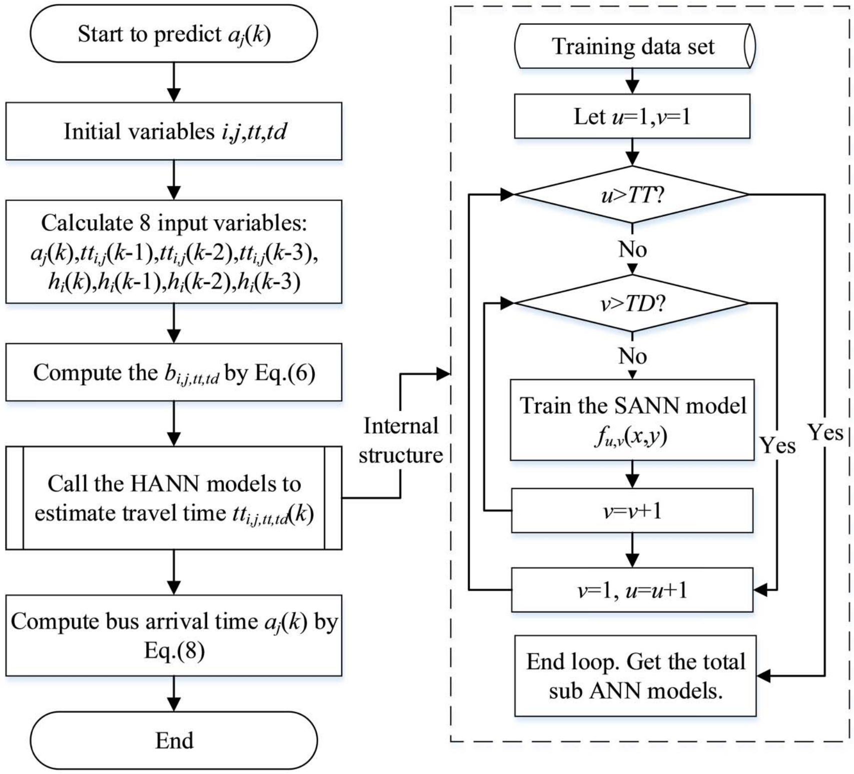

Fig. 6. Flowchart of the solution algorithm for the proposed HANN model

Results Analysis

To evaluate the performance of the proposed models, this paper selects six different scenarios with respect to different time periods (weekday a.m. peak hours, p.m. peak hours, off-peak hours, and weekends) and route lengths. Table 2 summarizes the detailed description of each scenario. The total sample size is 1,688, where 82% are used for parameter training and the rests are used for model validation.

Accuracy Analysis

To evaluate the prediction accuracy, two types of performance indices are defined

$$\text{Relative Average Error (RAE)} = \frac{\text{Average Prediction Error}}{\text{Average Travel Time}} \times 100\% \tag{9a}$$

$$\text{Relative Variance of Error (RVOR)} = \frac{\text{Variance of Prediction Error}}{\text{Average Travel Time}} \times 100\% \tag{9b}$$

where the prediction error is the absolute difference between predicted travel time and actual travel time. Also, this study implements the KF model (Shalaby and Farhan 2004) for comparisons, and the results from different models are shown in Figs. 7–10.

As shown in Fig. 7, for the scenarios S1–S3, the average prediction error (APE) of the proposed HANN model is less than 0.2 min. Meanwhile, the APEs of three scenarios having distances of 2.3 km are about 1 min. In Figs. 8 and 9, comparing the KF model and proposed models, one can find that the KF model produces the highest prediction errors. For the scenarios S1, S2, and S3, the HANN model provides the best predictions, while the ANN model offers the best prediction for scenario S4, S5, and S6. Moreover, the APE of HANN model is only 0.1 min. Fig. 10 also reveals that the HANN model can provide promising accuracy for scenarios S1, S2, and S3. Consequently, one can find that the HANN model is more potentially appropriate for short-distance route prediction while the ANN model is better for long-distance route prediction. The reason is that the ANN model can obtain a larger training sample set compared with the categorized HANN model. For short-distance route prediction, the category of the samples can help the neural network to arrive at better predictions. However, traffic conditions become more

Table 2. Detailed Descriptions of Six Scenarios

Scenario	Date	Time of day	Sample Size	Test Size	Description
S1	Nov 29, Monday	AM-Peak hours	163	30	Stop 3 to 4 (0.36 km in length)
S2	Nov 24, Wednesday	PM-Peak hours	147	21	
S3	Nov 27, Saturday	All day	415	85	
S4	Nov 29, Monday	AM-Peak hours	217	32	Stop 3 to 8 (2.3 km in length)
S5	Nov 24, Wednesday	Off-peak hours	416	51	
S6	Nov 28, Sunday	All day	330	88	

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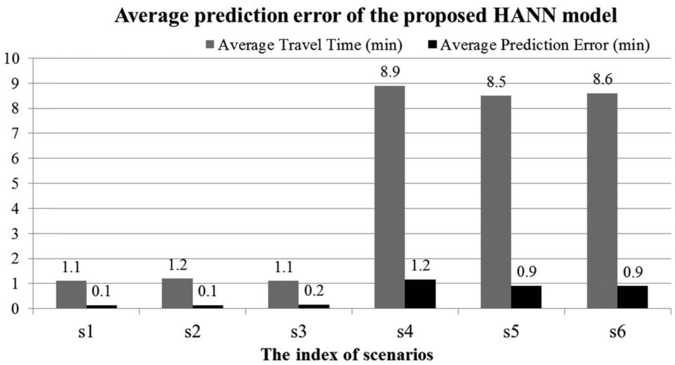

Fig. 7. Average prediction error

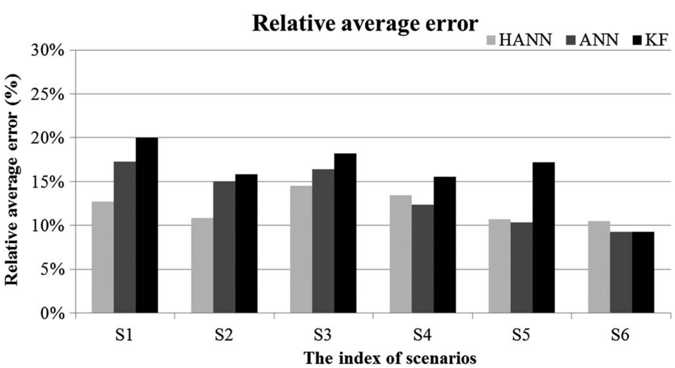

Fig. 8. Relative average error

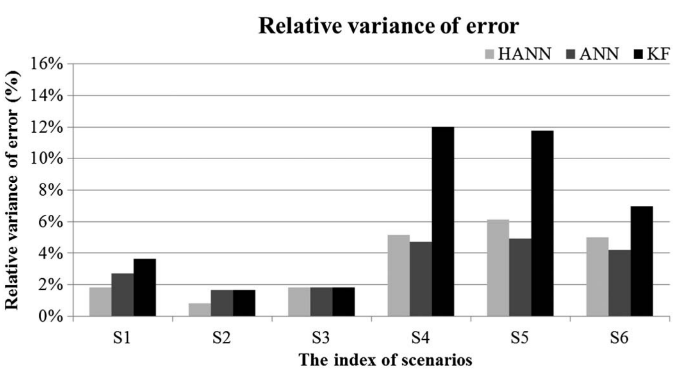

Fig. 9. Relative variance of error

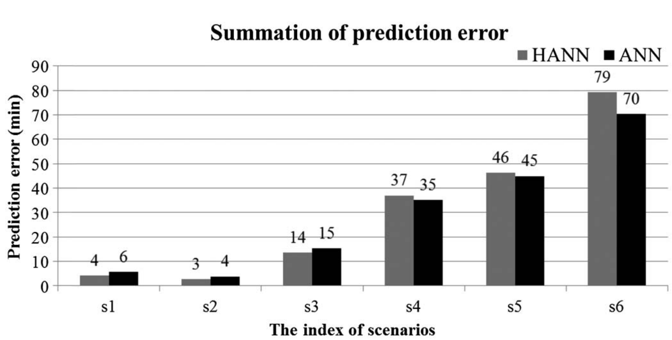

Fig. 10. Summation of prediction error

complex with increased bus travel distance, and under these conditions, a larger training sample size would be more helpful to further improve predictions.

Reliability Analysis

Based on the accuracy analysis, one can conclude that the proposed models can outperform the KF model. To further evaluate the reliability of these two models, this section selects another performance index, the relative prediction error (RPE), for analysis.

$$\text{Relative Prediction Error} = \frac{\text{PredictionError}}{\text{Actual Travel Time}} \times 100\% \qquad (10)$$

Based on the resulted RPE, Fig. 11 shows the cumulative distribution function for each scenario. From Figs. 11(a–e), it is easy to observe that the proposed models are more reliable than the KF model. For example, the HANN model produces the lowest RPE in scenarios S1 and S2. For scenario S6, Fig. 11(f) indicates the RPE distributions of these three models are almost identical. This paper further analyzed the actual data of scenario S6 and found that the traffic volume on that day is much lower and the travel time variance is quite small (0.8 min). In this situation, all three models can achieve a good prediction result, which also leads to the similar RPE distribution.

Generally speaking, the proposed ANN model and HANN model can provide a concurrently-acceptable prediction of bus arrival time in Jinan. Compared with the KF model, the evaluation results reveal the benefits of the proposed models, for both prediction accuracy and reliability. Also, the comparisons between the ANN model and HANN model indicate the HANN model is preferable for short-distance prediction when the training sample is sufficient.

Conclusions

This paper studies the characteristics of bus operations, and finds some key factors that affect bus arrival times. On the basis of nonlinear properties, the paper proposed the artificial neural network model and hierarchical artificial neural network to predict short-term bus arrival times based on available data, which includes four types of variables, namely, time index, the level of bus delay, arrival time, and headway distribution. In the case study, which included field data from GPS, the developed models outperformed existing Kalman Filter models, especially for predicting bus arrival between neighboring stops. Under recurrent traffic conditions, the relative prediction error within a 10 min prediction time window is less than 20% with a reliability probability of more than 85%, while the probability of having more than 40% relative prediction errors is no more than 7%. Most importantly, the proposed method is computation-friendly with a calibration time of less than 2 min, which makes it applicable in a real-time bus arrival prediction system.

Future research along this line will address some limitations of the proposed models: (1) the developed models may not provide promising results when the prediction time window is larger than ten minutes, so that it is necessary and valuable to further improve prediction accuracy by optimizing the ANN architecture; and (2) the tested scenarios are not sufficient to reflect the benefits of proposed models under different conditions, and it is important to collect more field data to perform statistical analysis.

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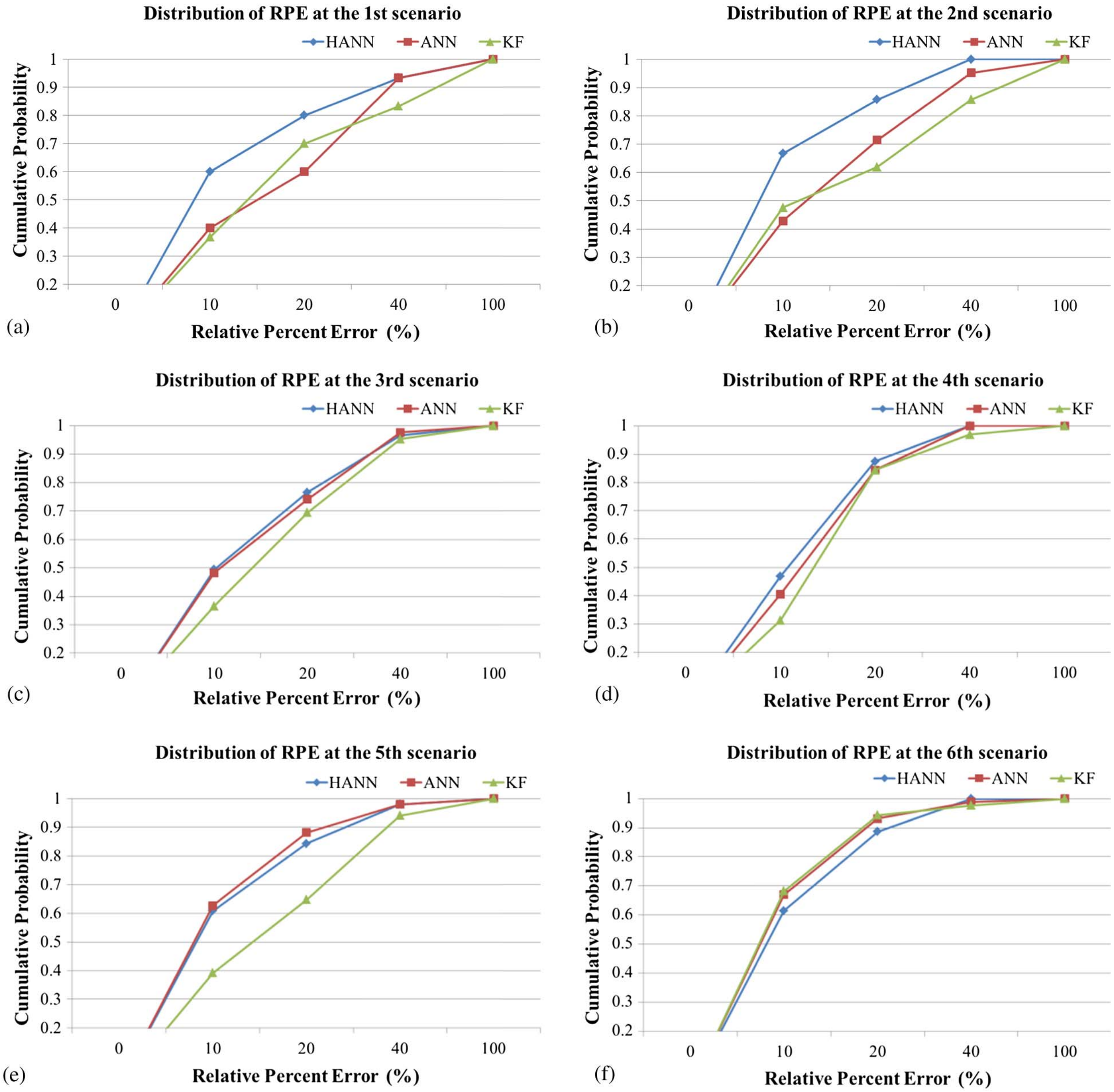

Fig. 11. Distribution of cumulative probability of RPE at six scenarios: (a) first scenario; (b) second scenario; (c) third scenario; (d) fourth scenario; (e) fifth scenario; (f) sixth scenario

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References

Alfa, A., Menzies, W., Purcha, J., and Mcpherson, R. (1988). "A regression model for bus running times in suburban areas of Winnipeg." *J. Adv. Transport.*, 21(3), 227–237.

Bladikas, A., Tsai, F. M., and Chien, S. I. (2009). "Evaluation of bus travel time and schedule adherence under adverse weather." *Transportation Research Board 88th Annual Meeting*, Transportation Research Board, Washington, DC.

Cathey, F. W., and Dailey, D. J. (2003). "A prescription for transit arrival/departure prediction using automatic vehicle location data." *Transport. Res. C Emerg. Tech.*, 11(3–4), 241–264.

Chen, G. J., Yang, X. G., An, J., and Zhang, D. (2012). "Bus-arrival-time prediction models: Link-based and section-based." *J. Transp. Eng.*, 138(1), 60–66.

Chen, M., Liu, X. B., and Xia, J. X. (2005). "Dynamic prediction method with schedule recovery effect for bus arrival time." *Transportation Research Record 1923*, Transportation Research Board, Washington, DC, 208–217.

Chen, M., Liu, X. B., and Xia, X. J. (2004). "A dynamic bus arrival time prediction model based on APC data." *Comput.-Aided Civil Infrastruct. Eng.*, 19(5), 364–376.

Chien, S., Ding, Y. Q., and Chien, H. W. (2002). "Dynamic bus arrival time prediction with artificial neural networks." *J. Transp. Eng.*, 128(5), 429–438.

Chien, S., and Kuchipudi, C. M., (2003). "Dynamic travel time prediction with real-time and historical data." *J. Transp. Eng.*, 129(6), 608–616.

Chu, H., Cai, Y., and Yang, X. G. (2007). "Research on bus arrival time prediction based on multi-source traffic information." *Proc., The 7th International Conference on ITS Telecommunications*, IEEE, New York, 4551–4557.

Hagan, M. T., Demuth, H. B., and Beale, M. (1996). *Neural network design*, PWS, Boston.
Jeong, R., and Rilent, L. R. (2005). "Bus arrival time prediction model for real-time applications." *Transportation Research Record 1927*, Transportation Research Board, Washington, DC, 195–204.
Jeong, R. H., and Rilett, L. R. (2004). "Bus arrival time prediction using artificial neural network model." *IEEE Intelligent Transportation Systems Conference*, IEEE, New York.
Kalaputapu, R., and Demetsky, M. J. (1995). "Application of artificial neural networks and automatic vehicle location data for bus transit schedule behavior modeling." *Transportation Research Record 1497*, Transportation Research Board, Washington, DC, 44–52.
Li, D. M., Lin, Y. J., Zhao, X. L., Song, H. J., and Zou, N. (2011). "Estimating a transit passenger trip origin-destination matrix using automatic fare collection system. Database systems for advanced applications." *Lect. Notes Comp. Sci.*, 6637, 502–513.
Lin, W., and Bertini, R. (2004). "Modeling schedule recovery processes in transit operations for bus arrival time prediction." *J. Adv. Transport.*, 38(3), 347–365.
Lin, W. H., and Zeng, J. (1999). "Experimental study on real-time bus arrival time prediction with GPS data." *Transportation Research Record 1666*, Transportation Research Board, Washington, DC, 101–109.
Padmanabanl, R. P. S., Divakarl, K., Vanajakshi, L., and Subramanian, S. C. (2010). "Development of a real-time bus arrival prediction system for Indian traffic conditions." *IET Intell. Transport. Syst.*, 4(3), 189–200.
Park, D., and Rilett, L. R. (1999). "Forecasting freeway link travel times with a multilayer feed forward neural network." *Comput.-Aided Civil Infrastruct. Eng.*, 14(5), 357–367.
Shalaby, A,, and Farhan, A. (2004). "Prediction model of bus arrival and departure times using AVL and APC data." *J. Public Transport.*, 7(1), 41–61.
Sun, A., and Hickman, M. (2006). "Vehicle travel time prediction using primitive AVL data." *Proc., 85th Transportation Research Board Annual Meeting*, Transportation Research Board, Washington, DC.
Sun, D. H., Luo, H., Fu, L. P., Liu, W. N., Liao, X. Y., and Zhao, M. (2007). "Predicting bus arrival time on the basis of global positioning system data." *Transportation Research Record 2034*, Transportation Research Board, Washington, DC, 62–72.
Tétreault, P. R., and El-Geneidy, A. M. (2010). "Estimating bus run times for new limited-stop service using archived AVL and APC data." *Transport. Res. Pol. Pract.*, 44(6), 390–402.
Vanajakshi, L., Subramanian, S. C., and Sivanandan, R. (2009). "Travel time prediction under heterogeneous traffic conditions using global positioning system data from buses." *Intell. Transport Syst.*, 3(1), 1–9.
Wall, Z., and Dailey, D. J. (1999). "An algorithm for predicting the arrival time of mass transit vehicles using automatic vehicle location data." *Proc., Transportation Research Board 78th Annual Meeting*, Transportation Research Board, Washington, DC.
Yeon, J., Elefteriadou, L., and Lawphongpanich, S. (2008). "Travel time estimation on a freeway using discrete time Markov chains." *Transport. Res. B Method.*, 42(4), 325–338.
Yu, B., Lama, W. H. K., and Tama, M. L. (2011). "Bus arrival time prediction at bus stop with multiple routes." *Transport. Res. C Emerg. Tech.*, 19(6), 1157–1170.

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