CEAI, Vol.13, No.3, pp. 65-73, 2011 Printed in Romania

A Short-term Traffic Flow Intelligent Hybrid Forecasting Model and Its Application

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Abstract: In order to transcend the limitation of existing individual traffic flow forecasting models on different traffic condition, a novel intelligent hybrid (IH) model for short-term traffic flow forecasting was presented. The IH model had three sub-models: Kalman filter (KF) model, artificial neural network (ANN) model and fuzzy combination (FC) model. The KF model forecasted the traffic flow by the linear iteration method based on the historical traffic data. Otherwise, the ANN model was a single-hidden-layer feed-forward neural network built by some common S-function neurons. The two individual models reflecting practical problems from different respects were combined by fuzzy logic. The FC model mixed the two individual forecast results and its output was regarded as the final forecasting of the traffic flow. Practical application results show that the IH model can produce more precise forecasting than that of two individual models.

Keywords: intelligent traffic system, short-term traffic flow forecasting, Kalman filter, artificial neural network, fuzzy logic.

1. INTRODUCTION

As the number of vehicles grows and the need for mobility increases on a world-wide scale, the frequency and duration of traffic jams in major cities increase (Robertson, & Bretherton, 1995). High fuel cost and environmental concerns provide important incentives for minimizing traffic delays. The most effective measures to deal with traffic jams is a more efficient use of the existing infrastructure and capacity through advanced Intelligent Traffic System (ITS) (YoungWoo, Kato, Okuma, & Narikiyo, 2008). However, the primary information of ITS is the short-term traffic flow forecasting results from kT to $(k+1)T$ where T is the forecasting cycle time. Hence, real-time traffic flow forecasting is critical to the high-effective realization of ITS so that traffic jam can be alleviated. The forecasting results can be sent to ITS directly and its quality is critical to the realization of the traffic control and guidance (Guan, 2004). In general, the forecasting method with $T \leq 15$ min belongs to short-term traffic flow forecasting.

The state-of-the-art of the real-time traffic flow forecasting in recent years can be divided into two areas as follow (Han, Song, & Wang, 2004). Ones are forecasting models based on traditional mathematics and physical methods (Si, Sun, & Zhao, 2006), such as statistics and calculus (Xiong, Wang, & Li, 2006). These models include Parametric Regression model, Auto Regression Moving Average model, Kalman Filter model (He, Li, & Ma, 2000), Exponential Smoothing model, Maximum Likelihood Formulation model, Markov model, etc (Yang, Jia, & Kong, 2005). The others are forecasting models by means of modern science and technology (Tan, 2005), which does not pay attention to rigorous mathematical derivation and clear physical meaning (Yin, Wong, & Xu, 2002), but emphasize whether it can fit precisely with the actual traffic flow phenomena, including Neural Network model (Ledous, 1997), Nonparametric Regression model, Spectral Basis Analysis and Wavelet Network, etc (Liu & Guan, 2004).

The various kinds of forecasting models mentioned above are set up from different perspectives. Although the improvement of individual forecasting model can reduce error to some extent, there is comparative restriction. Because the traffic system is a dynamic, complex and non-linear system, and the main characteristic of such system is uncertainty, the result obtained by individual forecasting method is not satisfying (Guan & Hua, 2006). If the individual models reflecting practical problems from different respects can be combined in a certain way, useful information of the individual model can be synthetically used to improve the forecasting effect further (Ding 1997). Bates and Granger (1969) presented the thought of hybrid forecasting firstly.

On the basis of that, the intelligent hybrid (IH) model for short-term traffic flow forecasting which includes the Kalman filter (KF) model and the artificial neural network (ANN) model is proposed in this paper. The IH model can take advantage of the useful information of the KF model and the ANN model to improve the forecasting effect further because the two individual models reflecting practical problems from different respects are combined by fuzzy logic. Practical application results prove that this IH model is an efficient method to the short-term traffic flow forecasting and can be applied to traffic control engineering.

The organization of the rest of this paper is as follows. In the next section, the related researches that are traffic flow correlation of two adjacent intersections and the IH model structure are proposed. In Section three, the details of the two individual traffic flow forecasting models respectively which are the KF model and the ANN model are presented. Section three also provides the construction of the Fuzzy Combination (FC) model based on the two individual forecasting models. Section Four describes the details of the application and shows our results. Finally the conclusion is given in section Five.

2. RELATED RESEARCH

2.1 A Fundamental Equation

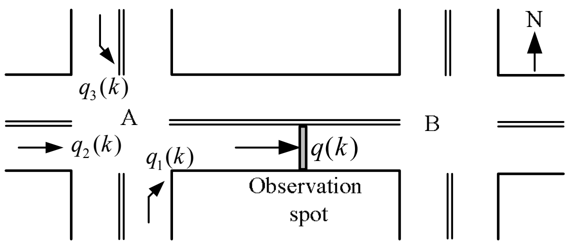


Fig. 1. Traffic flow correlations schematic diagram of two adjacent intersections.

There is an inherent law when the upstream vehicles pass through the intersection along the direction of right or left or straight. Fig.1 shows the traffic flow correlations of the two representative adjacent intersections in the urban traffic road network. We assume $q_1(k)$ is the right-turn traffic volume on the south corner of intersection A during $((k-1)T, kT]$ where $k = 1, 2, \cdots$. In the same way $q_2(k)$ and $q_3(k)$ are the straight-go traffic volume on the west corner and the left-turn traffic volume on the north corner respectively. Those three traffic flow will all enter the link between intersection A and B after several numbers of forecasting cycle time. $q(k)$ is the traffic volume on observation spot locating in the link between intersection A and B during $((k-1)T, kT]$. From Fig.1 we can find that the traffic volume $q(k+1)$ during $(kT, (k+1)T]$ has the nonlinear relation to not only $q(k)$, …, $q(k+1-m)$ but also $q_1(k)$ 、 $q_2(k)$ and $q_3(k)$, …, $q_1(k+1-m)$ 、 $q_2(k+1-m)$ and $q_3(k+1-m)$. Thus $q(k+1)$ can be expressed in the form

$$q(k+1) = f\left(\mathbf{L}(k), \mathbf{L}(k-1), \cdots, \mathbf{L}(k+1-m)\right), \qquad (1)$$

where $f(\bullet)$ is a nonlinear function and $\mathbf{L}(k) = [q_1(k), q_2(k), q_3(k), q(k)]$. Equation (1) can bring enough high degree of precision to the business of calculating traffic flow, in general, when m is 3. Hence, (1) can be simplified as follows

$$q(k+1) = f\left(\mathbf{L}(k), \mathbf{L}(k-1), \mathbf{L}(k-2)\right). \qquad (2)$$

2.2 Structure of IH Model

It is known to us that traffic flow in the urban road network has some universal regularity as flow:

1. Traffic flow movement has some static characters which recur by one-day period. For example, the morning-evening peak phenomena appear every day in the most cities. The longer forecasting cycle time is, the more obvious this static character is.

2. Traffic system being concerned with many people is one very large and sophisticated system, and the relation expressed by (1) has taken on the dynamic time-varying nonlinear character. The shorter forecasting cycle time is, the more obvious the dynamic character is. Thus it is very difficult to obtain analytic expression of traffic flow movement.

Kalman filter, as a method of forecasting traffic flow, has good adaptability. It can process non-smooth data as well as smooth data. Moreover, it reduces computer memory and computing time. However, the performance of the method probably gets worse while forecasting traffic flow in traffic mutation or traffic congestion periods.

The artificial neural network is a kind of non-linear forecasting method, which can consider complex influential factors and has good dynamic response. Recently, many artificial neural network models which can update the network with the real time traffic information are applied in short-term traffic flow forecasting, such as Back Propagation, Time Delayed Neural Network, Spectral Basis Artificial Neural Network and Radial Basis Function, etc. Nevertheless, those models have low convergence rate and their goal function is apt to fall into the point of local minimum.

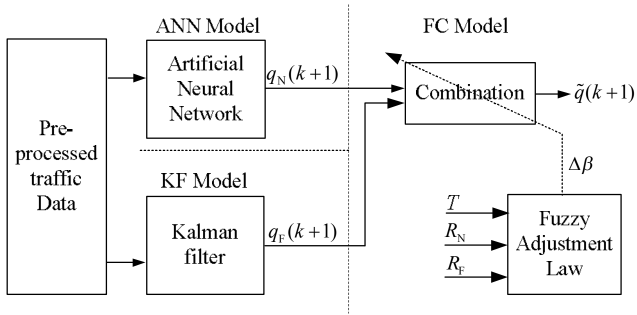


Fig. 2. The structure of IH model.

According to the forementioned analysis, we present an intelligent hybrid model used to improve the accuracy of short-term traffic flow forecasting. Fig.2 shows the structure of the IH model. The IH model has three sub-models: the KF model, the ANN model and the FC model. By means of the good static linear stabilization character of Kalman filter and the strong dynamic nonlinear mapping ability of Artificial neural network, the FC model and the ANN model are applied in short-term traffic flow forecasting simultaneously. The former is used to describe static stabilization character of traffic flow, and the latter reflects the time-varying nonlinear character. Then the two individual forecasting results are mixed in FC model by use of fuzzy logic, and the forecast result of the FC model are regarded as the final estimate of the traffic flow.

3. INTELLIGENT HYBRID MODEL

This section provides the construction of the models based on the KF model and the ANN model respectively. Then the FC model is also introduced. Finally, the detailed flow chart of the IH model is presented.

3.1 KF Model

According to the traffic flow correlations expressed by (2), the forecasting model based on Kalman filter can be described as follow

$$\begin{aligned} r(k+1) &= \mathbf{H}_0(k)\mathbf{V}(k)+\mathbf{H}_1(k)\mathbf{V}(k-1) \\ &\quad +\mathbf{H}_2(k)\mathbf{V}(k-2)+\omega(k) \end{aligned}, \tag{3}$$

where $\mathbf{H}_0(k)$, $\mathbf{H}_1(k)$ and $\mathbf{H}_2(k)$ are the parameter matrixes 1×4, and $\omega(k)$ is the noise that has zero mean and a known covariance matrix $\mathbf{R}(k)$. $r(k+1)$ and $\mathbf{V}(k)$ are defined respectively as follows

$$r(k+1)=\frac{q_{\mathrm{F}}(k+1)}{\overline{q}(k+1)}, \tag{4}$$

$$\mathbf{V}(k)=\left[\frac{q_1(k)}{\overline{q}_1(k)},\frac{q_2(k)}{\overline{q}_2(k)},\frac{q_3(k)}{\overline{q}_3(k)},\frac{q(k)}{\overline{q}(k)}\right]^{\mathrm{T}}, \tag{5}$$

where $q_{\mathbf{F}}(k+1)$ is the output of the KF model. In other words, $q_{\mathbf{F}}(k+1)$ is the traffic volume forecasted by the KF model on *KT* time-point. $\overline{q}_1(k)$, $\overline{q}_2(k)$, $\overline{q}_3(k)$ and $\overline{q}(k)$ are the history mean traffic volume of $q_1(k)$, $q_2(k)$, $q_3(k)$ and $q(k)$ during $((k-1)T, kT]$ respectively.

In china, the traffic flow movement characters in holiday, such as Spring Festival, National Day, May Day, etc., have obvious difference to those in other day. In holiday, we find the traffic congestion disappears in rush hour in urban road network, but the road traffic flow beside scenic spot is very heavy. Moreover, in the same week, the difference on traffic flow characters is also very apparent. In other words, traffic flow characters in weekend are contrasted with those in workday. Thus, in order to improve the forecasting precision, the dates of whole year are divided into four different categories as follow: 1. Holiday, 2. Weekend, 3. Monday or Friday, and 4. Tuesday, Wednesday or Thursday. In those four categories, the category of Holiday has the higher priority level than the others. For example, the day of Oct. 1, 2007 is Monday, and thus it belongs to the category of Monday or Friday. However, this day is National Day of China, and it also is the category of holiday. Finally we think this day belongs to the category of holiday. Thus each of $\overline{q}_1(k)$, $\overline{q}_2(k)$, $\overline{q}_3(k)$ and $\overline{q}(k)$ has four different values being relative to four categories. We can calculate the four different values of each kind of history mean traffic volume in advance according to the historical data and save them into traffic information database. Once new traffic dada is gained, those $\overline{q}_1(k)$, $\overline{q}_2(k)$, $\overline{q}_3(k)$ and $\overline{q}(k)$ should be updated.

To employ Kalman filter theory to estimate the state variables, transfer can be done as follows

$$\mathbf{A}(k)=\left[\mathbf{V}^{\mathrm{T}}(k),\mathbf{V}^{\mathrm{T}}(k-1),\mathbf{V}^{\mathrm{T}}(k-2)\right], \tag{6}$$

$$\mathbf{X}(k)=\left[\mathbf{H}_0(k),\mathbf{H}_1(k),\mathbf{H}_2(k)\right]^{\mathrm{T}}, \tag{7}$$

$$y(k)=r(k+1). \tag{8}$$

Thus, we can get the following state equation and measurement equation

$$\mathbf{X}(k)=\mathbf{B}(k)\mathbf{X}(k-1)+\mathbf{v}(k-1), \tag{9}$$

$$y(k)=\mathbf{A}(k)\mathbf{X}(k)+\omega(k), \tag{10}$$

where $y(k)$ is the observation variable, $\mathbf{X}(k)$ is the state vector, $\mathbf{A}(k)$ is observation vector, $\mathbf{B}(k)$ is the state transfer matrix and $\mathbf{B}(k)=\mathbf{I}$, $\mathbf{v}(k-1)$ is the model noise vector which has zero mean and a known covariance matrix $\mathbf{Q}(k-1)$. In this model, control vector $\mathbf{U}(k-1)$ is ignored.

Then we can get the following equations by Kalman filter theory.

$$\overline{\mathbf{X}}(k)=\overline{\mathbf{X}}(k\mid k-1)+\mathbf{K}(k)\left[y(k)-\mathbf{A}(k)\overline{\mathbf{X}}(k\mid k-1)\right], \tag{11}$$

$$\overline{\mathbf{X}}(k\mid k-1)=\mathbf{B}(k)\overline{\mathbf{X}}(k-1), \tag{12}$$

$$\begin{aligned} \mathbf{K}(k) &= \mathbf{P}(k\mid k-1)\mathbf{A}^{\mathrm{T}}(k) \\ &\quad \bullet\left[\mathbf{A}(k)\mathbf{P}(k\mid k-1)\mathbf{A}^{\mathrm{T}}(k)+\mathbf{R}(k)\right]^{-1} \end{aligned}, \tag{13}$$

$$\mathbf{P}(k\mid k-1)=\mathbf{B}(k-1)\mathbf{P}(k-1)\mathbf{B}^{\mathrm{T}}(k-1)+\mathbf{Q}(k-1), \tag{14}$$

$$\mathbf{P}(k)=\left[\mathbf{I}-\mathbf{K}(k)\mathbf{A}(k)\right]\mathbf{P}(k\mid k-1), \tag{15}$$

$$\mathbf{P}(0\mid 0)=\mathbf{P}_0, \tag{16}$$

$$\begin{aligned} \overline{\mathbf{X}}(k_0) &= \overline{\mathbf{X}}(k_0\mid k_0-1)+\mathbf{K}(k_0) \\ &\quad \bullet\left[y(k_0)-\mathbf{A}(k_0)\overline{\mathbf{X}}(k_0\mid k_0-1)\right] \end{aligned}, \tag{17}$$

where $\mathbf{K}(k)$ is Kalman gain, $\mathbf{P}(k)$ is filter error variance matrix.

After the optimal filter estimation $\overline{\mathbf{X}}(k)$ is obtained by (11)-(17), $r(k+1)$ can be got by the following equation

$$r(k+1)=\mathbf{A}(k)\overline{\mathbf{X}}(k)\,. \tag{18}$$

Finally, we can obtain the traffic volume forecasting value as follow

$$q_{\mathrm{F}}(k+1)=\mathbf{A}(k)\overline{\mathbf{X}}(k)\times\overline{q}(k+1)\,. \tag{19}$$

3.2 ANN Model

A potential method for traffic flow forecasting is one that employs learning so that dynamic changes in traffic are learned on-line and accommodated with the proper use of identification technique. One such method is based on the use of Artificial Neural Network. The ANN is main aspect of Artificial Intelligent. The learning capability and universal approximation property of ANN make them suitable for modeling of uncertain nonlinear and time-varying dynamic systems such as vehicular traffic. The ANN applied in traffic flow forecasting can answer the problem how to avoid precise mathematic model.

Here, we focus on one of the most popular neural networks, called sigmoidal feed-forward networks. The output of the processing element is the nonlinear sigmoidal function of the sum of the inputs and a possible threshold. A sigmoidal function $\sigma(\cdot)$, which is nondecreasing, satisfies the conditions that $\sigma(-\infty)=0$ and $\sigma(\infty)=1$. One choice of the smooth sigmoidal functions is expressed by

$$\sigma(x)=\frac{1}{1+e^{-cx}}\,, \tag{20}$$

where c is a constant determined by the shape of the function.

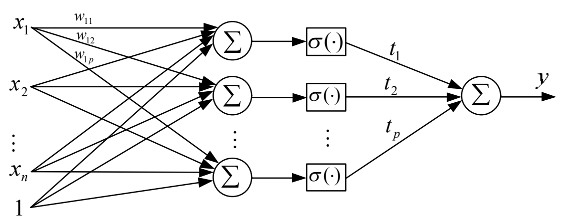


Fig. 3. A single-hidden-layer feed-forward network.

It has been shown by Hornik (1989) that multilayer feed-forward networks with as few as one hidden layer is capable of universal approximation in a very precise and satisfactory sense. Shown in Fig.3 it is a single-hidden-layer feed-forward network with p processing elements, and the output y is just a weighted sum of the outputs of the hidden layer. The mathematical expression of this network is given by

$$y=\sum_{j=1}^{p}t_j\sigma\left(\sum_{i=1}^{n}w_{ij}x_i+w_{n+1,j}\right), \tag{21}$$

where t_j and w_{ij} are adjustable weights.

Let $\mathbf{X}=\left[x_1,\cdots,x_n\right]^{\mathrm{T}}$ and $\boldsymbol{\theta}=\left[w_{11},\cdots,w_{n+1,p},t_1,\cdots,t_p\right]^{\mathrm{T}}$. Then the input-output relationship of the neural network can be expressed as

$$y=N(\mathbf{X};\boldsymbol{\theta})\,. \tag{22}$$

Let y_{p} be the output of an unknown system with the same input $\mathbf{X}=\left[x_1,\cdots,x_n\right]^{\mathrm{T}}$, i.e.,

$$y_{\mathrm{p}}=F(\mathbf{X};n)\,, \tag{23}$$

where $F(\cdot;\cdot)$ is a completely unknown function.

The difference between y_{p} and y is the error given by

$$e=y-y_{\mathrm{p}}=N(\mathbf{X};\boldsymbol{\theta})-F(\mathbf{X};n)\,. \tag{24}$$

If we now adjust the weights $\boldsymbol{\theta}$ such that $e\to 0$, i.e., $y\to y_{\mathrm{p}}$, then the input-output characteristics of the unknown system (23) are matched by the neural network (22). The adjustment mechanism for $\boldsymbol{\theta}$ may be developed using simple optimization technique to minimize a certain cost function of e.

In fact, the relation of $q(k+1)$ to $\left[q_1(k-1),q_2(k-1),q_3(k-1)\right]$ and $\left[q_1(k-2),q_2(k-2),q_3(k-2)\right]$ shown in (2) is little. Thus, the further simplification of (2) can be described as follow

$$q(k+1)=f'\left(\mathbf{L}(k),q(k-1),q(k-2)\right)\,. \tag{25}$$

Without loss of generality we express (1) in other form

$$q(k+1)=\lambda q(k)+g\left(\mathbf{H}(k)\right), \tag{26}$$

where $|\lambda|\le 1$ is an arbitrary constant, $\mathbf{H}(k)=\left[\mathbf{L}(k),q(k-1),q(k-2)\right]^{\mathrm{T}}$, $g(\cdot)$ is a nonlinear function and $g(\cdot)=f(\cdot)-\lambda q(k)$.

Our objective is to develop a neural network that identifies the nonlinear function $g(\cdot)$ that is used to generate the estimates $q_{\mathrm{N}}(k+1)$ that are as close to the measured $q(k+1)$ as possible. We achieve this objective as follows: Let $N_g(\cdot;\boldsymbol{\theta}_g)$ be the neural network approximation of the nonlinear function $g(\cdot)$ where $\boldsymbol{\theta}_g$ is a vector of the weights of the network. Then the following model generates the traffic flow estimate

$$q_{\mathrm{N}}(k+1)=\lambda q(k)+N_g\left(\mathbf{H}(k);\boldsymbol{\theta}_g(k)\right), \tag{27}$$

that corresponds to the weights $\boldsymbol{\theta}_g(k)$ at time point kT. The error is

$$e(k)=q_{\mathrm{N}}(k+1)-q(k+1)= N_g\left(\mathbf{H}(k);\boldsymbol{\theta}_g(k)\right)-g(\mathbf{H}(k)). \tag{28}$$

The adjustment rule for the weights $\boldsymbol{\theta}_g$ is chosen as (Ho & Ioannou, 1996)

$$\mathbf{u}(k+1)=\boldsymbol{\theta}_g(k)-\frac{\gamma_0}{\beta_0+\|\xi(k)\|^2}\xi(k)e(k), \tag{29}$$

$$\boldsymbol{\theta}_g(k+1)=\begin{cases}\mathbf{u}(k+1) & |\mathbf{u}(k+1)|\le M_\theta \\ \dfrac{M_\theta}{|\mathbf{u}(k+1)|}\mathbf{u}(k+1) & |\mathbf{u}(k+1)|> M_\theta\end{cases}, \tag{30}$$

where $0<\gamma_0<2$, $\beta_0>0$ and $M_\theta>0$ are design parameters and

$$\xi(k)=\frac{\partial^T N_g\left(\mathbf{H}(k);\boldsymbol{\theta}_g(k)\right)}{\partial\boldsymbol{\theta}_g(k)}. \tag{31}$$

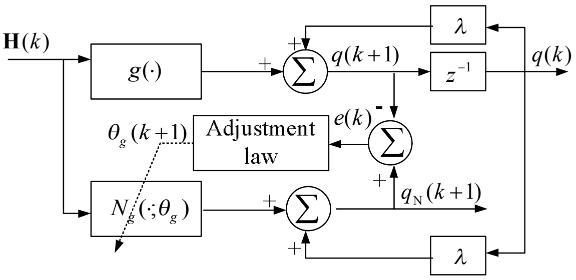


Fig. 4. Neural network configuration for traffic flow forecasting.

We illustrate $N_g(\cdot;\boldsymbol{\theta}_g)$ in the neural network configuration for traffic flow forecasting by Fig.4.

It can be shown [17] that if $N_g(\cdot;\boldsymbol{\theta}_g)$ is linear with respect to $\boldsymbol{\theta}_g$ and $g(\cdot)$ can be parameterized to be of the same as $N_g(\cdot;\boldsymbol{\theta}_g)$ with a corresponding unknown $\boldsymbol{\theta}'_g$ then [17] guarantees that $e(k)\to 0$ as $k\to\infty$.

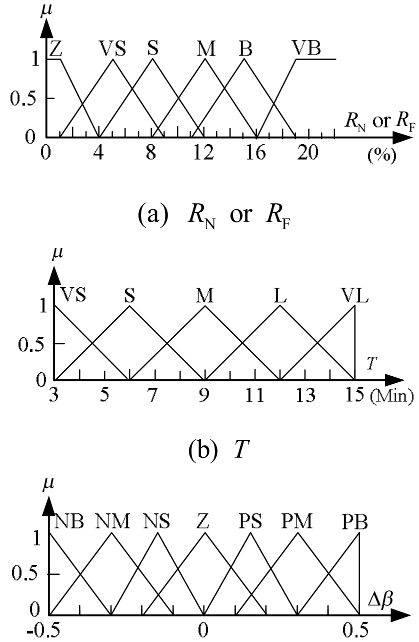
3.3 FC Model

Because the traffic system is a dynamic complex and non-linear system, and the main characteristic of such system is uncertainty, the forecasting result obtained by individual forecasting models mentioned above is unsatisfied. Hence the individual models reflecting practical problems from different respects can be combined in a certain way to improve the forecasting precision further. In the hybrid forecasting of traffic flow, useful information of the two individual forecasting models is utilized to obtain the final results. Because of various situations at different time-points and forecasting different of the individual models, a fuzzy combination model with an adjustable weight is applicated in this paper.

The FC model based on the two individual forecasting models can be expressed in the form

$$\tilde{q}(k+1)=\beta q_{\mathrm{N}}(k+1)+(1-\beta)q_{\mathrm{F}}(k+1) \tag{32}$$

where $\tilde{q}(k+1)$ is the output of the FC model that expresses the final traffic volume estimate on observation spot during $\left(kT,(k+1)T\right]$, β is an weight coefficient. In theory, $\beta\in[0,1]$, but in practical application, $\beta\in[0.1,0.9]$. The smaller β is, the bigger the weight of $q_{\mathrm{F}}(k+1)$ made up $\tilde{q}(k+1)$ is. In other words, if the small β is adopted, traffic condition means steady relatively.



(a) R_{N} or R_{F}

(b) T

(c) $\Delta\beta$

Fig. 5. Fuzzy sets definition.

The β is adjusted by a fuzzy decision with three fuzzy inputs and one fuzzy output as shown in Fig. 2. The inputs are T, R_{N} and R_{F} where $\mathrm{R}_{\mathrm{N}}=\left(|q_{\mathrm{N}}(k)-q(k)|/q(k)\right)\times 100\%$ and $R_{\mathrm{F}}=\left(|q_{\mathrm{F}}(k)-q(k)|/q(k)\right)\times 100\%$. R_{N} and R_{F} represent the forecasting precision of the ANN model and the KF model respectively. In theory, $\mathrm{R}_{\mathrm{N}}\in[0,\infty)$ and $\mathrm{R}_{\mathrm{F}}\in[0,\infty)$. R_{N} and R_{F} have the same language variables that are Z (Zero), VS (Very Small), S (Small), M(Middle) , B(Big), VB(Very Big). T is the forecasting cycle time. In theory, $T\in(0,\infty)$ min. However, in practical short-term traffic flow forecasting application, generally $T\in[3,15]$ min. Its language variables are VS (Very Short), S (Short), M (Middle), L (Long), VL (Very Long). The output of the fuzzy decision is $\Delta\beta$, that is a small positive or negative change of

β . $\Delta\beta \in [-0.5, 0.5]$, and its language variables are NB (Negative Big), NM (Negative Middle), NS (Negative Small), Z (Zero), PS (Positive Small), PM (Positive Middle), PB (Positive Big). Fig. 5 shows the fuzzy sets defined on R_N , R_F , T and $\Delta\beta$.

Table 1. Partial rules of fuzzy decision

	PRE	T	$\Delta\beta$
1	Z		NB
2	S	S	NS
3	S	RS	NM
4	S	M	NM
5	S	RL	NM
6	S	L	NB
7	S	VL	NB
…	…	…	…

The fuzzy rules of the fuzzy decision are generated by experts' experience so that $\Delta\beta$ is directly proportional to R_F , but inversely proportional to R_N and T. For example, if the forecasting precision of the ANN model is big, however the forecasting precision of the KF model is small and (or) the forecasting cycle time is long, then β will be decreased ($\Delta\beta$ is Negative). There are127 fuzzy rules and Table.1 lists partial rules.

The Mamdani's max-min inference method and the center of gravity defuzzification method are used here. After defuzzification, we get the new β by $\beta = \beta + \Delta\beta$. If the new $\beta > 0.9$, $\beta = 0.9$. Else if $\beta < 0.1$, then $\beta = 0.1$.

3.4 Flow Chart

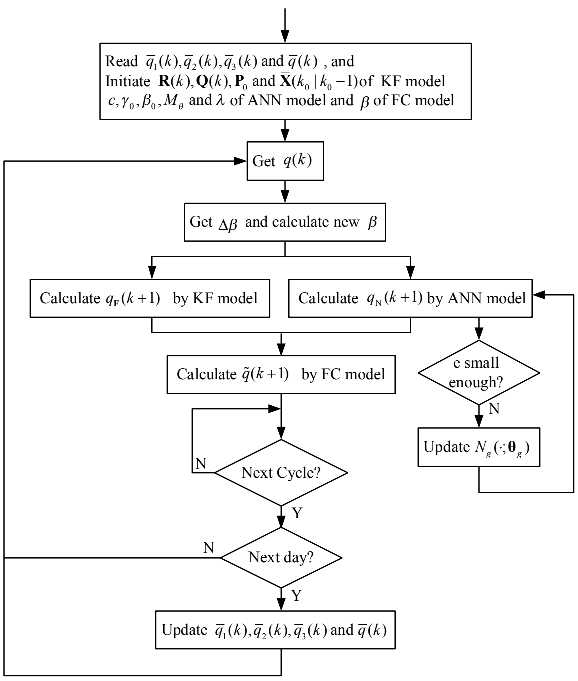


Fig. 6. Flow chart of the IH model.

The detailed flow chart of the IH model is shown in Fig.6.

4. APPLICATION AND ANALYSIS

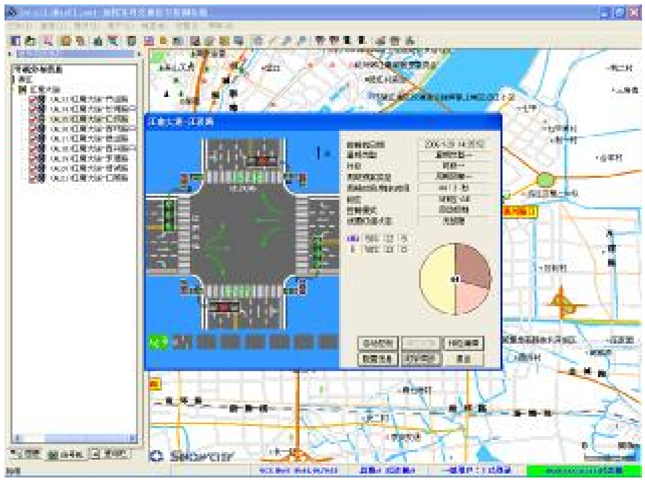


Fig. 7. TCMS traffic control software system.

The developed short-term traffic flow intelligent hybrid forecasting model has been implemented in C++ as a module of dynamic link library. The module has been used in TCMS traffic control platform software (shown in Fig.7) made by Zhejiang Supcon Information Co., Ltd, China. Supported by the National High Technology Research and Development Program of China (2007AA11Z216), Zhejiang University cooperates with Traffic Police Branch of the Department of Shaoxing Police and Zhejiang Supcon Information Co., Ltd in building a road network traffic coordination control system with bus priority at Yuecheng District Shaoxing City in 2007 (Shen & Kong, 2009). The traffic flow forecasting results are applied in road network traffic control and dynamic transportation guidance. At each main intersection of the controlled region, the inductive loop detectors are installed. The real-time traffic information is detected by the inductive loop detectors and transmitted to traffic control center by private network. Finally, all traffic information is saved into traffic database.

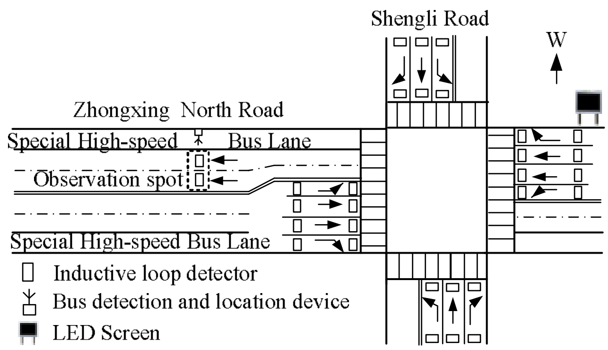


Fig. 8. The No.2 traffic flow observation spot.

The No.2 traffic flow observation spot is located on Zhongxing North Road and 280 meters distance away from the Shengli Road (shown in Fig. 8). Zhongxing North Road is two-way and has six lanes (three for one way). In the south and north corners with four lanes, the first lane from the center of a road is occupied by vehicles to turn-left, the second and the third lanes to go-straight, and the fourth lane to turn-right. The other two corners have three lanes, and thus the left-turn, go-straight, and turn-right have one lane respectively. The special bus lanes used by high-speed bus only lie on the two side of Zhongxing North Road (the other vehicles and buses are not permitted to enter it). The LED screen used for dynamic transportation guidance is on the side of Zhongxing South Road. There are two inductive loop detectors on the lane of the input corners. One is at the stop line and the other is at a certain distance after the stop line. The inductive loop detectors are also installed on each lane at the No. 2 traffic flow observation spot. The each detector can detect the vehicles and buses passing through it without failure. The radio-wave frequency technique is adopted in the bus detection and location device which can find when and how many high-speed buses will arrive in the intersection. The acceptor is located in the bus and the emitter is installed on the side of the road. The No. 2 traffic flow observation spot detects and saves traffic flow per 10 min, and then converts it to hourly traffic volume. The traffic information from the No. 2 traffic flow observation spot is used to evaluate the performance of the developed intelligent hybrid forecasting model presented in this article.

From Nov. 1, 2008 and Jun. 30, 2009, there are 99 days belonging to Tuesday, Wednesday or Thursday (removing New Year's Day, Spring Festival, Tomb-sweeping Day, May Day and Dragon Boat Festival). Traffic data in those 99 days are used to forecast the traffic volume in Jul. 1, 2009. In order to analyze the superiority of the hybrid forecasting method over the individual method, three approaches as follow are adopt.

Approach 1: the individual KF model. In this approach, $\overline{q}_1(k)$, $\overline{q}_2(k)$, $\overline{q}_3(k)$ and $\overline{q}(k)$ in (5) are prepared in advance based on the traffic data in those 99 days. $\mathbf{R}(k)$ in (12), $\mathbf{Q}(k)$ in (13) and $\mathbf{P}_0$ in (15) are set as diagonal matrix, and $\overline{\mathbf{X}}(k_0 \mid k_0 - 1)$ is a zero vector.

Approach 2: the individual ANN model by use of the single-hidden-layer feed-forward network $N_g(\cdot;\boldsymbol{\theta}_g)$ as shown in Fig. 3. The hidden layer has 12 neurons. 2880 sets of training data of 20 days are selected randomly from 114 days. In the same way, 288 sets of testing data of 2 days are selected. The constant in the sigmoidal function (20) is chosen as $c = 0.5$. The parameters in the adjustment law (29), (30) and (31) are chosen as: $\gamma_0 = 0.1$, $\beta_0 = 1.2$ and $M_\theta = 12$. We have also arbitrarily chosen $\lambda = 0.5$ in the traffic flow dynamic equation (26). During the course of training, the error signal e defined as (28) is decreasing and approaches a small number.

Approach 3: the IH model based on the KF model and the ANN model. In this approach, β is 0.7 firstly and adjusted in real-time by the developed fuzzy logic.

We assume that $\tilde{x}(k)$ is the estimated value of the traffic volume, $x(k)$ is the factual measured value, and n is the numbers of sample data. The following performance indexes are used to evaluate the three aforementioned approaches:

1. Percentage Relative Error E_{PR}

$$E_{\mathrm{PR}} = \frac{|\tilde{x}(k) - x(k)|}{x(k)} \times 100\% \tag{33}$$

2. Percentage Mean Relative Error E_{PMR}

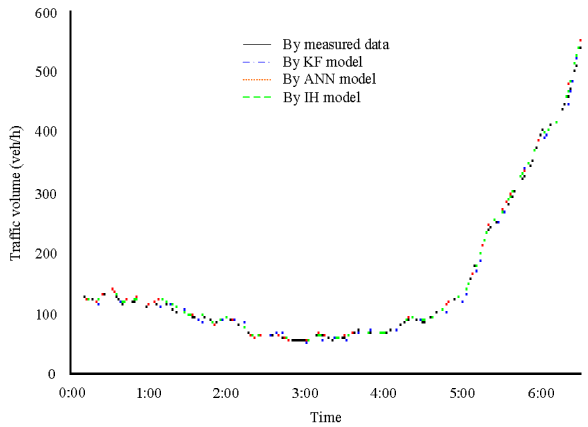
$$E_{\mathrm{PMR}} = \frac{1}{n}\sum_{k=1}^{n}\frac{|\tilde{x}(k) - x(k)|}{x(k)} \times 100\% \tag{34}$$

3. Root-mean-square Relative Error E_{RR}

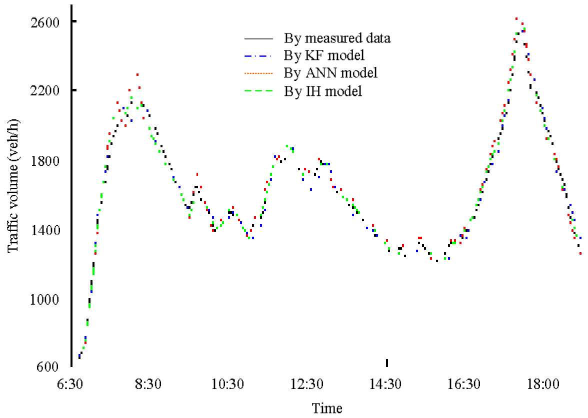
$$E_{\mathrm{RR}} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(\frac{\tilde{x}(k) - x(k)}{x(k)}\right)^2} \tag{35}$$

4. Equalization Coefficient C_{E}

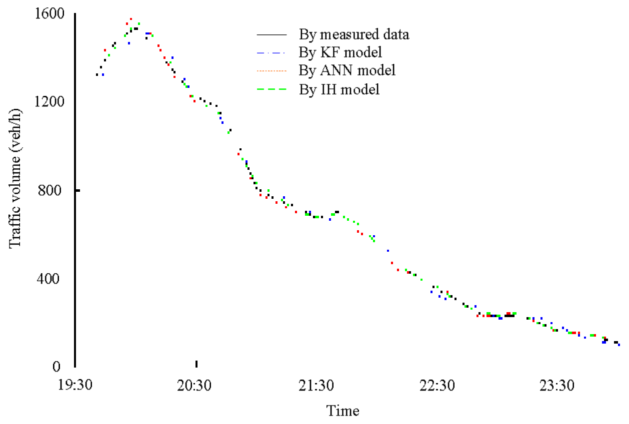
$$C_{\mathrm{E}} = 1 - \frac{\sqrt{\sum_{k=1}^{n}\left(\tilde{x}(k) - x(k)\right)^2}}{\sqrt{\sum_{k=1}^{n}\tilde{x}^2(k)} + \sqrt{\sum_{k=1}^{n}x^2(k)}} \tag{36}$$



(a) Between 0:00 to 6:30



(b) Between 6:30 to 19:30



(c) Between 19:30 to 23:59

Fig. 9. Comparison between measured data and forecasting results by three approaches.

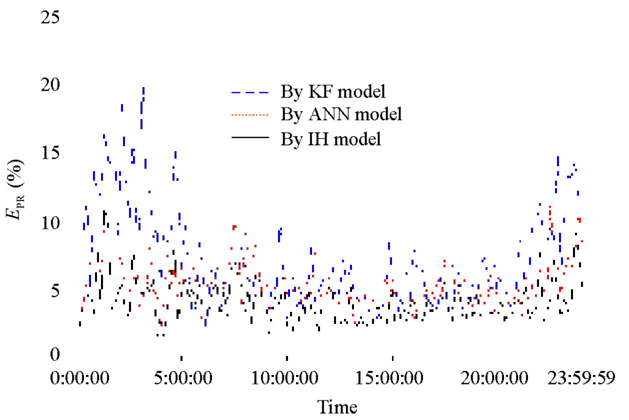


Fig. 10. Percentage relative errors of forecasting results by three approaches.

Table 2. Error analysis of forecasting results by three approaches

	KF model	ANN model	IH model
E_{PMR}	7.6264	5.5348	4.2769
E_{RR}	0.0675	0.0488	0.0374
C_E	0.9013	0.9217	0.9608

These aforementioned indexes can describe the model performance from different respects. E_{PR} and E_{PMR} show the degree of deviation between the estimated value and the measured value. E_{RR} reflects not only the size of relative error but also the distribution of error. C_E describes the degree of fitting between the estimated value and the measured value. It is known commonly to us that $C_E \geq 0.9$ is good.

Fig. 9 draws the comparison between measured data and forecasting results by three approaches. In order to make the comparison more clear, the continuous curves are divided into three segments according to traffic volume size. Fig 10 shows the percentage relative errors of forecasting results by three approaches. Moreover, percentage mean relative error, root-mean-square relative error and equalization coefficient of three approaches are listed in Table.2

By further analysis, the following results can be obtained:

1. In Fig. 9, we observe that the curves of forecasting results by three models can reflect the movements in the underlying traffic flow. The differences between measured data and forecasting results by three approaches are kept well in the satisfactory range.

2. It is shown in Fig.10 that the IH model based on the KF model and ANN model holds lower percentage relative errors all day than the two individual models. This super feature is owed mainly to the weight coefficient β that is adjusted automatically by a fuzzy strategy.

3. From Fig.10, we also can get the fact that the percentage relative errors of the KF model during daytime are relatively smaller than that during nighttime. The cause may be that during daytime traffic volume is heavier and traffic stability is more obvious than those during nighttime. On the contrary, the ANN model has more small percentage relative errors under the condition of medium and small sized traffic flow.

4. From Table.2, we can find that the IH model has the following three superiorities over the two individual models. Firstly, the IH model has the more high forecasting precision on the whole. Secondly, the distribution of forecasting error of the IH model seems be more centralized. Thirdly, the equalization coefficient of the IH model is 0.9608, in other words, the IH model has very good fitting between the estimated value and the measured value.

In summary, according to the application results and above-mentioned analysis we can make the conclusion that the IH model, which takes advantage of the unique strength of the KF model and the ANN model, can produce more precise forecasting than that of two individual models. Hence, this IH model is an efficient method to the short-term traffic flow forecasting and can be applied to traffic control engineering.

5. CONCLUSIONS

We find that although fluctuations in traffic flow are very intricate, there are some inherent law. If historical data is sufficient and the forecasting model is selected reasonably, traffic flow can be forecasted precisely. In this paper, Kalman filter model and artificial neural network model are simultaneously employed in the short-term traffic flow forecasting. The two individual forecasting results are mixed by fuzzy logic, and the output of the intelligent hybrid model is regarded as the final forecasting of the traffic flow. Practical application results show that the intelligent hybrid model can forecast traffic flow in a very precise and satisfactory sense.

On the basis of the analysis and the conclusion above, we can make efforts in three directions in future:

1. Our conclusions are derived from the actual application in Zhong Xing North Road where traffic flow is unsaturated. Hence the forecasting effectiveness under saturated or oversaturated traffic flow condition shall be verified further.

2. In this paper, we assume that detectors can give us what we want. However, in the real world such assumption is very fragile. The detectors cannot be fixed at every intersection and the detectors may fail in sometime. Thus, studies on uncertainty of detectors and the improved forecasting method which can cope with such problem are needed.

3. Some methods else may be selected to compose a more complex hybrid forecasting model.

ACKNOWLEDGMENT

This work was supported by Natural Science Foundation of China under grant 61174174, Zhejiang Province Natural Science Foundation of China under grant Y1090208, the Foundation of Key Laboratory of System Control and Information Processing, Ministry of Education, P.R. China under grant SCIP2011007, the Fundamental Research Funds for the Central Universities (DUT1600-852006), National High Technology Research and Development Program of China under grant 2007AA11Z216. The authors would like to thank the researchers being with the department of Control Science and Engineering and State Key Lab. of Industrial Control Technology, Zhejiang University, China for his/her help.

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