The Comparison of Fuzzy Inference Systems and Neural Network Approaches with ANFIS Method for Fuel Consumption Data

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ABSTRACT

In this paper, the prediction of the fuel consumption of automobiles (MPG-Mile per Gallon) according to their specifications have been determined by using Fuzzy Inference Systems, Neural Network Approaches and Adaptive Neuro-Fuzzy Inference System (ANFIS) methods. By comparing the results of these methods with one another, advantages and disadvantages of them have been discussed.

1. INTRODUCTION

The usage of artificial intelligence has been applied widely in most of the fields of computation studies. Main feature of this concept is the ability of self-learning and self-predicting some desired outputs. The learning may be done with a supervised or an unsupervised way. Neural Network study and Fuzzy Logic are the basic areas of artificial intelligence concept. Adaptive Neuro-Fuzzy study combines these two methods and uses the advantages of both methods. In order to see the capabilities of these three methods, MPG prediction of automobile-fuel consumption data has been applied to these methods. The data was obtained from UCI (University of California at Irvine). Although that the data was old, it has been used in several prediction studies. Table 1 shows some part of the data [1].

Table 1. Samples of the MPG training data set.

Cyl.	Disp.	HP	Weight	Accel.	Year	MPG	Car Name
8	307	130	3504	12.0	70	18	Chevrolet Chevelle Malibu
6	198	95	2833	15.5	70	22	Plymouth Duster
4	90	75	2108	15.5	74	24	Fiat 128
8	260	110	4060	19.0	77	17	Oldsmobile Cutlass Supreme
4	89	62	2050	17.3	81	37.7	Toyota Tercel
4	107	75	2205	14.5	82	36	Honda Accord
4	120	79	2625	18.6	82	28	Ford Ranger

The data is composed of 392 sample automobiles. Data set is divided into training and checking sets. Originally, it consists of six input features as given in Table 1. But for a six input data fitting problem, in order to determine the MPG prediction, 10^6(=1000000) samples are needed. Since 392 samples are available, two features of the data are taken as the input. Moreover, if six of them have been taken into account, at least 2^6(=64) fuzzy if-then rules must have been constructed. This situation needs huge amount of memory and consumes large amount of computational time. Therefore only two inputs were used. The two inputs “weight” and “year” were selected because of having the minimum RMSE (Root mean square error) values in contrast to the other features.

2. FUZZY LOGIC

Fuzzy Logic concept is close to human thinking style because it uses linguistic terms. It allows membership degrees to the variables. Different cases of each input’s fuzzy sets are evaluated according to if-then rules of the fuzzy system. As a result of this operation, the optimum outputs are obtained much close to the target outputs. The building of the optimum results for the system depends on the experience of the expert [2, 3].

3. NEURAL NETWORK

Neural networks are adaptive networks which are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. Commonly, neural networks are adjusted or trained so that a particular input leads to specific target output. Neural networks have been trained to perform complex functions in various fields of applications including pattern recognation, identification, classification, speech, vision and control systems. When the inputs of the network and target outputs are given, back-propagation gradient descent method is used. Because there is no initial knowledge about connection weights and biases, these parameters should be determined by minimization of error method to feedforward networks. After their determination, errors are distributed between layers towards backward direction[4]. There are a lot of methods of back-propagation; some of them works slowly, but some new methods are faster than the gradient descent method. The Resilient back-propagation (Rprop) training algorithm is an example for one of these methods. It eliminates the harmful effect of having small slope at the extreme ends of sigmoid squashing transfer functions. Only sign of the derivative of the transfer function is used to determine the direction of the weight update; but the magnitude of the derivative has no effect on the weight update. Rprop is generally much faster than the standart steepest descent algorithm. It also has the nice property that it requires only a modest increase in memory requirements [5].

4. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS)

ANFIS is an adaptive network which permits the usage of neural network topology together with fuzzy logic. It not only includes the characteristics of both methods, but also eliminates some disadvantages of their lonely-used case.
Operation of ANFIS looks like feed-forward back-propagation network. Consequent parameters are calculated forward while premise parameters are calculated backward. There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order Sugeno inference system or Tsukamoto inference system can be used [6, 7].
Output variables are obtained by applying fuzzy rules to fuzzy sets of input variables. For example,

Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A_1 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

Figure 1(a) shows graphically the first order Sugeno fuzzy inference system and Figure 1(b) shows its equivalent ANFIS architecture.

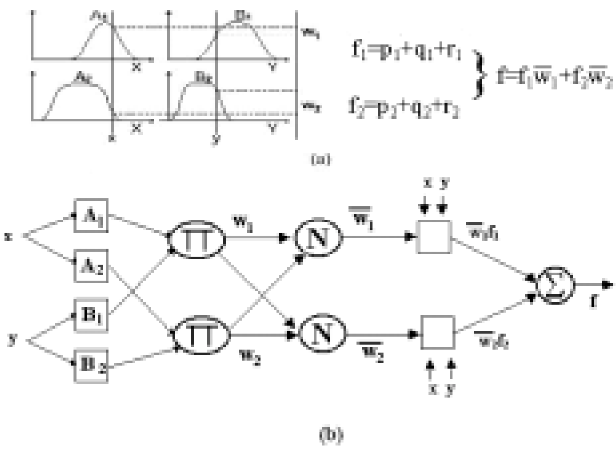

Figure 1. (a) First order Sugeno FIS.
(b) Corresponding ANFIS architecture.

Since ANFIS combines both neural network and fuzzy logic, it is capable of handling complex and nonlinear problems. Even if the targets are not given, ANFIS may reach the optimum result rapidly. The architecture of ANFIS consists of five layers and the number of neurons in each layer equals to the number of rules. In addition, there is no vagueness in ANFIS as opposed to neural networks [8].

5. COMPARISON OF THE RESULTS

The same data under the same conditions was applied to the three methods discussed above. The results obtained were compared with one another and target output. Finally, the performance of the methods was discussed. All of the simulations were performed in MATLAB (version 5.3) [9].
In the fuzzy simulation of the problem, input fuzzy sets, output fuzzy sets and fuzzy *if-then* rules are determined according to intuition and mathematical calculations for the system. Input membership functions of the system are given in Figure 2. Table 2 and Table 3 shows linguistic control (FAM) rules and linear consequent parameters.

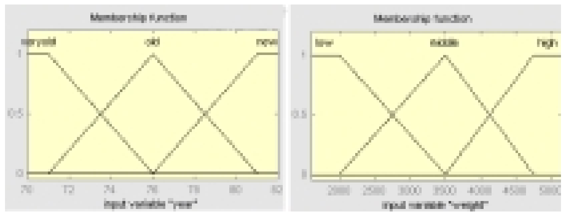

Figure 2. Input membership functions

Table 2. FAM table.

Weight / Year	Veryold	Old	High
Low	Out1	Out2	Out3
Middle	Out4	Out5	Out6
High	Out7	Out8	Out9

Table 3. Linear output parameters.

Output Fuzzy Set	p_i	q_i	r_i
Out1	-0.0125	0.7772	0
Out2	-0.0207	0.9463	0
Out3	-0.0075	0.6338	0
Out4	-0.0019	0.3342	0
Out5	-0.0025	0.3537	0
Out6	-0.1971	7.7088	0
Out7	-0.001	0.2616	0
Out8	-0.0044	0.4566	0
Out9	-0.0177	1.1941	0

Figure 3 shows the real output and the target output for fuzzy application.

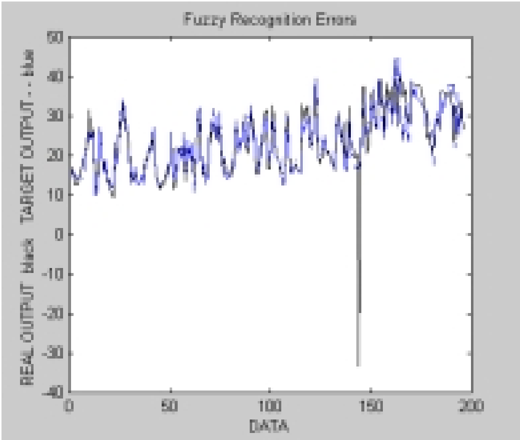

Figure 3. Fuzzy prediction error.

In the neural network case, among many back-propagation methods, the resilient back-propagation method was used because of its good performance. There are 196 neurons in the input layer, 25 neurons in hidden layer and one neuron in the output layer of Neural Network structure. Figure 4 shows the Neural Network structure[5].

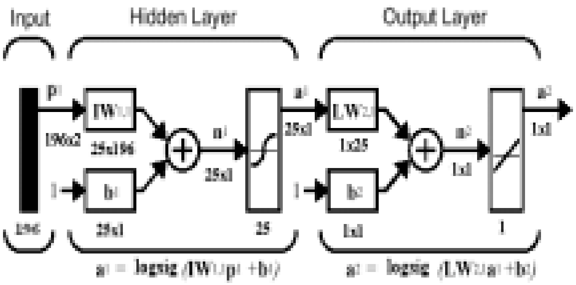

Figure 4. Neural network structure.

During the training operation if the local minimal is caught, small changes occur in the gradient. That’s why the network cannot reach the target at that moment. So, the obtained values in weights and bias parameters were trained twenty times. For the system to catch the target, a normalisation was applied to it. The results of the differences between real and target outputs may change randomly due to different trainings. Note that these results are not stable because the weights and biases are taken randomly at the beginning. Therefore obtaining different outputs in each run of the program is possible in which Figure 5 shows one of these results.
In ANFIS interpretation, the Sugeno Inference System was chosen which was previously used in Fuzzy Logic case of the previous study [10, 11].

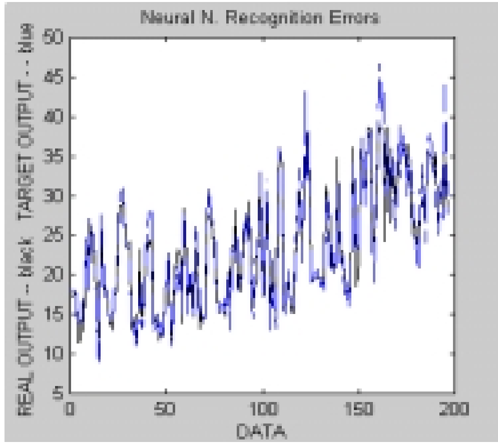

Figure 5. Neural Network prediction error.

After training, the consequent parameters were obtained from ANFIS output, which are shown in Table 4.

Table 4. Linear consequent parameters of ANFIS.

Output Fuzzy Set	p_i	q_i	r_i
Out1	-0.0106	-1.6701	168.0171
Out2	-0.0096	1.3896	-55.3620
Out3	-0.0031	-1.5797	171.9554
Out4	-0.0053	-0.2185	50.5473
Out5	-0.0063	0.4221	7.6099
Out6	-0.0061	-1.7875	188.5818
Out7	-0.0046	0.48013	-0.4732
Out8	-0.0022	0.4631	-8.9990
Out9	-0.6439	32.9362	0.4169

In ANFIS structure, the implication of the errors is different from that of the Neural Network case [9]. In order to find the optimal result, the epoch size is not limited. Figure 6 shows the real output and the target output for the ANFIS application.

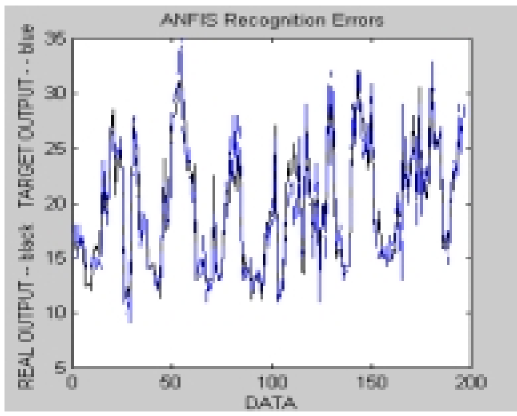

Figure 6. ANFIS prediction error.

In the comparison of the three methods, the error is accepted as the difference between the obtained output and the target output. Table 5 shows the epoch size, total error, and maximum error, average error and data type, which were obtained from each method. There are two data types shown in the table: training and checking data. Training data is used for obtaining the parameters of the system, i.e., weights, biases, etc. These parameters are applied to the checking data. Then, corresponding error values are calculated accordingly.

Table 5. Comparison table

Method	Epoch Number	Max. Error	Total Error	Average of Error	Data Type	
Fuzzy	0	9.53	416.6	2.125	Train	
Fuzzy	0	50.27	467.4	2.384	Check	
Neural	900-1000	8.93	363.6	1.855	Train	
Neural	900-1000	9.81	359.3	1.833	Check	
ANFIS	10	7.95	281.3	1.435	Train	
ANFIS	10	10.57	371.6	1.895	Check	

6. CONCLUSION

As seen from Table 5, the learning duration of ANFIS is very short than neural network case. It implies that ANFIS reaches to the target faster than neural network. When a more sophisticated system with a huge data is imagined, the use of ANFIS instead of neural network would be more useful to overcome faster the complexity of the problem.

In training of the data, ANFIS gives results with the minimum total error compared to other methods. This shows that the best learning method is ANFIS among the others. However, when the trained parameters were applied to checking data, total error of neural network is smaller than that of ANFIS. Although it looks like a contradiction, the reason of this situation is due to the amount of short data, which is not enough to good learning.

Fuzzy logic method seems to be the worst in contrast to others at a first look. But of course there are a lot of reasons of getting such results. First of all, the rule size was limited to only nine rules while the membership variables are restricted by just three variables. Secondly, rules and the number of membership functions of fuzzy sets were chosen according to the intuitions of the expert. If more membership variables and more rules had been used, a better result would have been available. The restriction of fuzzy rules and fuzzy sets is due to the ANFIS constraint. The aim was to choose the same FIS in both Fuzzy and in ANFIS methods to be able to compare with one another.

When the above discussions are all considered, it can be said that ANFIS is better system for the prediction of MPG problem than neural networks and fuzzy methods lonely. Because it combines the advantages of both neural network and fuzzy logic which offers good results.

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