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Adaptive Online Traffic Flow Prediction Using Aggregated Neuro Fuzzy Approach

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Abstract

Short term prediction of traffic flow is one of the most essential elements of all proactive traffic control systems. Although various methodologies have been applied to forecast traffic parameters, several researchers have showed that hybrid methods provide more accurate results. So this approach became a common method for prediction. In this paper, an aggregated approach is proposed for traffic flow prediction. The approach is based on the adaptive neuro-fuzzy inference system (ANFIS) and the macroscopic traffic flow model (METANET). Macroscopic modeling tool, METANET, is used to simulate the Hemmat highway/Tehran, and validation of the model was done using real measurements. In order to calibrate the model, genetic algorithm was followed. The outcome suggests that the proposed approach obtains a more accurate forecast than the neuro-fuzzy model alone.

Keywords: ITS, Traffic prediction, Flow modelling, Neuro-fuzzy, METANET, Hybrid model.
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1. Introduction

In many metropolitan areas, one of the major needs in the area of Intelligent Transportation Systems (ITS) is traffic prediction. The increasing number of vehicles has led to severe problems like recurrent and non-recurrent congestion causing many problems such as economic and environmental problems. Therefore traffic prediction is performed by traffic control centres (TCC) beside a variety of tasks such as traffic monitoring and control.

Traffic prediction provides reliable forecasts of the traffic conditions that will occur in a network over a predetermined future time horizon. It may be performed on-line or offline. The online traffic prediction enables operators of a TCC to anticipate the impact of various events that take place in the network, such as incidents or high demands at certain locations [1].

The successful performance of this task needs a reliable model which is able to anticipate the short-term traffic conditions that are likely to prevail.

Selecting an appropriate methodological approach is a major issue for traffic prediction. A step forward to achieve better accuracy seems to be the use of hybrid models. Hybrid methods using a mixture of methods to construct a smaller and more efficient network are one of the common approaches for traffic forecasting. There are many hybrid models with promising results which proves the effectiveness of this concept. Combining neural networks and fuzzy logic, also known as neuro-fuzzy systems, play an important role in this field. Some examples are Short-term traffic-flow forecasting on the dynamic traffic-flow data with a technique based on ANFIS and random factors [2], the fuzzy neural model with two basic modules: a gate network and an expert network [3] and a neuro-fuzzy system developed by Ishak and Alecsandru which applies an adaptive neuro-fuzzy inference system (ANFIS) to reduce the dimensionality of the input space [4].

This paper proposes an online hybrid model consisting of ANFIS and the traffic flow model (METANET). The most important advantages of this method is that it can adapts itself with the latest variations in the traffic trend in an online manner.

The rest of paper is organized as follows: section 2 describes the adaptive online predictor which is the core of the hybrid method. Section 3 describes the METANET model and its application to model the traffic of the studied highway. Section 4 discusses the data used in this study. Section 5 presents the calibration procedure of METANET and presents the results of this procedure. Section 6 introduces the hybrid model and section 7 reports the results of testing the hybrid model with real data gathered from modelled highway.

2. Adaptive Online Neuro-Fuzzy Framework

A) Fuzzy Inference System

Most traditional traffic prediction models, usually force the nonlinear behaviour of traffic into a linear context. Considering traffic's complexity, nonlinear nature, and non-stationary behaviour, obtaining a reliable traffic predictor is extremely difficult. One distinct advantage of fuzzy systems over traditional traffic predictors is their ability to handle the traffic's nonlinearity. Basically a Fuzzy Inference System (FIS) is composed of five functional blocks [5] (figure 1):

– A rule base containing a number of fuzzy if-then rules;
– A database which defines the membership functions of the fuzzy sets used in the fuzzy rules;
– A decision making unit which performs the inference operations of the rules;
– A fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values;
– A defuzzification interface which transform the fuzzy results of the interface into crisp output.

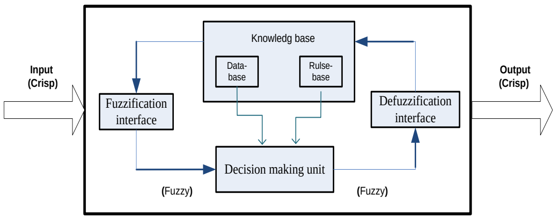

Fig. 1. Fuzzy inference system

B) Adaptive Fuzzy Inference System

The aim of this paper is to suggest an adaptive fuzzy inference system for traffic forecasting. Using FIS unfortunately poses a limitation; while the efficiency of a fuzzy system greatly depends on the selection of appropriate parameters, there is no formal framework to determine them. Apart from this, the absence of an effective adaptive scheme in adjusting the parameters can further limit the performance of a fuzzy system when it comes to a time-varying environment. Therefore, identifying the parameters of fuzzy systems in an adaptive way has become an important field for further studies. The application of the special neuro-fuzzy architecture to address this issue is discussed in this section of the paper.

In order to update the fuzzy set parameters, Adaptive Neuro Fuzzy Inference System (ANFIS) was used. Figure 2 shows the simple diagram of this hybrid learning with 4 inputs.

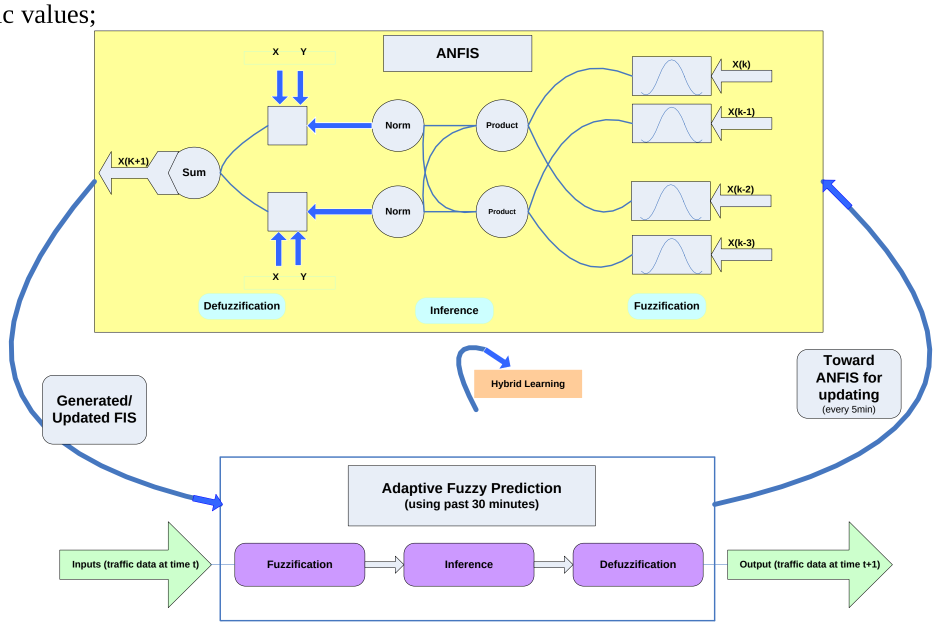

Fig. 2. Configuration of the adaptive-hybrid learning of fuzzy system

This model works based on the adaptive tuning of the fuzzy sets parameters in order to obtain the most compatible results with the latest variations in the traffic trend. In fact adaptive changing and tuning the parameters of the fuzzy sets, at specified time intervals (for example every 15 minutes), makes the model outputs closer to the actual values of traffic parameters. This procedure is useful when traffic patterns are subject to change or the gathered data is not accurate. Tuning the fuzzy sets parameters is done dynamically and automatically via a learning/optimization procedure. The carried out procedure to find the optimal parameters of fuzzy sets is the neural networks theory and more precisely, ANFIS. For this reason the final adaptive system is called the neuro-fuzzy system.

The procedure starts with a primary FIS created base on the data set given to the ANFIS structure. This data set is for the first 30 minutes of the day which is collected every minute. As shown in the above figure, generated FIS is used for about 15 minutes and then ANFIS updates the old FIS based on the last 30 minutes from the current time including the real data collected in the last 15 minutes (during traffic predicting using the old FIS).

3. The Macroscopic Traffic Flow Model

METANET is a macroscopic second-order traffic model that is discrete in both space and time. The model represents the network by a directed graph with the links corresponding to highway stretches and nodes corresponding to places with a major change in the road geometry (e.g., on-ramps or off-ramps). A highway link (m) is divided into (N_m) segments (indicated by the index i) of length ($l_{m,i}$) and by the number of lanes (n_m). Each segment (i) of link (m) at the time instant t = kT, $k = 0,1, \dots, K$ is macroscopically characterized by the traffic density $\rho_{m,i}(k)$ (veh/lane/km), the mean speed $v_{m,i}(k)$ (km/h) and the traffic volume $q_{m,i}(k)$ (veh/h). Each link has uniform characteristics i.e. no on-ramp or o_-ramp and no major changes in geometry. The nodes of the graph are placed between links where the major changes, such as on-ramps and off-ramps in road geometry occur. The time step used for simulation is denoted by T [6].

Table 1 describes the notations related to the METANET model [6]. The traffic stream models that capture the evolution of traffic on each segment at each time step are shown in Table 2, adapted from [6]. As mentioned before, major changes in the link characteristics, on-ramps and off-ramps should be considered as a node. Table 3, adapted from [6], shows the node equations.

A) Hybrid Model

In this section we will describe the final framework of our hybrid model generated from the models described above. Suppose that this framework has a core predictor element. This element is the adaptive fuzzy inference system (section 2). We want to improve the precision of this predictor by giving the opportunity of having an extra input which is the estimation of the value of the considered parameter in the next time interval. In other words if we want to predict the traffic flow (X) at time interval (k+1), we use this value (gained from another model) as one of the system inputs. So, our approach is to first calibrate the METANET model for the desired highway and then use it as a traffic simulator which can estimate the value of traffic parameters for the next time interval. This value will be entered as an input to the core predictor. The structure of the proposed hybrid model is illustrated in figure 3.

B) Study Data

In order to test the framework with a comprehensive set of data, data were collected from a four-lane section along the Hemmat-highway/Tehran with 1500 meters length for 4 hours (7-11 am) of a typical day in 2010. Graphical representation of the selected area and the organization of the loop detectors are shown in figure 4.

C) Calibrating METANET Model's Parameters

METANET includes a number of parameters which have to be estimated in order to accurately model the traffic flow of a particular network [1]. The model Calibration procedure aims at enabling the model to represent traffic conditions with sufficient accuracy. The macroscopic model includes a number of parameters that reflect the particular characteristics of a given highway stretch and depends to highway geometry, vehicle characteristics, drivers' behavior and etc. These parameters should be calibrated to fit a representative set of real data with maximum possible accuracy. Real data gathered from detectors along the modeled highway will be used as 'real world' data in order to be compared with the model output. The purpose of the calibration is minimizing the difference between 'real' data and model output. For this, the genetic algorithm toolbox of Matlab was used.

Genetic algorithm starts with an initial set of random solutions called population. Each individual in the population is called a chromosome, representing a solution to the calibration problem. The evolution operation simulates the process of Darwinian evolution to create population from generation to generation by selection, crossover and mutation operations. The success of genetic algorithm is founded in its ability to keep existing parts of solution, which have a positive effect on the outcome [7].

Table.1.
Notation used in METANET model

Notation	Descriptions
m, μ	Link index
i	Segment index
T	Simulation step size
k	Time step counter
$\rho_{m,i}(k)$	Density of segment I of freeway link m
$v_{m,i}(k)$	Speed of segment I of freeway link m
$q_{m,i}(k)$	Flow of segment I of freeway link m
N_m	Number of segments in link m
n_m	Number of lanes in link m
$l_{m,i}$	Length of segment I in link m
τ	Time constant of the speed relaxation term
κ	Speed anticipation term parameter(Veh/km/lane)
υ	Speed anticipation term parameter(km^2/h)
a_m	Parameter of the fundamental diagram
$\rho_{crit,m}$	Critical density of link m
$V(\rho_{m,i}(k))$	Speed of segment I of link m on a homogeneous freeway
$\rho_{max,m}$	Maximum density of link m
$v_{free,m}$	Free-flow speed of link m
$w_o(k)$	Length of the queue on on-ramp o at the time step k
$q_o(k)$	Flow that enters into the freeway at time step k
$d_o(k)$	Traffic demand at origin o at time step k
$r_o(k)$	Ramp metering rate of on-ramp o at time step k
Q_o	On-ramp capacity
δ	Speed drop term parameter caused by merging at an on-ramp
n	Node index
Q_n	Total flow that enters freeway node n
I_n	Set of link indexes that enter node n
O_n	Set of link indexes that leaves node n
β_n^m	Fraction of the traffic that leaves node n via link m
$v_{control,m,i}$	Speed limit applied in segment I of link m
α	Parameter expressing the disobedience of drivers with the displayed speed limits

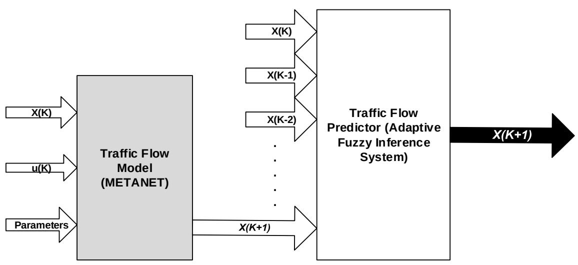

Fig. 3. The Proposed Hybrid Model

Table.2.
Link equations and description

Link equations and description

Flow-Density equation

$$q_{m,i}(k) = v_{m,i}(k)\rho_{m,i}(k)n_m$$

Conservation of vehicles

$$\rho_{m,i}(k+1) = \rho_{m,i}(k) + \frac{T}{l_{m,i}n_m}\left[q_{m,i-1}(k) - q_{m,i}(k)\right]$$

Speed dynamic
Relaxation term: drivers try to achieve desired speed V(ρ).
Convection Term: Speed decrease or increase caused by inflow of vehicles.
Anticipation Term: the speed decrease (increase)as drivers experience the density increase(decrease) in downstream.

$$v_{m,i}(k+1) = v_{m,i}(k) + \underbrace{\frac{T}{\tau_m}\{V[\rho_{m,i}(k)] - v_{m,i}(k)\}}_{Relaxtion\,Term} + \underbrace{\frac{T}{l_{m,i}}v_{m,i}(k)[v_{m,i-1}(k) - v_{m,i}(k)]}_{Convection\,Term} - \underbrace{\frac{\vartheta_m T}{\tau_m . l_{m,i}}\frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa_m}}_{Anticipation\,Term}$$

Speed-Density relation(fundamental diagram)

$$V[\rho_{m,i}(k)] = v_{free,m}\exp\left(\frac{-1}{a_m}\left(\frac{\rho_{m,i}(k)}{\rho_{crit,m}}\right)^{a_m}\right)$$

Origin's queuing model

$$w_o(k+1) = w_o(k) + T[d_o(k) - q_o(k)]$$

Ramp outflow equation
The outflow depends on the traffic condition in the mainstream and also on the metering rate,$r_o(k)\epsilon[0,1]$

$$V[\rho_{m,i}(k)] = \min\left\{v_{free,m}\exp\left(\frac{-1}{a_m}\left(\frac{\rho_{m,i}(k)}{\rho_{crit,m}}\right)^{a_m}\right), (1+\alpha)v_{control,m,i}(k)\right\}$$

Speed limit model
The desired speed is the minimum of the speed determined by (4) and the speed limit, which id displayed on variable message sign(VMS)

$$q_o(k) = \min\left\{d_o(k) + \frac{w_o(k)}{T}, Q_o . r_o(k), Q_o\frac{\rho_{max,m} - \rho_{m,1}(k)}{\rho_{max,m} - \rho_{crit,m}}\right\}$$

Speed drop caused by merging phenomena. If there is an on-ramp then the term must be added to (3)

$$-\frac{\delta T q_o(k) v_{m,1}}{l_{m,i}n_m(\rho_{m,1}(k) + \kappa)}$$

Table.3.
Node equations and description

Node equation	Descriptions
$Q_n(k) = \sum_{\mu \in I_n} q_{\mu,N_\mu}(k)$	Total traffic enter node n
$q_{m,O}(k) = \beta_n^m(k). Q_n(k)$	Traffic flow that leaves node n via link m
$\rho_{m,N_{m+1}} = \frac{\sum_{\mu \epsilon O_n} \rho_{\mu,1}^2(k)}{\sum_{\mu \epsilon O_n} \rho_{\mu,1}(k)}$	Virtual downstream density, when node n has more than one leaving link
$V_{m,O}(k) = \frac{\sum_{\mu \epsilon I_n} V_{\mu,N_\mu(k)} . q_{\mu,N_\mu}(k)}{\sum_{\mu \epsilon I_n} q_{\mu,N_\mu}(k)}$	Virtual upstream speed, when node n has more than one entering link.

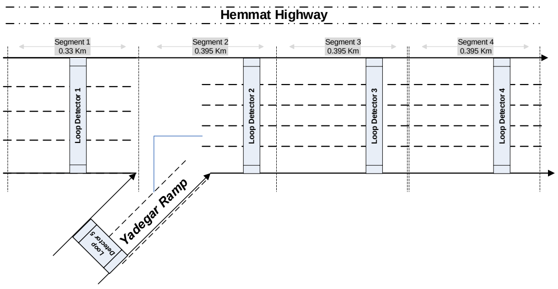

Fig. 4. Graphical representation of the selected area

The parameters of the METANET model which should be tuned during the calibration are: $p = (v_{free}, \delta, \tau, v, \kappa, a_m, c_{crit})$. To compromise between computation time and precision, 30 individuals were selected. After creating a new population the fitness value has to be calculated for each member in the population and then ranked based on the fitness value. The genetic algorithm selects 'parents' from the current population, using a selection probability. Then the reproduction of 'children' from the selected parents occurs by using recombination and mutation. The cycle of evaluation, selection and reproduction terminates when the convergence criteria is met [6].As previously discussed, calibration is an optimization procedure that minimizes the difference between the 'real data' and results of the METANET model. In particular we try to minimize the following objective function:

$J(p) =$
$\sum_{k=1}^{K} \|y(k) -$
$ym(k)2=k=1K(m,i)\epsilon Iall((qm,iml-qm,i\sim l)2+($
$vm,iml-vm,i\sim(l))2($

Where K is the prediction horizon, I_{all} is the set of indexes of all pairs of links and segments, $q_{m,i}^{m}$ and $v_{m,i}^{m}$ are the real values of traffic flow and speed. $q_{m,i}^{\sim}$ and $v_{m,i}^{\sim}$ are the values predicted by METANET.Described process is shown in the following flowchart (figure 5). U is the boundary-conditions vector.As shown in Fig. 11(a) and Fig. 11(b), the effect of LC filter on ADRC is negligible while it severely affects the response of PI controller. Therefore, the response of ADRC is independent of parameters of the LC filter.

D) Model Calibration

For the model calibration procedure, data from loop detectors for four consecutive hours were available (section 5). These data consist of one-minute measurements of flow and speed. They were used in order to determine the disturbances to the traffic system, and to provide the necessary boundary data. Considering the Genetic algorithm results a set of optimal parameters. The summarized outcome of this effort is presented in Table 4.Based on the set of parameters shown in Table 4, Figures 6, 7 and 8 depicts the speed, density and flow trajectory determined by the Calibrated model and compared with the actual measurements at segment number 2 (because we are going to predict the traffic flow at this segment). As it can be seen, after calibrating the model parameters the model is properly able to predict the network traffic conditions (but they don't have high accuracy).

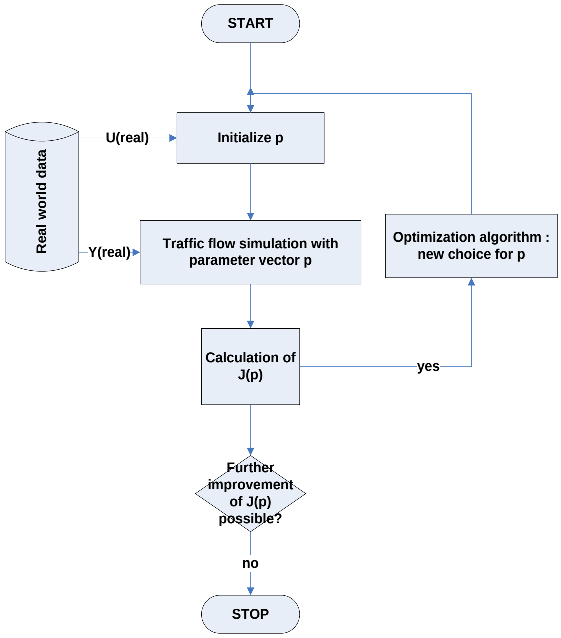

Fig. 5. Functional sketch of the parameter estimation procedure

Table.4.
Parameter sets for the Hemmat highway

Parameter	Optimum value	Parameter's interval (used in calibration procedure)
a	0.1144	[0.1, 2]
$\kappa(\frac{veh}{km})$	51.0402	[10, 100]
$v(\frac{km^2}{h})$	11.3750	[10, 100]
$\tau(seconds)$	0.1540	[0.1, 2]
ρ_{crit}	39.8451	[10, 40]
δ	1.9592	[0.1, 2]
$v_{free}(\frac{km}{h})$	70.5156	[70, 100]

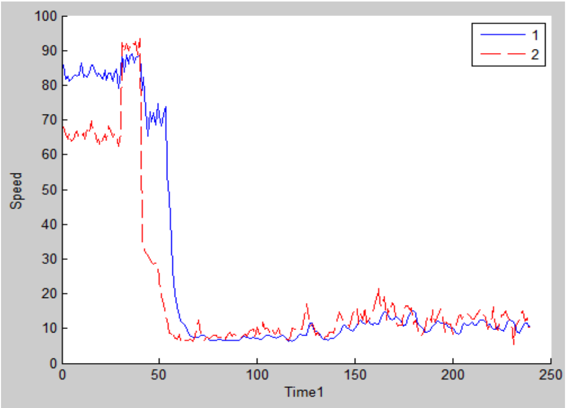

Fig. 6. Speed determined by the Calibrated model versus the actual measurements

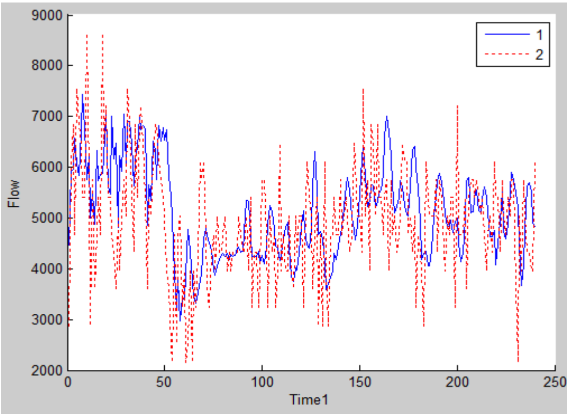

Fig. 7. Density determined by the Calibrated model versus the actual measurements

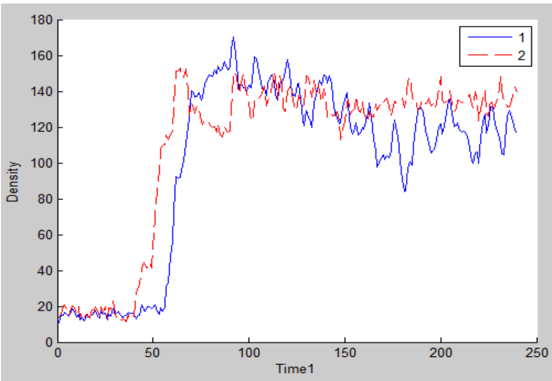

Fig. 8. Flow determined by the Calibrated model versus the actual measurements

4. Results

After calibrating the traffic flow model, it is time to test the before mentioned proposed hybrid model. In order to test the model we will use the data used before for METANET calibration. Data is gathered every 1 minute and our prediction horizons are 1, 3 and 5 minutes ahead.

First of all we have to use some data to create our base FIS which will be update later with ANFIS using the new inputs from real world. Consider the series of flow data which varies as a function of time, X(t). In order to predict X(t+1), As described before, one of the inputs for the system will be the desired value (X(t+1)) taken from the calibrated METANET. The other inputs can be different regarding the temporal and spatial characteristics of traffic data time series. Suppose that traffic data are collected using four detectors, one located in the desired section, two at the upstream and one at the downstream of the desired section. We name the data series as below format:

$\boldsymbol{X_{upstream(1)}(k), X_{upstream(2)}(k), X_{downstream}}$In order to predict the value of X(k+1), the system must be trained using pairs of input-output values, where the input values could be: ($X_{METANET}(k+1)$ is the estimated value of X(k+1) by METANET- $X_h(k+1)$ is the historical value of X(k+1))**:**

- $X(k+1) = f(X_{METANET}(k+1), X(k), X(k-1, Xk-2, Xhk+1)$
- $X(k+1) = f(X_{METANET}(k+1), X(k), X_h(k+1, Xupstream1k, Xupstream2k)$
- $X(k+1) = f(X_{METANET}(k+1), X(k), X_h(k+1, Xupstream1k, Xupstream2k, Xdownstreamk)$

So this is how the model works. First the base fuzzy inference system has to be created. For doing so, we will use the first 30 minutes data of the day (7-7:30 am) to create such a system. FIS will in fact extract the rules of the given data set and applies it to the future prediction. As mentioned before, our goal is to predict the traffic flow for the next 1, 3 and 5 minutes. As we know, ANFIS is a single output FIS. In order to produce three outputs at the same time and with the high accuracy, MANFIS can be used which can be created by running 3 parallel ANFIS, each one with a different FIS structure but created with the same inputs. In fact the input-output data sets for creating the very first fuzzy inference systems will be the same but the outputs will be the traffic flow for the next 1, 3 and 5 minutes. This way, we will have one MANFIS which is trained to predict three different horizons using the same input. After this step we have 3 Fuzzy systems; one trained for predicting the next minute, one for predicting the next 3 minutes and the last one for predicting the next 5 minutes. These generated systems will be used for predicting for about 15 minutes and then MANFIS updates the old FIS based on the last 30 minutes from the current time including the real data collected in the last 15 minutes (during traffic predicting using the old FIS).In order to compare the effect of $X_{METANET}(k+1)$ on the predicted value, all these data sets will be given to the FIS again, this time without using the estimated value of the

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METANET model and the results will be compared. Table 5 shows the accuracy of the results for the 3 prediction horizon using 3 different input-output data sets. RMSEP (Root Mean Square Error Percentage), AREP (Average Relative Error Percentage), and the NRMSE (Normalized Root Mean Square Error), between the actual and predicted flow series are the performance measures used to compare the predicted values against the actual values. They are defined as follows:

$$RMSEP = \frac{\sqrt{N.\sum_i^N (x_i^{observed} - x_i^{predicted})^2}}{\sum_i^N x_i^{observed}}$$

$$AREP = \frac{1}{N}.\sum_{i=1}^{N}\left|\frac{x_i^{observed} - x_i^{predicted}}{x_i^{observed}}\right| \times 100\%$$

$$\boldsymbol{NRMSE} = \sqrt{\frac{\sum_i^N \left(x_i^{observed} - x_i^{predicted}\right)^2}{\sum_i^N (x_i^{observed})^2}}$$

Where $x_i^{predicted}$ is the predicted value for observation i, $x_i^{observed}$ is the actual value for observation i, and N is the number of observations.

From the table, all of the errors are smaller when we use $X_{METANET}(k+1)$ as one of the inputs of the adaptive fuzzy inference system. It can be said that using an extra input (the future value of the parameter which is desired to be predicted), coming from a traffic flow model which is calibrated based on the traffic behaviours of the selected site, can have a positive effect on the accuracy of the results. Figures 9 to 11 show the predicted versus actual values of flow for the next 1, 3 and 5 minutes, respectively. The predicted values are the results of the hybrid model using $X_{METANET}(k+1)$.

5. Conclusion

The ability to predict the future values of traffic parameters helps to improve the performance of traffic control systems. In this paper, an online hybrid and adaptive neuro fuzzy system has been proposed to predict the traffic flow with sufficient accuracy in the selected part of Hemmat highway/Tehran. In the proposed hybrid model we take advantage of the METANET macroscopic model in order to give the FIS predictor an estimated knowledge about the future value of the parameter which is to be predicted. To do so, METANET was calibrated by genetic algorithm to enable the model to represent traffic conditions with sufficient accuracy. One advantage of the proposed model is the application of fuzzy logic in prediction. The ability to capture the dynamic behaviour of traffic makes it a powerful tool in this field. Another advantage is its online structure. Researcher's reason for using offline models is that they are faster but in contrast they can't support the abnormal changes in traffic flow behaviour. The proposed online model has the ability to adapt itself with the latest changes in traffic flow and thus has somehow obviate this disadvantage of the offline models. The main idea of the proposed framework is that having a simulator which is calibrated based on the typical and normal traffic flow of a section, we can model the traffic flow of that section and have the future value of the traffic parameters. The problem is that it is an offline model and can't produce the results according to non-recurrent congestions. In order to give this ability to offline traffic simulators, we can improve their outputs by using another online predictor. The value of the desired parameter in the next time interval is taken from the simulator (which is calibrated to model the normal traffic flow). Then an online FIS uses this data and other real time inputs to improve it considering the real time traffic behaviour. This paper demonstrates the ability of this kind of hybrid models to predict traffic flow and the results adduce that the accuracy of the model is satisfactory.

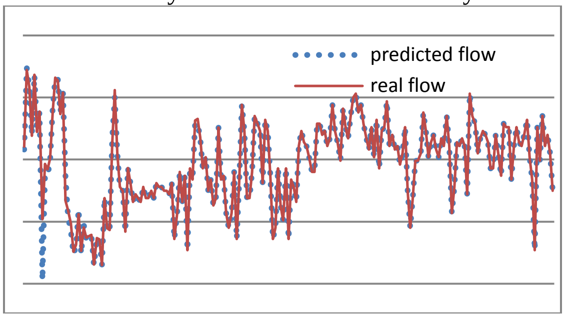

Fig. 9. Measured versus predicted traffic flow, 1 minute

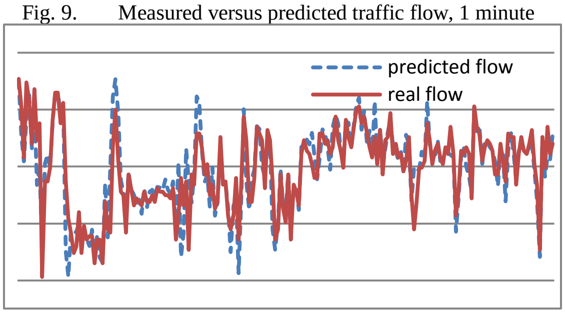

Fig. 10. Measured versus predicted traffic flow, 3 minutes

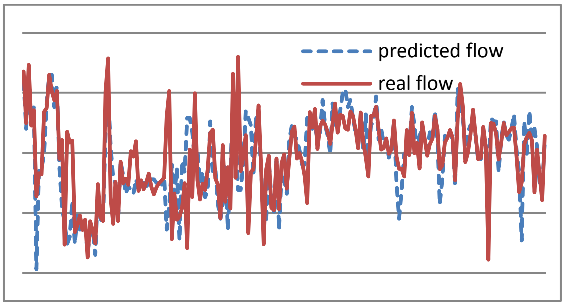

Fig. 11. Measured versus predicted traffic flow, 5 minutes

Parameter sets for the Hemmat highway

		AREP error		
Input type 1	Using $X_{METANET}(k+1)$	5 minutes ahead	3 minutes ahead	1 minute ahead
	Without using $X_{METANET}(k+1)$	5.74	4.98	0.36
Input type 2	Using $X_{METANET}(k+1)$	7.20	5.16	1.84
	Without using $X_{METANET}(k+1)$	5.47	4.07	4.42
Input type 3	Using $X_{METANET}(k+1)$	6.10	6.33	6.04
	Without using $X_{METANET}(k+1)$	5.43	5.32	5.05
		6.03	5.59	5.47
		NRMS error		
Input type 1	Using $X_{METANET}(k+1)$	5 minutes ahead	3 minutes ahead	1 minute ahead
	Without using $X_{METANET}(k+1)$	0.088856	0.015719	0.071964
Input type 2	Using $X_{METANET}(k+1)$	0.109114	0.052359	0.075294
	Without using $X_{METANET}(k+1)$	0.077669	0.060594	0.062052
Input type 3	Using $X_{METANET}(k+1)$	0.085429	0.09891	0.094767
	Without using $X_{METANET}(k+1)$	0.083722	0.078216	0.070846
		0.086137	0.085019	0.077
		RMSEP error		
Input type 1	Using $X_{METANET}(k+1)$	5 minutes ahead	3 minutes ahead	1 minute ahead
	Without using $X_{METANET}(k+1)$	0.0004376	7.74e-5	0.0003546
Input type 2	Using $X_{METANET}(k+1)$	0.000537	0.0002579	0.000371
	Without using $X_{METANET}(k+1)$	0.0003825	0.000298	0.000306
Input type 3	Using $X_{METANET}(k+1)$	0.000421	0.0004872	0.0004669
	Without using $X_{METANET}(k+1)$	0.000412	0.000385	0.000349
		0.0004242	0.0004187	0.0003794

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