An Improved Adaptive Exponential Smoothing Model for Short-term Travel Time Forecasting of Urban Arterial Street

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Abstract Short-term forecasting of travel time is essential for the success of intelligent transportation system. In this paper, we review the state-of-art of short-term traffic forecasting models and outline their basic ideas, related works, advantages and disadvantages of each model. An improved adaptive exponential smoothing (IAES) model is also proposed to overcome the drawbacks of the previous adaptive exponential smoothing model. Then, comparing experiments are carried out under normal traffic condition and abnormal traffic condition to evaluate the performance of four main branches of forecasting models on direct travel time data obtained by license plate matching (LPM). The results of experiments show each model seems to have its own strength and weakness. The forecasting performance of IASE is superior to other models in shorter forecasting horizon (one and two step forecasting) and the IASE is capable of dealing with all kind of traffic conditions.

Key words Travel time, short-term forecasting, license plate matching (LPM), exponential smoothing

Urban traffic congestion has been a global issue. The underlying reason is that the capacity of transportation traffic system is regularly exceeded by traffic demand. There are three basic strategies to relieve congestion[1]. The first is to increase the transportation infrastructure. This strategy is very expensive and can only be accomplished in the long term. The second is to limit the traffic demand or make traveling more expensive, which will be strongly disapproved of by travelers. The third is to focus on efficient and intelligent utilization of the existing transportation infrastructure. This strategy is the best trade-off and gains more and more attention. Currently, the intelligent transportation system (ITS) is the most promising approach to implementation of the third strategy.

The success of ITS relies on the accurate forecasting of future traffic condition rather than historical or current traffic condition[2]. For example, as predictive information becomes more available to the traveling public, better decisions can be made that will help spread travel demand over time and space, and thus, reducing the amount of congestion in urban areas. With the help of predictive traffic information, the traffic management center can apply appropriate controlling strategy in advance, instead of responding to traffic congestion passively.

While forecasting of future traffic condition can be made for various traffic parameters, such as point speed, lane occupancy, and traffic volume, travelers most care for travel time information in making their trip decision. The degree of congestion can be reasonably defined by the deviation between travel time under fluent condition and that under congested condition[3].

There has been much research contributing to the field of travel time forecasting[4−7]. However, most previous studies used "indirect" travel time data (e.g., volume, occupancy, and speed), and the travel time is estimated by a function of these parameters[8]. Even though the general relation among these parameters has been explored widely, the coefficients in the function are most likely site specific. Moreover, this general relationship may not be consistent with saturated flow condition and can be affected by interruptions, such as traffic control devices, etc., in urban environment.

Recently, direct travel time data can be collected by many emerging advanced techniques, such as image-processing-based license plate matching (LPM), GPS-based floating car, and automatic vehicle identification (AVI). Those advanced techniques make it possible to directly forecast travel time based on the observed travel time data.

The objectives of this research are to evaluate the performance of existing forecasting models based on direct travel time data obtained by LPM technique and to propose an improved adaptive exponential smoothing model for short-term forecasting. The paper is organized as follows. First, a brief introduction of LPM is given in Section 1. Section 2 reviews the state-of-art of short-term traffic forecasting models and outlines their basic ideas, related works, advantages and disadvantages of each model. After that, an improved adaptive exponential smoothing model is proposed in Section 3, followed by comparing experiments of various models under normal and abnormal traffic condition in Section 4. Section 5 concludes this paper.

1 Travel time based on licence plate matching

LPM is one of the main direct approaches to collection of travel time information. In general, license plate matching techniques consist of collecting vehicular license plate characters and arrival time at various checkpoints, matching the license plate between consecutive checkpoints and computing travel time. Many years ago, LPM was carried out manually and only used in small-scale traffic survey. In recent years, LPM gained popular and can perform automatically with the advance of image-processing technique and widespread installation of video detecting devices.

Travel time over an arterial street is in nature a continuous and time-varying random variable, however, for practical purposes the observed travel time by LPM is often aggregated and stored in a discrete time interval. Fig. 1 illustrates the process. Each back dot in Fig. 1 is a sample corresponding to a matched license plate pair and I represents the I-th time interval . The aggregate mean travel time of each time interval forms a time series. Then, forecasting models use the observed mean travel time data of the previous time intervals as input and forecast the mean travel time for discrete future time intervals.

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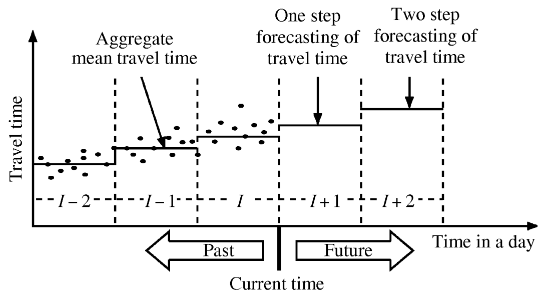

Fig. 1 Travel time forecasting based on LPM data

2 State-of-art of short-term traffic forecasting

There are few published works related to short-term traffic forecasting occuring in the traffic published works before 1990s[1]. In recent decade, however, the number of published works concerning short-term traffic forecasting expands rapidly with the advent of intelligent transportation system that spurs the demand of traffic forecasting. This section reviews the main branches of short-term traffic forecasting models and outlines their basic ideas, related works, advantages and disadvantages of each model.

2.1 Exponential smoothing model

Exponential smoothing is an intuitive forecasting method that weights the observed time series unequally. Recent observations are weighted more heavily than remote observations. The unequal weighting is accomplished by using one or more smoothing parameters, which determine how much weight is given to each observation.

Exponential smoothing model is a widely used method in time series analysis and has been adopted in traffic forecasting for decades. [3] provided a comprehensive review on the application of exponential smoothing in traffic forecasting.

The major advantage of exponential smoothing methods is that they are simple, intuitive, and easily understood. Generally, exponential smoothing is regarded as an inexpensive technique that gives good forecast in a wide variety of applications. In addition, data storage and computing requirements are minimal, which makes exponential smoothing suitable for real-time application.

The major disadvantage of exponential smoothing methods derives from its basic premise about the model: the level of time series should fluctuate about a constant level or change slowly over time. When the time series takes on an obvious trend, even adaptive exponential smoothing methods will fail to give good forecasting[3].

To overcome the disadvantage, an improved adaptive exponential smoothing model is proposed in this paper. Details about the model are given in Section 4.

2.2 ARIMA model

Auto regression integrated moving average model (ARIMA) is a classical method for time series analysis. The basic principle of ARIMA is to find the systematic component of a non-stationary time series by removing the lag and seasonality to make it stationary[9−10]. When fitting an ARIMA model to traffic time series data, there are three basic steps, which are used iteratively until a successful model is achieved: 1) Model identification: this is determination of the likely orders of auto regression, differencing, and moving average. Often there will be several plausible models to be examined. 2) Parameter estimation: once a set of possible models has been selected, parameter values are determined for each. 3) Diagnostic checking: this involves both checking how well the fitted model conforms the data and the use of diagnostic tests that are designed to suggest how the model should be changed in case of a lack of good fit. Once a good fitting ARIMA model has been found by this method, it can be used to make forecast of the future behavior of the system.

Reference [11] first proposed an ARIMA model for analysis of freeway travel time series data. References [12−15] adopted specific ARIMA or seasonal ARIMA models to make traffic forecasting. Reference [16] investigated the use of ARIMA for predicting arterial traffic flow.

The advantage of ARIMA model is that there is a systematic, and iterative methodology for applying the model, and ARIMA is one of the most mature techniques theoretically and practically in time series analysis. Although ARIMA model performs well in traffic forecasting, the fitting and maintenance of ARIMA models are quite time-consuming, which is a main obstacle in real-time application.

2.3 Non-parameter regression (NPR) model

NPR is a forecasting technique similar to case-based reasoning that does not make any rigid assumptions about the data[17]. In short, the method searches a collection of historical observations for records similar to the current conditions and uses them to estimate the future state of the system. Unlike the parametric models that compress all training data into a set of equations through the process of parameter fitting, NPR retains all possible patterns and trends of the data and searches through them for past similar cases each time a forecast is made. Furthermore, only enough data to sufficiently describe the underlying process is required and not knowledge about the system being modeled. No prior knowledge about the system being modeled is required.

Researchers have proposed many NPR-based models[18−20]. Reference [2] reviewed the NPR model and outlined four challenges related to the implementation of non-parametric regression methods: 1) choice of an appropriate state space; 2) definition of a distance metric to determine nearness of historical observations to the current conditions; 3) selection of a forecast generation method given a collection of nearest neighbors, and 4) management of the potential neighbors′ database. Reference [15] enhanced NPR for using in real-time system by reducing execution time using advanced data structures and imprecise search and developed a methodology for applying NPR, similar to the way Box and Jenkins provided a methodology for conducting time series analysis.

2.4 Artificial neural network (ANN) model

The motivation for using neural network is based on the factor that the model is capable of handling nonlinear relationship. In general, ANN consists of three kinds of layers: an input layer, one or a number of hidden layers, and an output layer[21]. The output layer is formed by a neuron that represents the forecasted variable. The input variables can be assigned to neurons in the input layer. By feeding the network with training data, relationships between neurons in all layers can be established. These relationships are defined by the weights given to the connections between the neurons during the training process.

A review of civil engineering applications of neural networks was presented by [22]. Recent research on traffic forecasting of NN can be referred to [23−26]. In those studies, emphasis was put on three aspects: the selection of suitable input variables, the choice of network structure, and the determination of training algorithms.

There are two drawbacks for ANN: one is that ANN is essentially a black box; the other is that its network structure and the weights between neurons are fixed and cannot be adjusted adaptively during the forecasting process.

3 Improved adaptive exponential smoothing model

This section firstly gives a brief introduction to simple exponential smoothing and adaptive exponential smoothing. Then, an improved adaptive exponential smoothing model is proposed to overcome the drawbacks of the previous exponential smoothing model and a comparing experiment is carried out to illustrate the advantages of the proposed model.

3.1 Simple exponential smoothing (SES)

Exponential smoothing is usually based on the premise that the level of time series should fluctuate about a constant level or change slowly over time[7]. Under such a premise, the travel time series $y(t)$ can be described by

$$y(t) = \beta(t) + \varepsilon(t) \tag{1}$$

where, $\beta(t)$ takes a constant at time t and may change slowly over time, $\varepsilon(t)$ is a random variable and is used to describe the effect of stochastic fluctuation.

Under the model, $\beta(t)$ is a sound forecast for $\hat{y}(t+\tau)$ at time t, and forecast is given as

$$\hat{y}(t+\tau) = \beta(t) \tag{2}$$

where τ is the forecasting horizon.

SES applies unequal weights to the time series observations. Given an estimate of $\beta(t-1)$ at the time period $t-1$ and a new observation $y(t)$ at the time period t, SES updates estimate of $\beta(t)$ in the following way.

$$\beta(t) = \alpha y(t) + (1-\alpha)\beta(t-1) \tag{3}$$

where α is a smoothing parameter between 0 and 1 and it determines how much weight is attached to each observation. The more the average level of the process changes, the more a newly observed time series should influence the estimate, and thus, the larger the smoothing parameter α should be.

3.2 Adaptive exponential smoothing (AES)

Sometimes, it is necessary to change the smoothing parameter α used in exponential smoothing when the rate at which β changes over time changes. This suggests that an adaptive smoothing parameter would produce improved forecasts.

First, we introduce two error signals:

Smoothed error signal

$$E(t) = re(t) + (1-r)E(t-1) \tag{4}$$

Absolute error signal

$$A(t) = r\,|e(t)| + (1-r)A(t-1) \tag{5}$$

where $e(t) = y(t) - \hat{y}(t)$ and r is a parameter.

Based on the above two signals, a tracking signal is constructed as

$$TS(t) = \left|\frac{E_t}{A_t}\right| \tag{6}$$

The tracking signal has some useful characteristics[3]. First, tracking signal varies between 0 and 1. Second, when the level of time series keeps stationary and the tracking signal approaches to 0. However, with the increase of the trend of the level of time series changes, the tracking signal will increase. The two characteristics make the tracking signal an appropriate candidate for adaptive smoothing parameter. With the tracking signal as the smoothing parameter, the exponential smoothing can be adaptively adjusted to fit for the pattern of time series.

3.3 Improved adaptive exponential smoothing (IAES)

When travel time series change rapidly and take on strong trend because of some abnormal conditions such as accident or heavy congestion, etc., even adaptive exponential smoothing methods cannot capture the dynamics of travel time series[3] (see Fig. 4). The reason derivers from violation of the basic premise about the exponential smoothing model: the level of time series should fluctuate about a constant level or change slowly over time.

The idea of the proposed IAES comes from the philosophy of forecasting. Forecasting usually works in the following way[9]. First, the historical data are analyzed in order to identify a pattern that can be used to describes time series. Then, this pattern is extrapolated, or extended, into the future in order to prepare a forecast. The validity of forecasting rests on the assumption that the pattern that has been identified will continue in the future. A forecasting technique cannot be expected to give good predictions unless this assumption is valid. If the data pattern that has been identified does not persist in the future, this indicates that the forecasting technique being used is likely to produce inaccurate predictions. Then, changes in pattern of data should be monitored so that appropriate changes in the forecasting system can be made before the prediction becoming too inaccurate.

The proposed IAES consists of two models and one detector (see Fig. 2). For the two models, one is used to describe the pattern of travel time series with level changing slowly and is named as Model I, the other is used to describe the pattern of travel time series taking on strong trend and is named as Model II. The detector monitors the current pattern of travel time series and determines which model is used for forecasting.

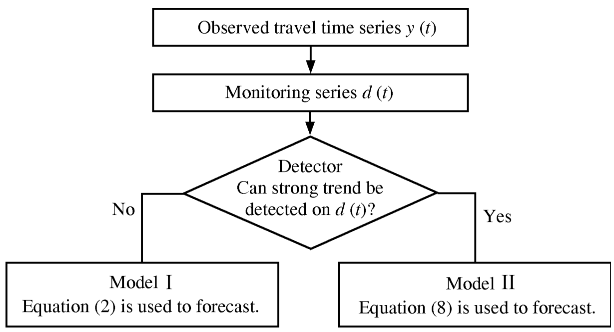

Fig. 2 Procedure for IAES algorithm

Model I is given by (1) and AES is applied to forecast for the model.

The Model II has the following form

$$y(t) = \beta(t) + \phi(t)t + \varepsilon(t) \tag{7}$$

where $\beta(t)$ and $\varepsilon(t)$ have the same meanings as in (1), and $\phi(t)$ represents the rate at which the trend of series changes.

Under the model, forecasting is given in the following way

$$\hat{y}(t+\tau) = \beta(t) + \phi(t)\Delta t \tag{8}$$

where Δt is the forecasting step, $\beta(t)$ is estimated by (3), and $\phi(t)$ is estimated by

$$\phi(t) = y(t) - \hat{y}(t) \tag{9}$$

Detector monitors a time series $d(t)$: the first order difference of $y(t)$

$$d(t) = y(t) - y(t-1) \tag{10}$$

If $y(t)$ can be appropriately described by Model I, $d(t)$ will fluctuate around zero (see Fig. 3: span of 8:30 ~ 9:30 and 10:20 ~ 11:20). On the contrary, if $y(t)$s follow Model II, a number of successive $d(t)$s will be greater or lower than zero with significant magnitudes (see Fig. 3: span of 9:30 ~ 10:20 and 11:20 ~ 12:15). The detector exploits this characteristic as a rule to choose right model for forecasting: If the number of successive $d(t)$s with the same sign exceeds a certain threshold and their magnitudes also exceed a certain threshold, then, (8) is used to forecast, otherwise, the forecasting is switched to (2).

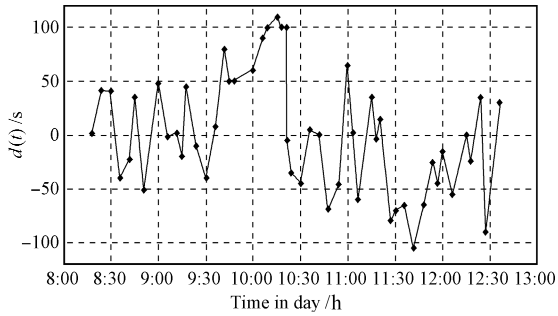

Fig. 3 The first order difference of travel time series (see Fig. 4 for original travel time series)

Fig. 4 shows the results of forecasting of AES and IAES. From the result, both AES and IAES perform well before 9:30. However, during the span of 9:30 ~ 10:30, travel time changes rapidly with strong trend, and AES fail to trace the changes. On the contrary, IAES is capable of capturing the dynamics of travel time successfully.

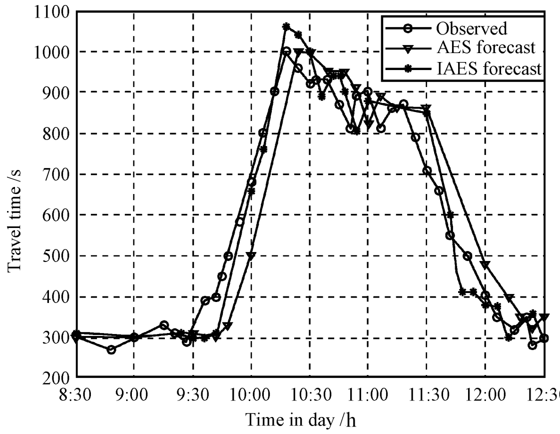

Fig. 4 The forecasting performances of AES and IAES on travel time series with strong trend

4 Comparing experiments

4.1 Data preparation

The comparing experiments were based on Zhaojiaobang Road (see Fig. 5) — an arterial street in Xuhui District, Shanghai, P. R. China. The distance of this arterial is about 2.5 km. The plate matching data were provided by SEARI Group Co. Ltd., who is responsible for the traffic surveillance system of Shanghai. The span of the data covers from Feb. 1 to Feb. 28, 2005.

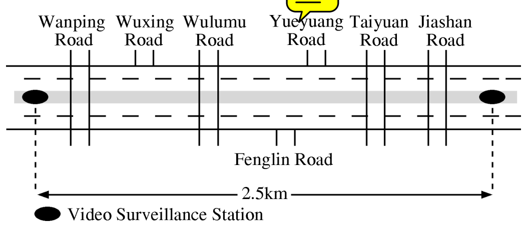

Fig. 5 Sketch map of testing arterial street, Zhaojiaobang Road, Shanghai, P. R. China

The row travel time data was firstly preprocessed to remove the outlier samples that had singular values larger than their neighboring samples. Outlier samples usually correspond to those vehicles that stop midway for a while. Then, the processed travel time data were accumulated every five minutes to form an aggregate mean travel time series.

Browsing through all dynamic profiles of travel time series in a month (see Fig. 6), we obviously found that the profiles fell into two kinds. For most days of the month, the profiles of travel time changed slowly over time and took on a similar pattern. However, there were seldom days with profiles changing acutely and having abnormal larger travel time in certain time spans. The latter kind of days often means that there are abnormal traffic conditions such as accidents or heavy congestion. For example, the day with abnormal profile in Fig. 6 corresponded to Feb. 2, which was the day before Spring Festival (the most important festival in China), and most people would go out for shopping in that day, so heavy congestion occurred.

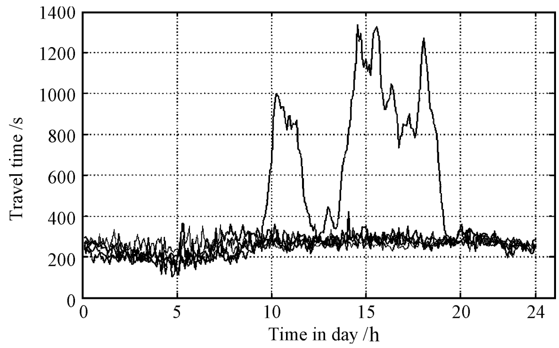

Fig. 6 Travel time profiles (For the purpose of clarity, only four days′ profiles are displayed, including one profile corresponding to a day with abnormal traffic condition and three profiles corresponding to days with normal traffic condition.)

4.2 Comparing forecasting models

The four kinds of forecasting models introduced in Section 2 were implemented and compared.

The IAES presented in Section 3 was adopted for exponential smoothing model. For the ARIMA model, ARIMA (0, 1, 2) was chosen as the appropriate model for our data after the selecting route presented in Section 2 with the help of Matlab toolkit ARMASA. The improved NPR algorithm proposed by [19] was used for NPR model. The choice of state vectors, nearest neighbor searching rule, similarity rule, and prediction algorithm were, respectively, adjusted for our data. For ANN model, we use a multiplayer feed-forward neural network presented by [25]. The implemented ANN consisted of three layers. The hidden layer has four nodes as suggested in [25].

4.3 Design of experiments and measurements

Two comparing experiments were carried out.

One experiment aimed at comparing the performance of the four forecasting models on days with normal traffic condition. In this experiment, the forecasting horizons in the range of one step to four steps were studied for each model. We used 20 days in the 25 days with normal traffic condition as training set for NPR, ANN, and ARIMA and the data of the other 5 days were used as the testing set.

The other experiment tested the performance of the four forecasting models on days with abnormal traffic condition. In this experiment, the forecasting models trained in the first experiment were applied to the day with abnormal traffic condition.

Mean absolute error (MAE) and mean absolute percentage error (MAPE) were applied as performance indices.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y(t_i) - \hat{y}(t_i)|}{n} \tag{11}$$

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n} \dfrac{|y(t_i) - \hat{y}(t_i)|}{y(t_i)}}{n} \times 100\,\% \tag{12}$$

where $y(t_i)$ is the observed travel time and $\hat{y}(t_i)$ is the forecasting travel time for $y(t_i)$.

Fig. 7, Tables 1 and 2 show the forecasting results of the four models under normal traffic condition. From these results, it can be found that the forecasting accuracies of models almost deteriorates with the increase of forecasting horizon. However, the rate at which the forecasting accuracy of each model reduces is different. The proposed IAES has the best performance in shorter forecasting horizon (one step and two steps), but rapidly deteriorates with the increase of forecasting horizon. On the contrary, the ANN and NPR models perform more stability when the forecasting horizon gets longer.

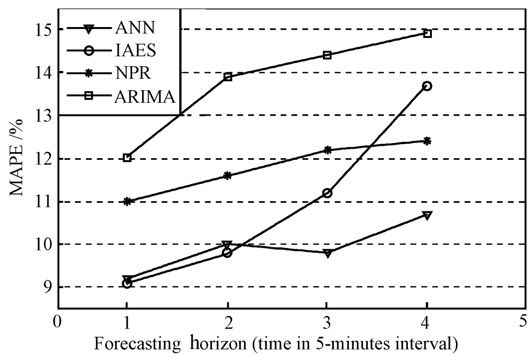

Fig. 7 Forecasting results of four comparing models on days with normal traffic condition

Fig. 8 and Table 3 present the comparative results of the four models under abnormal traffic condition. Under such scenario, IAES is overwhelmingly advantageous. The success of IAES should owe to its ability to effectively detect the change of travel time pattern and switch to appropriate forecasting algorithm. However, other models are trained with "normal" data, so they fail to give good travel time forecasting under abnormal traffic conditions. It is interesting to point out that [21] just made use of the deviation of observed travel time and forecasted travel time by NPR to automatically detect traffic incident: when the deviation is larger than a predefined threshold, an alarming signal will be given for a possible incident.

Table 1 Performance comparison on days with normal traffic condition in terms of MAPE (%)

Forecasting horizon	1	2	3	4
IAES	9.11	9.72	11.3	13.60
ANN	9.24	9.94	9.83	10.67
NPR	11.04	11.60	12.24	12.40
ARIMA	11.90	13.87	14.42	14.91

Table 2 Performance comparison on days with normal traffic condition in terms of MAE (s)

Forecasting horizon	1	2	3	4
IAES	21.9	22.72	26.57	32.16
ANN	21.63	23.27	23.03	25.94
NPR	26.25	27.68	29.27	29.55
ARIMA	27.89	33.18	35.27	36.42

Table 3 Performance comparison on days with abnormal traffic condition (one step forecasting)

	IAES	ARIMA	ANN	NPR
MAE (s)	53.25	68.95	104.26	191.95
MAPE (%)	8.06	11.31	13.69	22.45

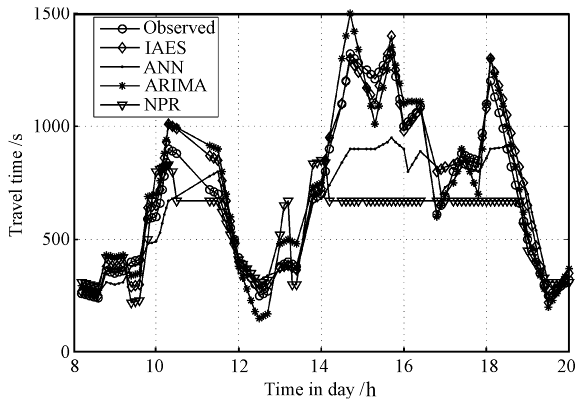

Fig. 8 Forecasting results of four comparing models on day with abnormal traffic condition

From the results of experiments, the proposed IAES takes on two notable advantages: 1) The forecasting performance of IASE is superior to other models in shorter forecasting horizon; 2) IASE has the ability to deal with all kinds of traffic conditions.

Generally speaking, each model seems to have its own strength and weakness and have a sort of typical or optimal forecasting horizon, and no single model is expected to be the best in all aspects. So a versatile forecasting model may lie in the fusion of different models.

5 Conclusion

The purpose of this paper is to evaluate the performance of existing forecasting models based on direct travel time data obtained by LPM. The main contribution of this paper is threefold. First, a brief review on state-of-art of short-term traffic forecasting is given with their basic ideas, related works, advantages and disadvantages of each mode. Second, an IAES model is proposed, which overcomes the drawbacks of previous adaptive exponential smoothing model. Third, the comparative experiments of four kinds of models were carried out on travel time data obtained by LPM. The results of experiments show the forecasting performance of IASE is superior to other models in shorter forecasting horizon (one and two step forecasting) and the IASE is capable of dealing with abnormal traffic condition.

However, each model seems to have its own strength and weakness, and have a sort of typical or optimal forecasting horizon; no single model is expected to be the best in all aspects. Our future study will be laid on a versatile forecasting model that combines the existing forecasting models and has good performance on all spans of forecasting horizons and traffic conditions.

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