State Space Modeling and Short-Term Traffic Speed Prediction Using Kalman Filter Based on ANFIS

Nasim Barimani, Behzad Moshiri, and Mohammad Teshnehlab

***Abstract*—Speed is an important component in any traffic control or monitoring systems especially for road safety. This paper presents a novel short-term traffic speed prediction model using Adaptive Neuro Fuzzy Inference System (ANFIS). By applying this method, despite nonlinear nature of traffic, linear time variant state space model will be presented. Kalman Filter (KF), based on this model, will reduce modeling error and modify prediction accuracy. Using this method, KF will be applied to the nonlinear system so Jacobian computations of Extended Kalman Filter (EKF) that is essential for nonlinear systems are not needed. Another advantage of suggested method is that there is no need to design different ANFIS structure for different predict horizons in order to obtain acceptable prediction accuracy, because the error due to the model structure is to some extent reduced by filter. Simulation results with real data sets indicate that this model is an efficient way which surpasses a common multilayer feed forward Neural Network (MLFNN) and an ANFIS predictive model.**

***Index Terms*—Prediction, adaptive neuro fuzzy inference system, kalman filter, state space.**

I. Introduction

Due to economic and space limitations, building new roads to overcome congestion problems is impossible so Intelligent Transportation Systems (ITS) have caused the people to make smart travel decisions in order to reduce congestion. Short-term prediction means the ability to make online predictions of traffic variables for several minutes in future and this is a major requirement for ITS. Short-term prediction of traffic variables such as traffic speed, volume, flow, travel time and occupancy based on real time data, is one of the main fields to reduce traffic congestion, mobility improvement, energy saving, enhancing air quality and providing dynamic traffic control strategies.

There are many efforts on short-term traffic flow prediction and a variety of methodologies has been applied. These methods are divided into two groups: statistical and artificial intelligence models. Statistical models such as the KF method [1], the multivariate time-series models [2]-[6], Exponential smoothing [7] and the nonparametric regression models [8]-[9]. Artificial intelligence models are mentioned as neural network models [10]-[13] and Fuzzy Logic systems [14]. Additionally, combined methods are more interested in recent years. Neuro-genetic [15], Neural networks combined together [16]-[17], ARIMA combined with neural network [18], KF mixed to the ARIMA [14] are the examples.

All available prediction methods have their own defects and strengths e.g. a suddenly changes of states is a reason for increase the KF prediction error. Determining a suitable smooth constant is a cumbersome task in the Exponential Smoothing Method [14]. Auto Regressive Integrated Moving Average (ARIMA) is based on the stationary stochastic processes theory and normality and linearity assumptions, therefore predicted traffic variables by time series is not precise [18]. For most of the discussed methods, the missing or inaccurate data imposes troubles [14].

In this paper, short term traffic speed prediction model is proposed to overcome some above obstacles. This method produces more accurate prediction especially when states change suddenly and when the horizon of prediction heightens. To tackle the modeling problems, the ANFIS applied to modeling unknown but observable nonlinear traffic speed process. Using collected speed time series, state-space of the system depending on time varying traffic manner will be formed. KF based on the obtained model will be implemented to reduce model error and improve prediction accuracy.

The remainder of this paper is organized as follows: In section II, some related prediction methods are reviewed. In section III used ANFIS structure is presented. State space representation and KF implementation is presented in section IV. In section V, to confirm our suggested method, simulation results of real traffic data and comparison results with ANFIS and MLFNN is illustrated. Finally the main conclusions are summarized in section VI.

II. Related Prediction Methods

KF, MLFNN and ANFIS methods will be used in the following parts of the paper. So they are briefly described.

A. Kalman Filter Method

KF is a recursive solution to the discrete-data linear filtering problem. Its purpose is to use observed measurements that contain noise and other inaccuracies to produce values that tend to be closer to the true values. The common method of using KF in traffic variable prediction is explained in this section.

KF applied to short-term prediction of traffic volume [1]. $Z(k)$ considered as the traffic volume that needed to be predicted. Present and past n measured traffic volume data generate $H(k) = [Z(k), Z(k-1), ..., Z(k-n)]$ that is $1\times(n+1)$ matrix. Linear combination of present and past

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measured data is assumed to be the predicted state. These combination coefficients are $a_i, i = 0, \ldots, n$ and $x(k) = [a_0, a_1, \ldots, a_n]^T$ represent the model states. The predicted traffic volume is:

$$Z(k+1) = H(k)X(k) + v(k) \qquad (1)$$

where $v(k)$ is white Gaussian noise. According to correlation and prediction equations of KF, the states are estimated.

B. Multilayer Feed Forward Neural Network

MLFNN is the most common method in complicated nonlinear processes modeling. It consists of input, hidden and output layers. Fig. 1 shows the MLFNN structure.

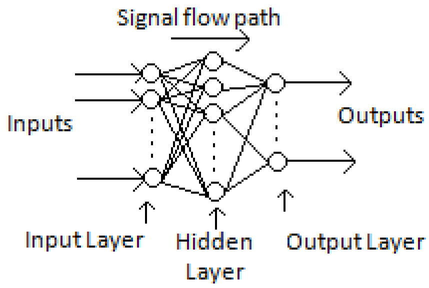

Fig. 1. Multilayer neural network structure

In each layer, in forward process, layer's inputs transmit through weighted sum and activation functions to the next layer till network output is made. The next stage is feedback process that the difference between network output and desired output values propagate back to the layers to train network's parameters. This procedure must be repeated till the parameters will be trained and appropriate minimum error will be obtained. By this training procedure network's weights will be fitted.

In this paper, MLFNN will be used only for comparison purpose.

C. Adaptive Nero Fuzzy Inference System

The ANFIS introduces as a universal approximator of nonlinear functions [19]. The ANFIS has five layer structure shown in Fig. 2. For simplification, we assume the ANFIS has only two inputs and one output and two fuzzy if-then rules. A1, A2, B1, and B2 are possible input's sets and p1, p2, q1, q2, r1, and r2 are network parameters. If-then rules are in the following form:

$$\begin{aligned}
&Rule\,1: \\
&If\ x\ is\ A_1\ and\ y\ is\ B_1 \quad Then \quad F_1 = p_1 x + q_1 y + r_1 \\
&Rule\,2: \\
&If\ x\ is\ A_2\ and\ y\ is\ B_2 \quad Then \quad F_2 = p_2 x + q_2 y + r_2
\end{aligned} \qquad (2)$$

The ANFIS layers have the following duties:

1- Fuzzification process is applied on Crisp inputs in the first layer, 2- The second layer executes the fuzzy AND of the first layer outputs or antecedent part of the fuzzy rules, 3- Membership Functions (MFs) are normalized in the third layer according to (5), 4- The fourth layer accomplishes the conclusion part of the fuzzy rules $F_i = p_i x + q_i y + r_i$ and produces normalized weighted of $F_i s$, and 5- in the last layer, by sum of the fourth layer's outputs, defuzzification process is done [20].

Equations (3) – (5) are held for ANFIS structure.

$$\begin{aligned}
W1 &= mf_{A1} \times mf_{B1} \\
W2 &= mf_{A2} \times mf_{B2}
\end{aligned} \qquad (3)$$

$$F = \frac{W_1 F_1 + W_2 F_2}{W_1 + W_2} = \bar{W}1\, F_1 + \bar{W}2\, F_2 \qquad (4)$$

$$\bar{W}1 = \frac{W_1}{W_1 + W_2}, \quad \bar{W}2 = \frac{W_2}{W_1 + W_2} \qquad (5)$$

where $mf_{A1}, mf_{A2}, mf_{B1}$ and mf_{B2} are input's MFs. As a consequence of training process, all parameters of MFs in antecedent and consequent parts will be fitted. There is no considerable attention on ANFIS in traffic modeling. In [21] ANFIS with 4 inputs and 8 MFs and 16 rules has been used for prediction of traffic flow.

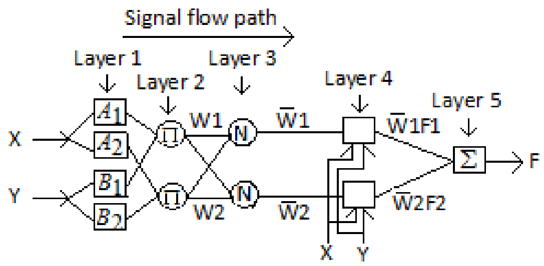

Fig. 2. ANFIS structure

III. TRAFFIC SPEED MODELING

In this paper, an ANFIS with three inputs containing the last three speed measured data and an output which is speed in next time intervals depending on target prediction horizons is designed for identification of traffic speed process.

In this model Gaussian distributions with mean c_i and variance a_i have been selected to be the input's membership functions.

$$mf_{A_i}(x) = \exp\left(\frac{(x - c_i)^2}{2a_i^2}\right) \qquad i = 1, \ldots, 6 \qquad (6)$$

Thus, 6 MFs and 2×6 independent parameters in antecedent part and 2^3 if-then rules attained. The rules are expressed as bellows:

$$\begin{aligned}
&Rule\,1: If\ v_{i-2}\ is\ A_1\ and\ v_{i-1}\ is\ A_3\ and\ v_i\ is\ A_5 \\
&\qquad Then\ f_1 = p_1 v_{i-2} + q_1 v_{i-1} + r_1 v_i + s_1 \\
&\vdots \\
&Rule\,8: If\ v_{i-2}\ is\ A_2\ and\ v_{i-1}\ is\ A_4\ and\ v_i\ is\ A_6 \\
&\qquad Then\ f_8 = p_8 v_{i-2} + q_8 v_{i-1} + r_8 v_i + s_8
\end{aligned} \qquad (7)$$

where v_i is speed in step i and v_{i+k} is predicted speed in k step ahead. In Fig. 3, the ANFIS structure is shown.

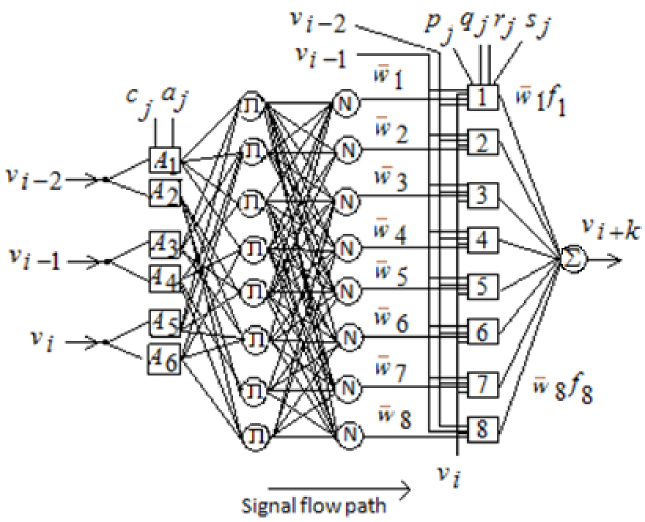

Fig. 3. Proposed ANFIS structure for traffic speed modeling

In order to prevent divergence of our network, normalization processing of original data is needed. To adjust 44 network weights, training of ANFIS with back propagation gradient descent learning algorithm is done. After that the predicted data should be transformed into the original space.

IV. State Space Representation

State space modeling for k step ahead speed prediction is explained in this section. As explained in Section II part C and III, following equations are held:

$$v_{i+k} = \sum_{j=1}^{8} \bar{w}_j f_j$$
$$v_{i+k} = \sum_{j=1}^{8} \bar{w}_j \left[p_j v_{i-2} + q_j v_{i-1} + r_j v_i + s_j \right] \tag{8}$$

The nonlinear system is depicted in the form of time-varying auto regressive model.

$$v_{i+k} = \left[\sum_{j=1}^{8} \bar{w}_j p_j\right] v_{i-2} + \left[\sum_{j=1}^{8} \bar{w}_j q_j\right] v_{i-1} + \left[\sum_{j=1}^{8} \bar{w}_j r_j\right] v_i + \left[\sum_{j=1}^{8} \bar{w}_j s_j\right] \tag{9}$$

The corresponding terms with v_{i-2} and $\left[\sum_{j=1}^{8} \bar{w}_j s_j\right]$ considered as system input:

$$u_i = \left[\sum_{j=1}^{8} \bar{w}_j p_j\right] v_{i-2} + \left[\sum_{j=1}^{8} \bar{w}_j s_j\right] \tag{10}$$

Selection of state variables is as (11).

$$\begin{aligned} x_1(i) &= v_{i-1} \\ x_2(i) &= v_i \\ &\vdots \\ x_k(i) &= v_{i+k-2} \\ x_1(i+1) &= x_2(i) \\ x_2(i+1) &= x_3(i) \\ &\vdots \\ x_k(i+1) &= x_{k+1}(i) \end{aligned} \tag{11}$$

Using (9), (10) and (11) we have following equation.

$$x_{k+1}(i+1) = v_{i+k} = \left[\sum_{j=1}^{8} \bar{w}_j q_j\right] x_1(i) + \left[\sum_{j=1}^{8} \bar{w}_j r_j\right] x_2(i) + u_i \tag{12}$$

Let $X(i+1)$ be the $(k+1)\times 1$ vector of states $x_j(i+1),\ j=1,\dots,k+1$. The linear time variant state space model is formed.

$$X(i+1) = \begin{bmatrix} 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \\ \vdots & & & & & \\ 0 & 0 & 0 & 0 & \dots & 1 \\ \sum_{j=1}^{8} \bar{w}_j q_j & \sum_{j=1}^{8} \bar{w}_j r_j & 0 & 0 & \dots & 0 \end{bmatrix}_{(k+1)\times(k+1)} X(i) + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} u_i \tag{13}$$

$$y(i) = \begin{bmatrix} \sum_{j=1}^{8} \bar{w}_j q_j & \sum_{j=1}^{8} \bar{w}_j r_j & 0 & \dots & 0 \end{bmatrix}_{1\times(k+1)} X(i) + u_i$$

KF will be implemented based on this state space model. ANFIS modeling error is considered as measurement noise and will be reduced in KF so predicted state from ANFIS will be estimated more accurately in KF. The suggested predictive model block diagram is shown in Fig. 4.

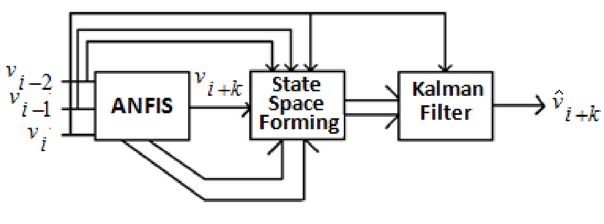

Fig. 4. Improved predictive model block diagram

V. Simulation Analysis

Real-time traffic measured data in Minnesota, located in Midwestern United States, are collected. The detector unit

I-494, EB, station 702 is selected for data acquisition. The data are archived From January 25th to 28th, 2010 with 5 minutes time intervals, then 864 samples achieved. The purpose is to predict traffic speed in the next 5 minutes, 10 minutes and 15 minutes. The prediction system inputs are selected as speed in time intervals of t-5' to t and t-10' to t-5' and t-15' to t-10'. The first 644 samples of data are used recyclely for train the ANFIS, and the last 220 samples are used for test of suggested model. By choosing almost 19 hours test data, our model tests in transition and steady speed hours.

To compare our predictive model with an ANFIS and MLFNN model, four performance indices are selected [17],[22].These performance indices are Root Mean Squared Error (RMSE), Max Absolute Relative Error (MARE), Mean Absolute Relative Error (MEARE) and Relative Mean Error (RME).

Mean squared error (MSE) had converged at around epoch 160. The convergence of the MSE for train and test process is shown in Fig. 5. The primarily mean and variance of membership functions and consequent parameters are randomly chosen as, $\{a_i = 1 | i = 1{:}6\}$, $\{c_i = 0.5 | i = 1{:}6\}$, $\{p_i = 0.005 | i = 1{:}8\}$, $\{q_i = 0.2 | i = 1{:}8\}$, $\{r_i = 0.25 | i = 1{:}8\}$ and $\{s_i = 1 | i = 1{:}8\}$. The ANFIS learning rate η is selected 0.001 by process of trial and error. In MLFNN design, three layers NN with 3 neurons in input layer and 10 neurons in hidden layer and one output neuron is adopted. Activation functions for hidden and output layer are chosen tangent sigmoid and linear transfer functions respectively. Initial weights and biases are chose randomly and the best learning rate was 0.001. Real traffic speed and prediction of ANFIS and suggested model are illustrated in Fig. 6, (a), (b), (c). To see more details, transition and steady part of the speed depicted separately.

Improvement of prediction accuracy is appearing in simulations, especially when the prediction horizon heightens. The numerical comparison results in Table I indicated that suggested model improved the performance of prediction.

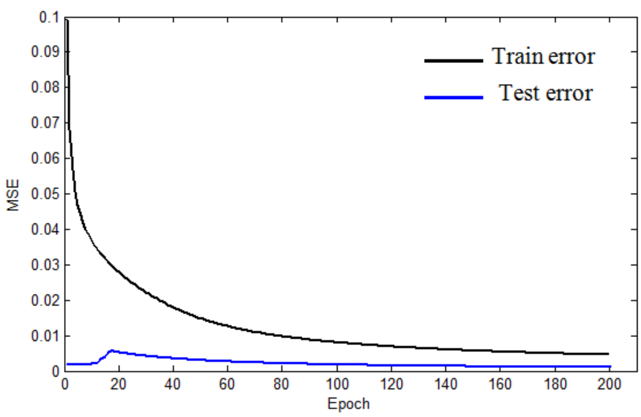

Fig. 5. Showing convergence of ANFIS train and test

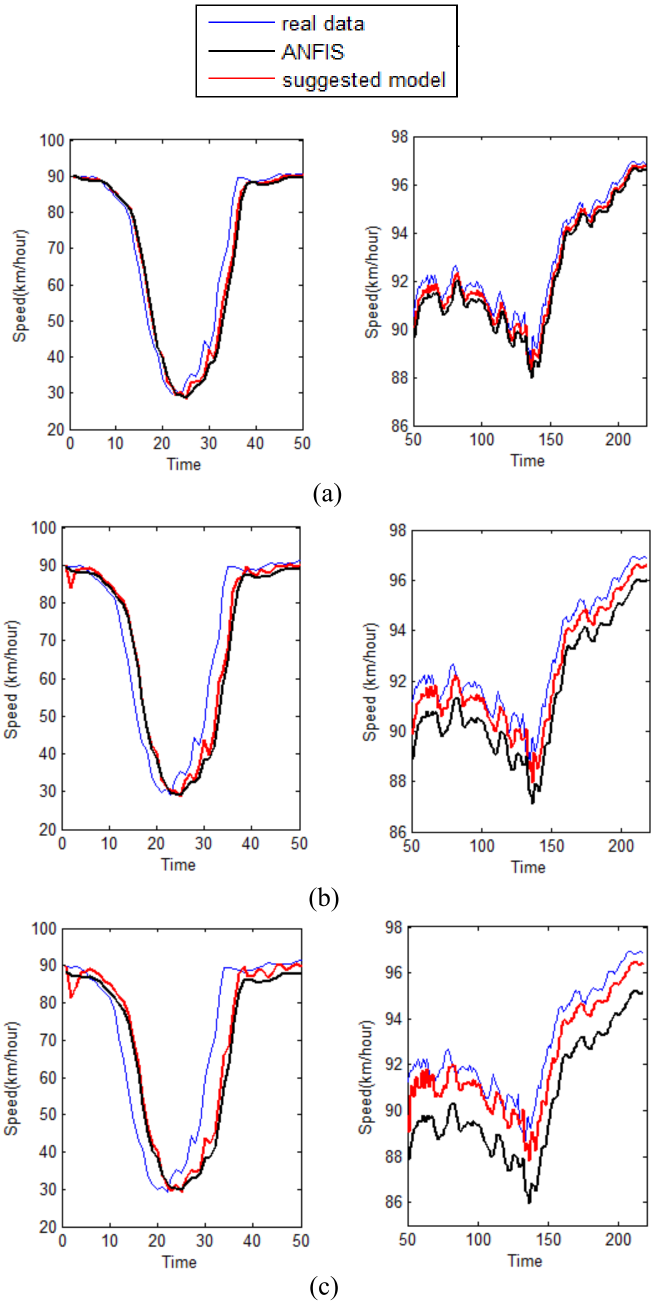

Fig. 6. Speed prediction :(a) 5 min ahead prediction (b) 10 min ahead prediction (c) 15 min ahead prediction. Time sample is 5 min.

VI. Conclusion Remarks

This article presented a novel approach to modeling traffic speed based on linear time variant state space model through an ANFIS network. KF by estimating predicted speed from undertrained obtained model for the purpose of reduce modeling error and improve prediction performance applied.

Another advantage of this method is achieving acceptable prediction from simple ANFIS structure for more than one prediction horizon. In order to achieve acceptable accuracy for different time horizons, this method does not need to structurally redesign the predictor. Therefore it is not time-consuming and has less computational complexity compared with other Neural Networks for this reason. The obtained results provided strong evidence of the good performance of the approach for the prediction of freeway traffic speed Compare to ANFIS and MLFNN prediction model.

TABLE I: NUMERICAL COMPARISON RESULTS

	MLFNN	ANFIS	Suggested model
5 min traffic speed prediction			
RMSE %	4.82	5.18	4.21
MARE %	.12	.14	.11
MEARE %	1.9	2.19	1.64
RME %	0.871×10^{-2}	1.005×10^{-2}	$.0733\times10^{-2}$
10 min traffic speed prediction			
RMSE %	7.25	7.58	6.85
MARE %	2.78	3.65	2.67
MEARE %	.18	.17	.15
RME %	1.28×10^{-2}	1.67×10^{-2}	1.22×10^{-2}
15 min traffic speed prediction			
RMSE %	12.67	10.1	9.5
MARE %	4.82	5.38	3.82
MEARE %	.31	.22	.19
RME %	2.21×10^{-2}	2.46×10^{-2}	1.75×10^{-2}

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