NEURAL NETWORK MODEL BASED ON FUZZY ARTMAP FOR FORECASTING OF HIGHWAY TRAFFIC DATA

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Abstract: In this article, a neural network model is presented for forecasting the average speed values at highway traffic detectors locations using the Fuzzy ARTMAP theory. The performance of the model is measured by the deviation between the speed values provided by the loop detectors and the predicted speed values. Different Fuzzy ARTMAP configuration cases are analysed in their training and testing phases. Some ad-hoc mechanisms added to the basic Fuzzy ARTMAP structure are also described to improve the entire model performance. The achieved results make this model suitable for being implemented on advanced traffic management systems (ATMS) and advanced traveller information system (ATIS).

1 INTRODUCTION

Traditional models of traffic congestion and management lack the adaptability and sophistication needed to effectively and reliably deal with increasing traffic volume on certain road stretches. A realistic estimate of planned routes travel cost with reasonable accuracy is essential for successful implementation on an advanced traveller information system (ATIS) for use in an intelligent transportation system (ITS). An ATIS consists of a route guiding system (RGS) that recommend the most suitable route based on the traveller's requirements, using the information gathered from various sources as loop detectors and probe vehicles. The success of an RGS will depend on its ability to predict the anticipatory travel cost in addition to the historical and real-time travel cost. (Dharia, A. and Adeli, H., 2003)

Several aspects should be taken into account to evaluate the travel cost such as distance, time, economy, danger or personal preferences. From the distance point of view, the travel cost quantification will be strictly static, only dependent on the sum of the stretches length. A time based estimate will be dynamic and dependent on multiple factors. It could be directly measured or by the distance-speed relationship. For a economic estimate, toll fares, vehicle consumption and wear will be considered. Road accident risks as well as driving easiness at some particular stretches might be a decisive factor to rule out a route. Finally the traveller's preferences for route services or particular scenarios such as mountain or landscape roads could affect the decision eventually. This article will focus on speed estimate in road stretches with traffic detectors using a Fuzzy ARTMAP neural network structure. As said before, speed may be used to calculated the travel time cost as long as distance is known.

Neural network computing applied to travel cost forecast appeared to overcome the shortcomings of preceding methods whose forecasts deteriorate over multiple time steps (Park, D. and Rilett, L.R., 1999). A neural network provides a mapping between a set of inputs and corresponding outputs (Adeli, H. and Hung, S.L., 1995). The network is trained to learn this mapping using a number of training examples. Backpropagation (BP) is the most widely used neural network model in civil engineering applications, primarily due to its simplicity. However, backpropagation has shortcomings, including a very slow rate of convergence and arbitrary and problem-dependent selection of the learning and momentum ratios (Adeli, H. and Hung, S.L., 1994).

A neural model for forecasting the freeway link travel time using counter propagation neural (CPN) network is presented in (Dharia, A. and Adeli, H., 2003). There, it was showed that CPN model was nearly two orders of magnitudes faster than BP training algorithm for the same level of accuracy. In

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this article, a neural network model based on Fuzzy ARTMAP is presented for forecasting the average speed values at highway traffic detectors locations. Faster as the aforesaid CPN model, the presented model gives lightly better average errors in forecasting values in more realistic both training and testing scenarios.

2 FUZZY ARTMAP BASIS

The Fuzzy ARTMAP, introduced by (Carpenter et al., 1992) is a supervised network composed of two Fuzzy ARTs (ART_a and ART_b) interconnected by a series of connections between their output layers. Each connection has an associated weight value (w_{ij}) between 0 and 1, and may be considered as the membership function value in the fuzzy sets theory of the corresponding network category.

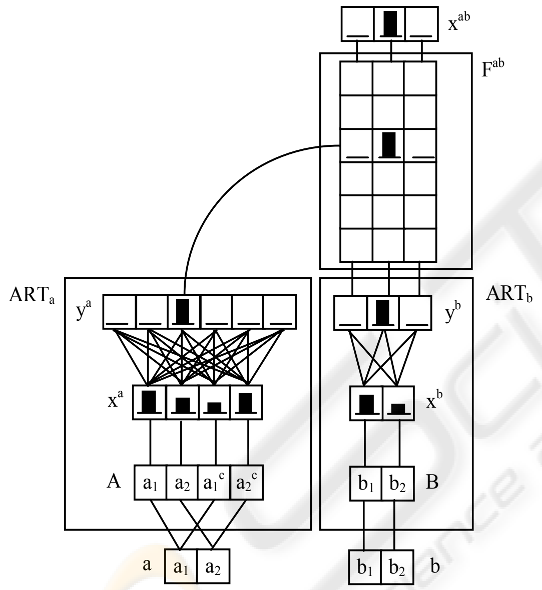


Figure 1: Sample Fuzzy ARTMAP network.

These connections form what is called the map field F_{ab}. The weights of the map field are all initialised to 1. The map field has two parameters: the learning rate β_{ab}, and vigilance criterion ρ_{ab}, and an output vector x_{ab}. Figure 1 shows a graphic sample representation of a Fuzzy ARTMAP network.

The input data of both ART_a and ART_b are normalized values, between 0 and 1 (minimum and maximum expected input values respectively), and form the network input vectors a and b. This normalization ensures a proportional response of the network from the input data. Input vector of ART_a is put in complement coding form, resulting in vector A. Complement coding is not necessary in ART_b so the input vector B directly presented to the network.

2.1 Training

Fuzzy ARTMAP networks usage requires a training process before being able to classify input data. In this process, a vector representing a data pattern is presented to ARTa, and a vector which is the desired output corresponding to this pattern is presented to ART_b. The relationship between these two vectors is learned through the weight values of the map field. The vigilance criterion of ART_a, ρ_a, varies during learning from a initial value called the baseline vigilance $\overline{\rho}_a$. The vigilance parameter of ART_b, ρ_b, is set to 1 to perfectly distinguish the desired output vectors.

When vectors A and B are presented to ART_a and ART_b, both networks soon enter resonance. The map field vigilance criterion is then evaluated to verify if the winning neuron of ART_a corresponds to the desired output vector presented to ART_b. This criterion is:

$$\frac{\left|y^b \wedge w_J^{ab}\right|}{\left|y^b\right|} \geq \rho_{ab} \tag{1}$$

where y^b is the output vector of ART_b, J is the index of the winning neuron on the output layer of ART_a, w_{ab}^J corresponds to the weights of the connections to the Jth neuron of the output layer of ART_a and $\rho_{ab} \in [0,1]$ is the vigilance criterion of the map field. If the criterion is not respected, the vigilance of ART_a is increased just enough to select another winning neuron ($\rho_a > |A \wedge w_J|/|A|$) and the vector A is repropagated in ART_a.

When the vigilance criterion is respected, the vigilance value of ART_a is set to its initial baseline value $\overline{\rho}_a$ and the map field learns the association between vectors A and B by modifying its weights as follows:

$$w_J^{ab} = \beta_{ab} x^{ab} + \left(1 - \beta_{ab}\right) w_J^{ab} \tag{2}$$

The weights in ART_a are also modified as:

$$w_J = \beta_a \left(A \wedge w_J\right) + \left(1 - \beta_a\right) w_J \tag{3}$$

In practice, the ART_a learning rate, β_a, is set equal to β_{ab}, or simply β, defining the learning network capability.

2.2 Classifying

During the training process the weight values of the Fuzzy ARTMAP were updating, as new patterns were presented to the network, till they reached a final value. At this point the network can be used as a classifier of the vector data presented to ART_a. ART_b is not used during this classifying process and learning network capability is deactivated (β=0).

ART_a will establish a winning node on its output layer from each input vector A presented to the network. The output vector of the map field is then set to:

$$x^{ab} = w_J^{ab} \tag{4}$$

where J is the index of the winning node on output layer of ART_a, and w_{ab}^J is the corresponding weight values vector on the map field . The index J of this component is the number of the category in which the input vector A has been classified. The use of the map field is thus to associate a category number to each neuron of ART_a's output layer. However, not just the category that best fits an input is the only result of the classifying process. The weight values associated with this category may also be useful to get ulterior information about the relationship between the input vector and the categories learned by the network in the training process.

3 WORKING MODEL

3.1 Training the Network

The data for this experiment were collected through the Freeway Performance Measurement System (PeMS) project, and could be obtained thanks to the Next Generation Simulation (NGSIM) and Federal Highway Administration (FHWA) web page at http://ngsim.fhwa.dot.gov. PeMS project was conducted by the Department of Electrical Engineering and Computer Sciences at the University of California, at Berkeley, with the cooperation of California Department of Transportation. Available data from 5 detector stations on US 101 South for 11 days, from June 8 to June 22, excluding the weekends, are provided in this data set. Speed, volume and occupancy at each detector for the 5-minute time step are presented at each detector in each lane.

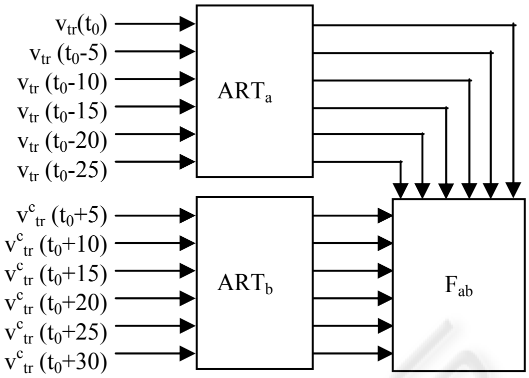


Figure 2: Fuzzy ARTMAP training structure. $v_{tr}(t)$: training speed value at instant t; $v^c_{tr}(t)$: training speed categorized value at instant t.

Average speed data from June 13 to June 17 (5 consecutive weekdays, making a total of 1440 samples) collected from two stations with different traffic congestion levels (717486, light; 717489, heavy), were employed to train the net. Figure 2 shows the structure of the Fuzzy ARTMAP during this process.

Table 1: Training cases.

Case	Input training subsets time step (min)	ART_a input nodes	ART_b input nodes	No. of Categories
A	6*5	6	1	9
B	6*5	6	1	81
C	6*5	6	6	81
D	6*5	4	4	81
E	6*5	8	8	81
F	1*5	6	6	81

Six different structure model cases, shown in Table 1, were considered with different number of input and output nodes, categories and time step between consecutive input training subsets. In Case A, six ART_a input nodes and one ART_b input node were used to associate six consecutive 5-min time step normalized past speed values to one categorized future speed value in the map field of the Fuzzy ARTMAP, F_{ab}. This categorized speed value is calculated as the average of the six 5-min time step speed values following the normalized speed values presented to ART_a, and categorized into one of 9 possible categories. Numerically, these categories are linearly spaced and normalized speed values in the range of 0-80 mph. In Case B, and following ones, the number of categories were increased to 81. In Case C, each six consecutive 5-min time step normalized past speed values presented to ART_a

were associated to six consecutive 5-min time step normalized future speed values presented to ART_b. In Case D and E the number of input nodes were changed to 4 and 8 respectively. Finally in Case F, with six input nodes anew, the consecutive sets of values presented to the ART_a and ART_b were 5 minutes ahead of the former, instead of 30 minutes.

A one-shot stable learning configuration, as shown in Table 2, has been adopted: conservative limit ($\alpha \cong 0$) and fast learning ($\beta=1$), holding for fuzzy ART modules with constant vigilance (Carpenter, G.A. et al., 1992).

Table 2: Training configuration network parameters.

α	β	$\overline{\rho}_a$	ρ_{ab}	ε
0.001	1	0	0.95	0.001

3.2 Testing the Network

Average speed data from June 20 to June 22 (3 consecutive weekdays following the training ones, making a total of 864 samples) collected from the same two stations that in the training process and shown in Figure 4.(a) and Figure 5.(a), were employed to make a test of the speed forecasting net capability. A test performance was made for each training case.

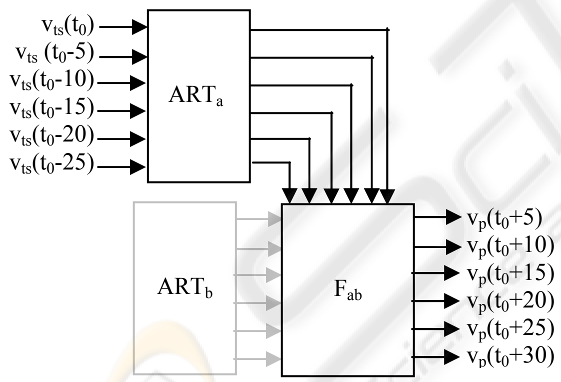


Figure 3: Fuzzy ARTMAP testing structure. vts(t): testing speed value at instant t; vp(t): forecasting speed value for instant t.

Figure 3 shows the structure of the Fuzzy ARTMAP during this process. Sets of consecutive 5-min time step normalized speed testing values were presented to ART_a. ART_b in testing phase is not used. A number of forecasting speed values, equals to the number of input nodes in ART_b in the training phase, were obtained from each set. These forecasting speed values were calculated from the weight vectors of the map field F_{ab}, w_{ab}, multiplying the selected weight vector, w_{ab}^J, by the speed value associated to the higher training category.

The fuzzy ARTMAP configuration for the testing phase was similar to the one adopted in the training phase but with the learning capability deactivated ($\beta=0$), as shown in Table 3.

Table 3: Testing configuration parameters.

α	β	$\overline{\rho}_a$	ρ_{ab}	ε
0.001	0	0	0.95	0.001

3.3 Forecasting Results

The Fuzzy ARTMAP model have been implemented in MATLAB® Release 12 technical language on a mobile AMD Athlon™ XP 2000+ computer. In order to measure the forecasting accuracy, an average error term was defined in the following form:

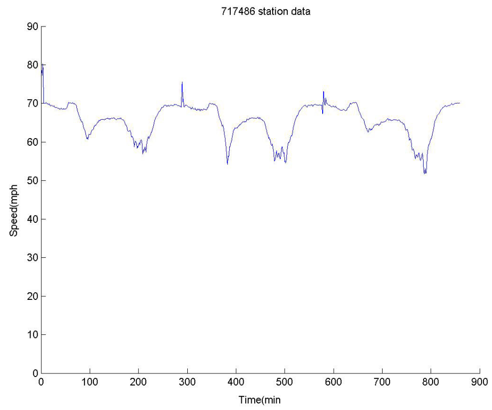
$$E(\%) = \frac{100}{N} \sum_{t=1}^{N} \frac{\left| v_t[t] - v_p[t] \right|}{v_t[t]} \tag{5}$$

where N is the number of predicted speed values; $v_p[t]$, the predicted speed value for moment t; $v_t[t]$, the testing speed value measured by the station detector at moment t.

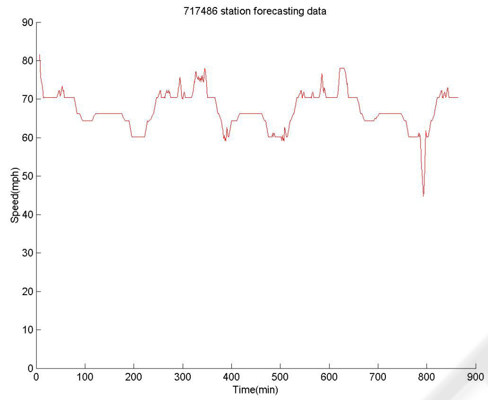
Figure 4 and Figure 5 show the forecasting speed (b) and the forecasting error (c) values over the testing days time. The maximum error values occur close to high traffic congestion situations in 717489 station, when vehicles speed changes too fast in the 5-min step time. This maximum error values are dramatically high but are quickly reduced as the next forecasting speed values are available. Hence, global error performance keeps a satisfactory level. Table 4 shows the average error in forecasting speed for the considered cases.

Table 4: Average error in forecasting speed.

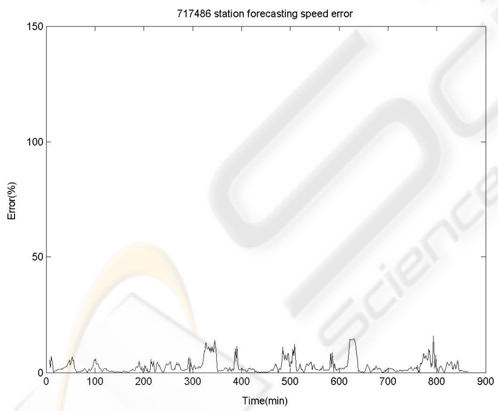
Station	E(%)					
	Case A	Case B	Case C	Case D	Case E	Case F
717486	4.12	2.91	3.16	3.77	3.12	2.64
717489	14.78	13.95	10.96	9.67	15.84	7.78



(a) 717486 station detector speed data

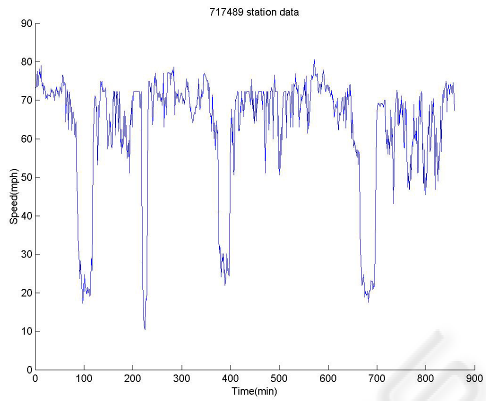


(b) 717486 station forecasting speed data

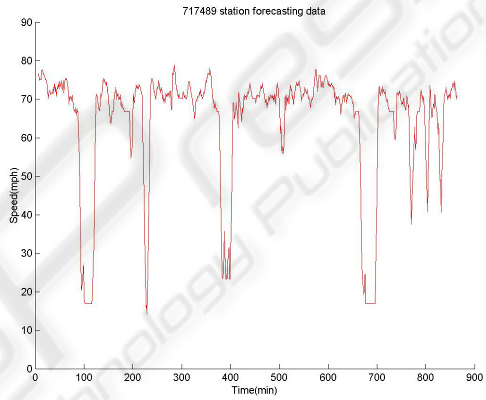


(c) 717486 station forecasting speed error

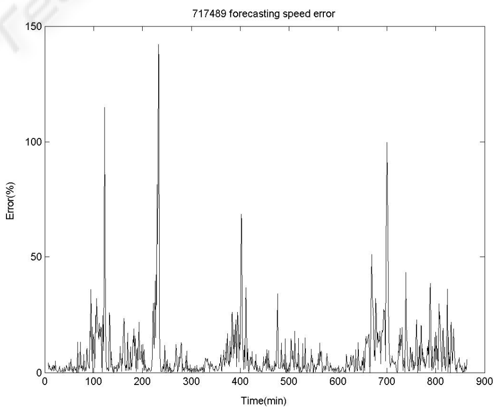
Figure 4: 717486 station data and forecasting results.



(a) 717489 station detector speed data



(b) 717489 station forecasting speed data



(c) 717489 station forecasting speed error

Figure 5: 717489 station data and forecasting results.

Case B improves Case A forecasting precision by simply increasing the number of categories, particularly with the 717486 station in which all speed values concentrate in a range of 30 mph.

Forecasting precision for 717489 station, in which speed values change quickly close to high congestion situations, strongly improves in Case C as more predicted speed values are given (six instead of one) for the 30-min forecasting time interval considered. Applying no interpolation rule, six is the highest number of predicted values since detectors present new data each 5 minutes.

The increase in the number of nodes in Case E implies that both the time interval of past speed values presented to the net and the time interval of forecasting speed values are longer, since the number of nodes in ART_a and ART_b were equal in the training process. For the 717489 station, with speed values changing quickly close to high traffic congestion situations, the longer the forecasting time interval , the bigger the error will be. In Case D, the opposite situation occurs but the processing time increases substantially for the same forecasting time interval. No significantly error variation for 717486 station in Cases D and E.

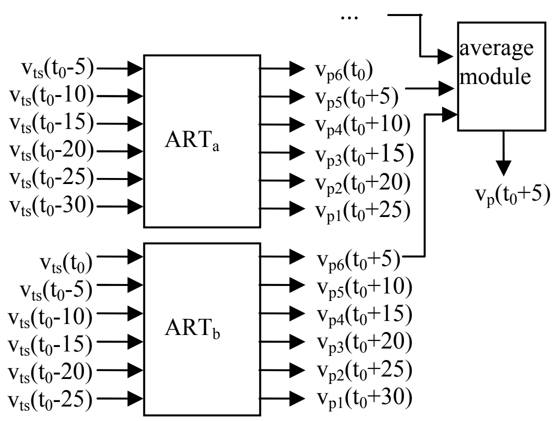


Figure 6: Case F model structure.$v_{ts}(t)$: testing speed value at instant t; $v_{pi}(t)$: ith forecasting speed value for instant t; $v_p(t)$: forecasting speed value for instant t.

The best error performance is achieved in Case F in which several forecasting speed values (up to the number of input nodes) are obtained for a particular moment into the future (due to the time overlap of the input set speed values). An average of them is then made to get the final forecasting speed value. Figure 6shows the model structure designed for this particular case.

3.4 Comparative Results

The average errors in forecasting values presented in (Dharia, A. and Adeli, H., 2003) for BP and CPN models with the same duration of time step (5min) and the same number of input and output nodes (6), were slightly higher (11.5% and 10.9% respectively) than the one achieved for the Case F (7.8% for the station with the most congested traffic level) in the Fuzzy ARTMAP model. However, speed travel values, instead of travel time values, were predicted in the model presented in this article and real traffic data were used instead of simulated traffic data. Case F did not take more than 10 seconds (a rough measure was made) of processing time to carry out both training and testing phases with the conditions described above. BP and CPN models took 312.7 and 3.8 seconds respectively just for the training process. Convergence behaviour of Fuzzy ARTMAP networks are faster and more independent of the initial weights than Back or Counter propagation networks. Actually, training convergence can be guaranteed as far as Fuzzy ART Stable Category Learning Theorem (Carpenter, G.A. et al., 1992) is satisfied.

4 CONCLUSIONS

The Fuzzy ARTMAP neural network model described in this article provides an appropriated forecasting travel cost mechanism, in terms of average speed values for being integrated in travel cost estimates systems supplied with traffic dynamic parameters such as speed, occupancy or volume data. Multiple training and working configurations for the network are possible in order to match host system requirements, all of them with a remarkable time processing and forecasting error performance. Forecasting test results obtained accuracy levels under the 8% of precision from real congested highway traffic data. A figure slightly lower than previous neural network models developed for highway traffic predictions. So it represents a promising challenge in the evolution of neural networks appliance to intelligent transportation system (ITS).

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NGSIM Website - Home of the Next Generation Simulation Community, at http://ngsim.camsys.com - for the traffic data set.

REFERENCES

Adeli, H., 2002. “Automatic detection of traffic incidents using data obtained from sensors embedded in intelligent freeways ”. Sensor Review; Volume: 22 Issue: 2; 2002 Research paper.

Adeli, H., Hung, S.L., 1995. “Machine Learning-Neural Networks, Genetic Algorithms, and Fuzzy Systems”. Wiley, New York.

Adeli, H., Hung, S.L., 1994. “An adaptive conjugate gradient learning algorithm for efficient training of neural networks”. Applied Mathematics and Computatio n 62 (1), 81–100.

Carpenter, G.A., 2003. “Default ARTMAP”. Neural Networks, 2003. Proceedings of the International Joint

Conference on Volume 2, 20-24 July 2003 Page(s):1396 – 1401 vol.2.

Carpenter, G.A., et al., 1992."Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps". Neural Networks, IEEE Transactions on Volume 3, Issue 5, Sept. 1992 Page(s):698 – 713.

Dharia, A. and Adeli, H., 2003. "Neural network model for rapid forecasting of freeway link travel time". Engineering Applications of Artificial Intelligence, Volume 16, Issues 7-8, October-December 2003, Pages 607-613.

Jiang, G., et al., 2003. "The study on the application of fuzzy clustering analysis in the dynamic identification of road traffic state". Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE. Volume 1, 2003 Page(s):408 – 411 vol.1.

Park, D., Rilett, L.R., 1999. "Forecasting freeway link travel times with a multilayer feedforward neural network". Computer-Aided Civil and Infrastructure Engineering 14 (5), 357–367.

Wang, X-H, Xiao, J.M.,2003."A radial basis function neural network approach to traffic flow forecasting". Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE. Volume 1, 2003 Page(s):614 – 617 vol.1.