Applied Soft Computing 24 (2014) 232–238

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems

Gökhan Özkan [a], Melih İnal [b,*]

[a] Kocaeli University, Graduate School of Natural and Applied Sciences, Electronics and Computer Education Department, Umuttepe Campus, 41380 İzmit, Kocaeli, Turkey
[b] Kocaeli University, Technical Education Faculty, Electronics and Computer Education Department, Umuttepe Campus, 41380 İzmit, Kocaeli, Turkey

ARTICLE INFO

Article history:
Received 13 November 2012
Received in revised form 6 January 2014
Accepted 22 June 2014
Available online 17 July 2014

Keywords:
ANFIS
Decision making
Neural Networks
Supplier Evaluation

ABSTRACT

In this study, Adaptive Neuro-Fuzzy Inference System (ANFIS) is used for multi-criteria decision making in supplier evaluation and selection problem. The contemporary supply-chain management is looking for both quantitative and qualitative measures other than just getting the lowest price. After evaluating a number of distinct suppliers, determining the reliable suppliers by ANFIS model with better approximation will support decision makers. To this end, ANFIS is evaluated for different data sets with the attributes of the suppliers and their scores that are gathered from a previous study conducted for the same problem under the name of Neural Network (NN) application for fuzzy multi-criteria decision-making model. In the proposed ANFIS model built for determining supplier score, linear regression analysis (*R*-value) and Mean Square Error (MSE) were 0.8467 and 0.0134, respectively, while they were 0.7733 and 0.0193 for NN for fuzzy. ANFIS gives better results according to MSEs. Hence, it is determined that ANFIS algorithm can be used in multi-criteria decision making problems for supplier evaluation and selection with more precise and reliable results.

Introduction

In an increasingly complex world, decision support systems are aimed to give leverage to the users in operational, tactical or strategic problems they face to increase efficiency. On the other hand, as alternatives of choice become more complicated and are characterized by numerous attributes as well as multiple objectives, the problem of combining these various aspects into a single measure of utility gets more difficult and less practical.

Today, there are many multi-criteria decision making methods in use to facilitate decision makers' supplier evaluation and selection task. Ho et al. [1] reviewed the literature of the multi-criteria decision making approaches for supplier evaluation and selection from 2000 to 2008. In Ho et al's study solo or hybrid techniques used in supplier evaluation and selection problems are listed as Case-Based Reasoning (CBR), Fuzzy Set Theory, Analytic Network Process (ANP), Data Envelopment Analysis (DEA), Analytic Hierarchy Process (AHP), Simple Multi-Attribute Rating Technique (SMART), Mathematical Programming, Genetic Algorithm (GA), and they also provided the proportion to the population of the techniques covered in that time period. According to the importance of the supplier selection and evaluation process, a number of studies on this subject have been published since 2008 too. Most of these researches use sole or combined soft computing constituents for better results. According to Jang et al. [2], Soft Computing (SC) is an innovative approach to build intelligent systems that can mimic humanlike expertise within a specific domain, adjust themselves to the changing conditions, and provide traceability and reasoning capability in its decision processes. Neural Networks, Genetic Algorithm, Fuzzy Set Theory, Simulated Annealing and Conventional Artificial Intelligence can be counted as soft computing constituents. Since Ho et al.'s [1] literature review, new studies with integrated and individual approaches concerning supplier evaluation and selection problem have been published. These are Golmohammadi and Mellat-Parast [3]'s study about AHP and Gray-based decision making models; fuzzy set supported models [4–13] and neural network supported models [14,15]. According to Ho et al. [1], ANFIS method has not been used in this area since 2008. However, Güneri et al. [16] used an ANFIS based new model for supplier input selection problem which outperforms then Multiple Linear Regression (MLR) in terms of Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

In supplier selection and evaluation process, the number of criteria with different weights and position that can be taken into consideration is too much. Companies have to take into account

* Corresponding author. Tel.: +90 262 303 22 41; fax: +90 262 303 22 03.
E-mail addresses: g_ozkan@hotmail.com, mrgokhan.ozkan@gmail.com (G. Özkan), minal@kocaeli.edu.tr (M. İnal).

http://dx.doi.org/10.1016/j.asoc.2014.06.032
1568-4946/

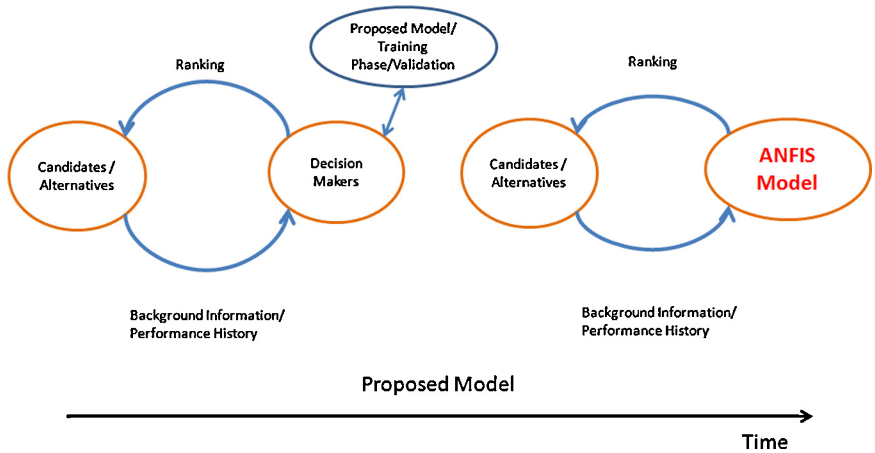

Fig. 1. The enhancing difference between the proposed and the Golmohammadi's models.

their strategies, business priorities, stakeholders and customers' requirements. Some of the requirements are quantitative, and some are qualitative in nature. In order to find a global optimum of that much requirements, Multi-Criteria Decision Making (MCDM) approaches are inevitable.

MCDM problem in supplier selection includes tangible and intangible factors which cause uncertainty [17]. This uncertainty often addresses subjective human preferences to determine the categories when using the same word as a label for a set [18]. Moreover, Saghaei and Didehkhani list various challenges in their study. Some of those challenges are [19]:

- Most of the MCDM models cannot consider the inner dependencies and relations among criteria, so the validity of these models, where these inner dependencies exist, is questionable.
- Most of the MCDM models need predetermined weights of criteria. In particular, when there is more than one decision maker (DM), it is very hard to obtain reliable weights of criteria.

In case of ambiguity about the structure of criteria and sub-criteria, it is not reasonable to use structural approaches like AHP. To handle these challenges, neural networks and especially ANFIS which are efficient models for function approximation, clustering and pattern recognition [19].

Robust properties of both Artificial Neural Networks (ANN) and Fuzzy Set Theory are integrated into ANFIS. ANFIS automatically produces adequate rules with respect to input and output data and takes advantage of the learning capability of neural networks [16]. While there are lots of criteria with different weights and position in supplier selection and evaluation process, it does not appear possible to take into account all criteria in a proper manner. However, in training procedure of ANFIS the weights of criteria and the position of criteria are not important; ANFIS chooses the best combination of criteria for the best solution with minimum error [19].

In this paper, MCDM problem and ANFIS are explained first in supplier selection and evaluation process. The rest of the paper is organized as follows: "Discussion" section gives discussion of the proposed ANFIS model and Golmohammadi's NN model; "Adaptive Neuro-Fuzzy Inference System (ANFIS)" section provides a brief description of ANFIS; "Experimental data" section describes experimental data used in both Golmohammadi's NN and the proposed ANFIS models; "Model design" describes the designed ANFIS model in detail, and in "Results of NN application for fuzzy method" section results of NN application for fuzzy method are discussed. "Results of ANFIS model" section discusses the training and test results of ANFIS model, and in "Comparison of NN for Fuzzy and ANFIS" section comparisons of NN for fuzzy and ANFIS models' findings can be found. Finally, "Conclusion" section discusses the major conclusions and findings of the study.

Discussion

As real-world problems become more complex, new models, which combine knowledge, techniques and methodologies from various sources, became necessary in decision-making processes. To this end, Golmohammadi's [14] model based on Neural Network (NN) application for fuzzy multi-criteria decision making in supplier evaluation and selection case is analyzed. In that study, Golmohammadi's model simulated the decision maker "thinking and judgment" process with neural network application to forecast the suppliers' score with the model without the decision makers' judgment [14].

In the proposed model, neural networks section is replaced with the ANFIS to get more precise results with less error than the Golmohammadi's model by achieving the same objectives. The enhancing difference between the proposed ANFIS model and Golmohammadi's is shown in Fig. 1.

Results of NN Application for fuzzy method and of proposed ANFIS model are represented in sections "Results of NN application for fuzzy method" and "Results of ANFIS model", respectively.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Artificial intelligence has been efficiently used for function approximation, clustering, pattern recognition and regression. Intelligence analysis gives researchers the ability to model both experimental design and data in a number of different forms than the statistical approaches [20,21]. ANFIS is a feed-forward artificial neural network where each layer is a neuro-fuzzy system component which is developed by Jang et al. [2], Jang [22], Jang [23]. Fig. 2 illustrates basic ANFIS architecture for Sugeno-type. In this architecture, similar functions are used in each layers' nodes.

ANFIS has a hybrid learning rule algorithm which integrates the gradient descent method and the least square methods to train parameters. In the forward pass of the algorithm, functional signals go forward until layer 4 and the consequent parameters are identified by the least squares method to minimize the measured error. In the backward pass, the premise parameters are updated by the gradient descent method [2].

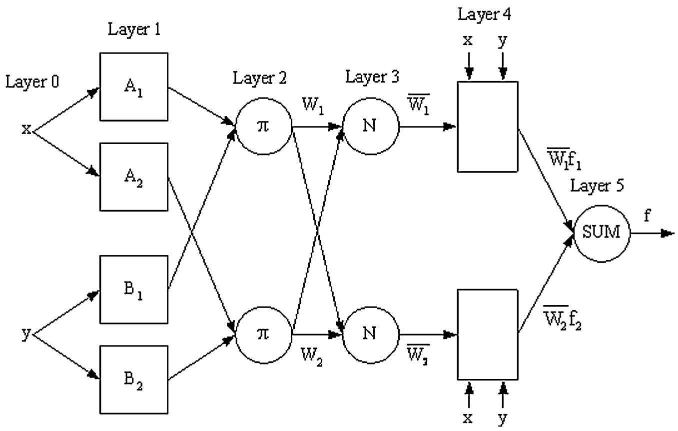

Fig. 2. Basic ANFIS structure.

Experimental data

The supplier evaluation and selection problem is a typical nonlinear regression problem. In this study, suppliers' attributes (Quality, Delivery, Technology, Price and Location) are used as input parameters to predict another continuous attribute of supplier score as output. According to the Golmohammadi's study, input parameters are gathered from the past contracts of the suppliers while supplier scores are calculated by the decision makers. Golmohammadi has two different data sets in his study. In the first data set, which is given in Table 1, is the row data gathered from the contracts and decision makers' judgment for suppliers' performance evaluation. The second one which is analyzed and improved version of the first data set with AHP pair wise comparison technique is given in Table 2. For the comparison purposes, these two different data sets are used separately both in training and testing stages with Mean Squared Errors (MSEs) in the proposed ANFIS model consecutively.

Firstly, the original data set is sorted and marked for training and testing phases of the ANFIS model. The database was processed using MATLAB© R2008b. Since Supplier Score-Sc has been wanted to predict as output of ANFIS, the data rearranged and separated for training and testing as shown in Table 1.

Model design

The process flow chart for proposed ANFIS model is given in Fig. 3.

MSE of proposed ANFIS model is defined as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Sc_{predict} - Sc_{target})^2 \quad (1)$$

where n is the number of points, $Sc_{predict}$ and Sc_{target} is the predicted and target values of Supplier Score-Sc, respectively.

MATLAB routine post-regression (*postreg*) is also used to measure the *R*-value of ANFIS performance, which implements a linear regression analysis between target values and output values of ANFIS model. *R*-value can be defined as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Sc_{predict} - Sc_{target})^2}{\sum_{i=1}^{n}(Sc_{predict} - AvSc_{target})^2} \quad (2)$$

where $AvSc_{target}$ is the average value of target values of Supplier Score-Sc.

The structure of proposed Sugeno-type ANFIS model is presented in Fig. 4. Since five suppliers' attributes defined as inputs

Table 1
Training and test data sets.

Quality	Delivery	Technology	Price	Location	Supplier Score
3.0	6.0	3.5	4.0	1.5	0.05
3.5	3.5	6.0	6.0	1.5	0.05[a]
3.0	4.0	5.0	4.0	7.0	0.07
7.0	6.0	4.5	6.0	3.0	0.10[a]
6.5	6.5	6.5	6.5	5.5	0.11
5.0	4.0	5.5	4.0	5.0	0.11[a]
5.0	6.0	6.0	5.5	2.5	0.12
3.5	5.0	6.0	6.5	3.5	0.13[a]
5.5	4.5	6.0	4.5	7.0	0.15
5.0	6.5	3.5	3.5	8.0	0.16[a]
5.5	6.5	5.5	7.0	5.5	0.19
5.0	7.0	5.5	7.0	5.5	0.19[a]
4.0	6.0	7.0	5.0	9.0	0.19
2.0	6.5	2.0	8.0	4.0	0.22[a]
5.5	7.5	5.5	3.5	7.5	0.23
5.0	7.0	9.0	4.5	5.0	0.23[a]
4.0	4.0	7.0	6.5	6.0	0.25
6.0	6.5	8.0	4.5	5.0	0.27[a]
4.0	5.5	7.0	8.0	4.0	0.28
5.0	6.5	8.0	5.0	6.0	0.30[a]
7.0	8.0	7.0	4.5	2.5	0.34
6.5	7.5	6.0	6.5	3.0	0.36[a]
6.0	7.0	9.0	7.0	8.0	0.42
7.0	8.0	7.0	6.0	3.0	0.44[a]
8.5	8.0	7.5	2.5	7.5	0.46
7.0	6.5	7.0	5.0	8.0	0.47[a]
6.0	7.0	6.0	5.0	6.0	0.48
7.5	6.0	7.0	5.5	8.0	0.49[a]
7.5	7.5	9.0	3.0	4.5	0.59
8.0	9.0	8.0	4.0	5.0	0.59[a]
8.5	7.0	6.5	4.0	7.0	0.61
8.0	9.0	8.0	5.0	4.0	0.61[a]
8.0	8.0	8.5	6.0	4.0	0.64

[a] The test data.

Table 2
Training and test data sets of the new design.

Quality	Delivery	Technology	Price	Location	Supplier Score
0.078	0.28	60	0.23	0.25	0.03
0.031	0.14	50	0.29	0.25	0.04[a]
0.038	0.13	55	0.33	0.11	0.04
0.039	0.13	55	0.37	0.16	0.06[a]
0.012	0.18	60	0.27	0.18	0.08
0.039	0.21	60	0.23	0.19	0.08[a]
0.009	0.12	70	0.25	0.11	0.10
0.021	0.19	65	0.24	0.15	0.10[a]
0.021	0.19	60	0.27	0.11	0.11
0.011	0.01	55	0.34	0.09	0.12[a]
0.023	0.06	60	0.22	0.15	0.13
0.019	0.22	55	0.19	0.15	0.14[a]
0.009	0.12	80	0.28	0.08	0.14
0.014	0.15	90	0.31	0.16	0.18[a]
0.014	0.07	65	0.35	0.13	0.19
0.056	0.11	70	0.22	0.17	0.19[a]
0.024	0.13	70	0.22	0.13	0.21
0.018	0.19	70	0.20	0.17	0.21[a]
0.014	0.17	85	0.29	0.16	0.23
0.012	0.03	75	0.31	0.11	0.26[a]
0.013	0.11	90	0.26	0.13	0.26
0.009	0.05	80	0.26	0.18	0.32[a]
0.012	0.08	60	0.25	0.18	0.34
0.009	0.08	70	0.23	0.09	0.34[a]
0.013	0.08	70	0.31	0.13	0.40
0.005	0.05	80	0.44	0.13	0.41[a]
0.010	0.09	75	0.25	0.09	0.42
0.010	0.09	80	0.27	0.09	0.46[a]
0.007	0.06	90	0.40	0.22	0.52
0.003	0.04	90	0.29	0.11	0.53[a]
0.004	0.01	85	0.35	0.16	0.54
0.003	0.01	85	0.29	0.17	0.56[a]
0.005	0.03	90	0.24	0.17	0.63

[a] The test data.

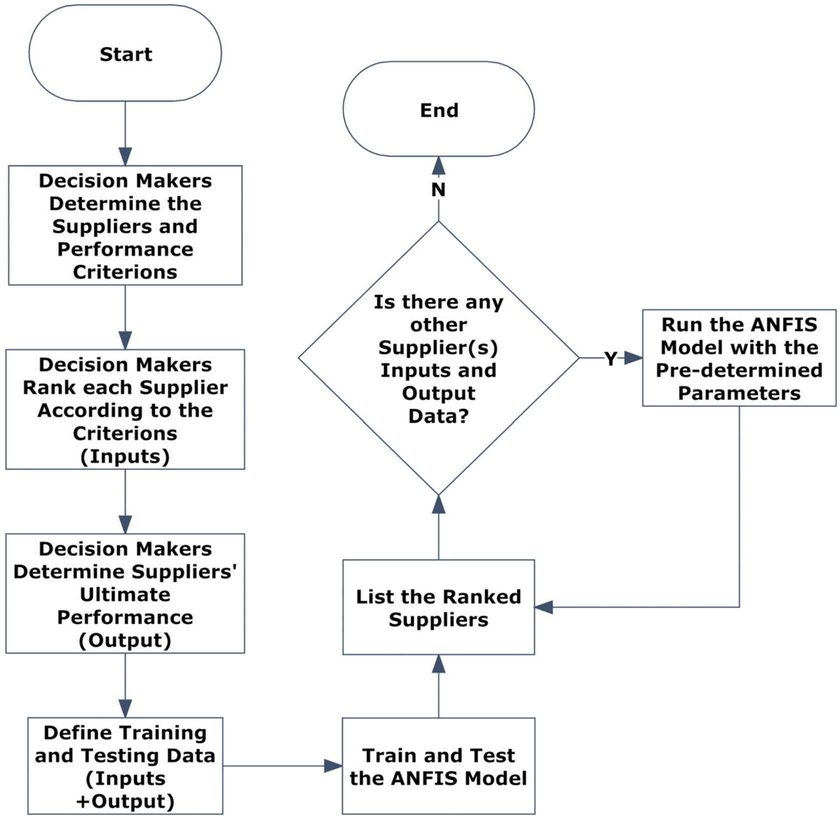

Fig. 3. Process flow chart for our ANFIS model.

and each input has two Gaussian membership functions (gaussmf), the ANFIS has totally 32 rules ($2\ \text{rules}^{5\ \text{inputs}} = 32$).

The gaussmf has been chosen between the membership functions for the lowest MSE result. The sample of Gaussian membership functions of input Quality-Q is shown in Fig. 5.

Results of NN application for fuzzy method

In Golmohammadi's study, there are two neural network models in the problem solution. The first model is designed based on one by one managers' judgment with the defined parameters to evaluate each supplier's performance. Golmohammadi found that this model is not good at providing support to the managers both in ranking alternatives and indicating the degree of importance for better performance prediction issues. In order to diminish the drawbacks of the first model, AHP supported second model is redesigned. Input and output data gathered from this redesigned model is given in Table 2. In Golmohammadi's both in first and second NN model, one hidden layer with the sigmoid transfer function is used for the performance of the model. The learning rate and momentum values were 0.5 and 0.2, respectively, with four hidden nodes. MSE for the first design at training and testing is 0.01 and 0.09 respectively. After the redesign, MSE for training and testing become 0.002 and 0.01 respectively with 0.7733 residual at the end of 1000 epochs. Thus, the second design of Golmohammadi's NN model which was used the data of Table 2 gives better

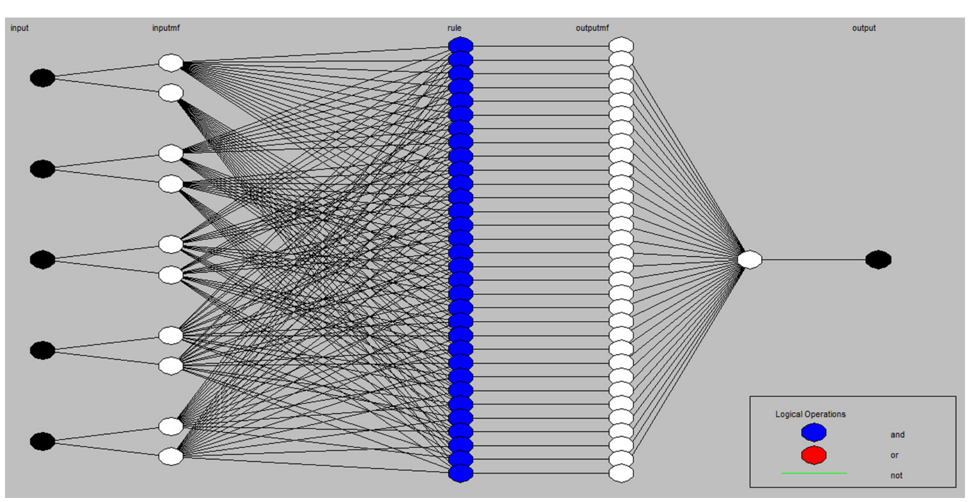

Fig. 4. Architecture of proposed ANFIS model.

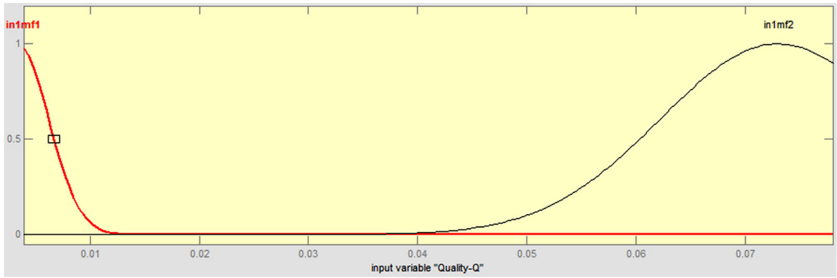

Fig. 5. Sample of gaussmf of the input Quality-Q.

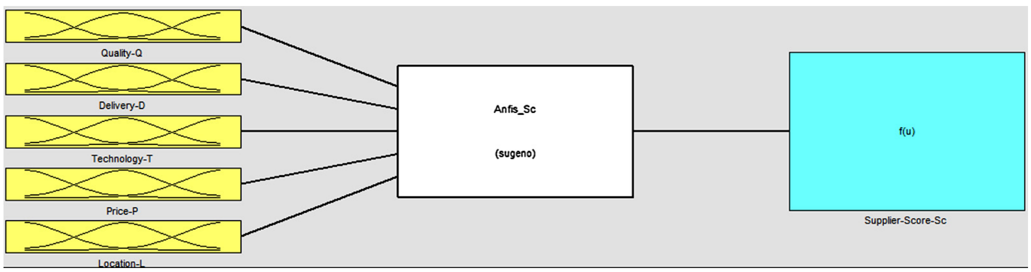

Fig. 6. Sugeno type FIS for training the ANFIS model.

result than the first one of the NN model. Descriptions in terms of the fundamentals of ANN and AHP techniques and related applications can be readily found in Golmohammadi [14]'s and other studies which are given as follows. Furthermore, most of the published decision making approaches, e.g., Analytic Hierarchy Process (AHP), appear incapable of dealing with the imprecise and vague comparisons of qualitative criteria [24]. A statistical analysis for the validation process shows that the performance of the proposed model is significantly higher in comparison with the recent model in the literature [3].

Results of ANFIS model

The ANFIS model is trained for 500 epochs with the 50% of the data in Table 1. Finally, the MSE is founded as 2.6798×10^{-17} for the training set. The result of the ANFIS is much better than the first design of Golmohammadi's NN application. Since its MSE of the test result is 0.09 while the ANFIS' is 0.0279.

As seen in Table 2, the system output is just depending on the Technology-T input. Because, the T input has values in the range of 100 while the other inputs are in the range of 1. Since the effect of the T input dominated the effects of the other inputs, its values are divided by 100 to be normalized to the range of 1 in proposed ANFIS model.

Generated a Sugeno type Fuzzy Inference System (FIS) for training of ANFIS can be seen in Fig. 6. Initially, the output of the ANFIS is zero. After the training stage, the data, both training and testing are evaluated for the prediction performance of the proposed ANFIS model.

The prediction results of proposed ANFIS model are shown in Fig. 7. The results give promise between target and predicted values. It is obvious that ANFIS results are in harmony with the

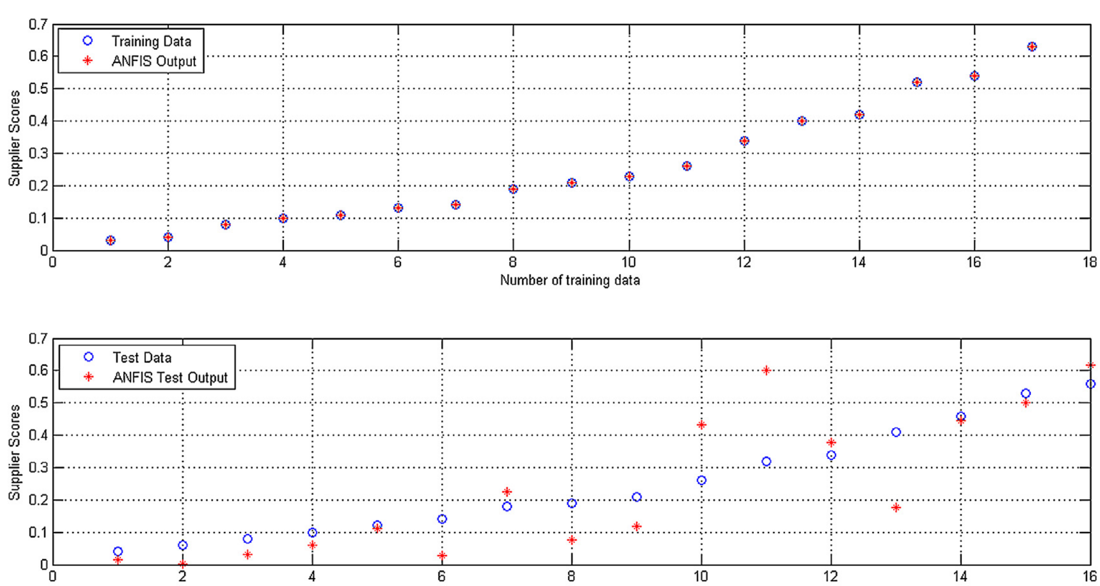

Fig. 7. Training and test stages of the ANFIS model.

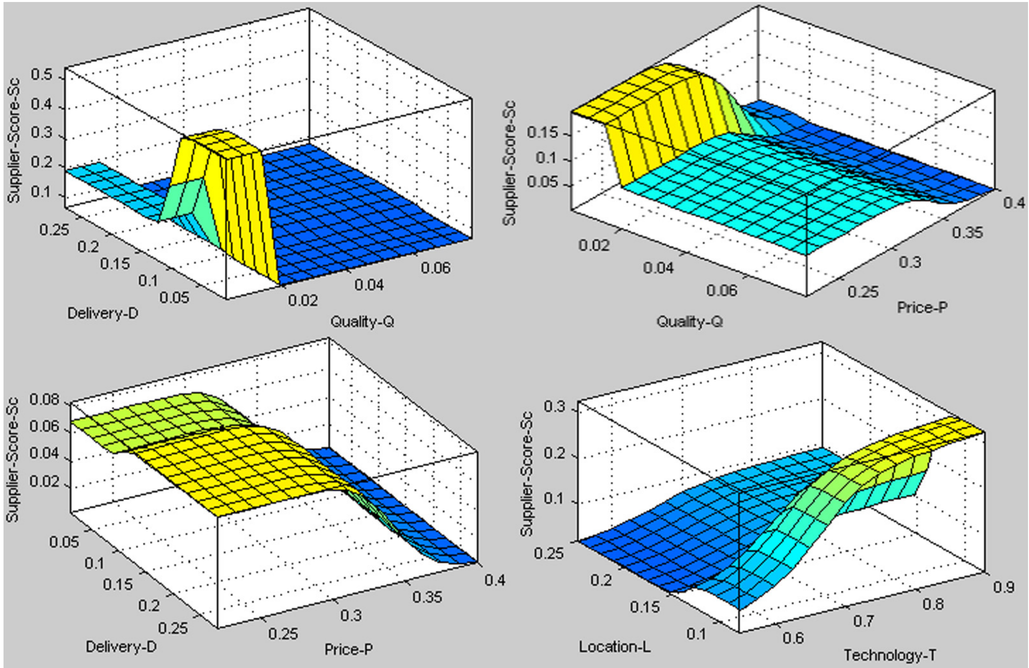

Fig. 8. After the training the changes in the output of ANFIS.

Table 3
The test result of ANFIS model.

Inputs					Target output	ANFIS model	
Quality-Q	Delivery-D	Technology-T	Price-P	Location-L	Supplier Score-Sc	Predicted output	Residual
0.0310	0.1400	0.5000	0.2900	0.2500	0.0400	0.0160	0.0240
0.0390	0.1300	0.5500	0.3700	0.1600	0.0600	0.0017	0.0583
0.0390	0.2100	0.6000	0.2300	0.1900	0.0800	0.0298	0.0502
0.0210	0.1900	0.6500	0.2400	0.1500	0.1000	0.0606	0.0394
0.0110	0.0100	0.5500	0.3400	0.0900	0.1200	0.1127	0.0073
0.0190	0.2200	0.5500	0.1900	0.1500	0.1400	0.0264	0.1136
0.0140	0.1500	0.9000	0.3100	0.1600	0.1800	0.2247	−0.0447
0.0560	0.1100	0.7000	0.2200	0.1700	0.1900	0.0751	0.1149
0.0180	0.1900	0.7000	0.2000	0.1700	0.2100	0.1175	0.0925
0.0120	0.0300	0.7500	0.3100	0.1100	0.2600	0.4334	−0.1734
0.0090	0.0500	0.8000	0.2600	0.1800	0.3200	0.6006	−0.2806
0.0090	0.0800	0.7000	0.2300	0.0900	0.3400	0.3783	−0.0383
0.0050	0.0500	0.8000	0.4400	0.1300	0.4100	0.1769	0.2331
0.0100	0.0900	0.8000	0.2700	0.0900	0.4600	0.4459	0.0141
0.0030	0.0400	0.9000	0.2900	0.1100	0.5300	0.5002	0.0298
0.0030	0.0100	0.8500	0.2900	0.1700	0.5600	0.6173	−0.0573

training result. The MSE values of both training and test stages are 6.1350×10^{-14} and 0.0134 respectively.

The output of the trained ANFIS is investigated according to the input's combinations. The output of Supplier Score proportionally decreases with the inputs such as Quality, Delivery and Price, whereas it increases with the inputs such as Technology and Location. These investigations can be seen in Fig. 8. It can be clearly seen in Fig. 8, the output of ANFIS meets the each state of the inputs. The ANFIS model was discovered by its prediction ability. The prediction of test results of ANFIS model is given in Table 3 for the multi criteria decision making of Supplier Scores. As shown in Fig. 9, R-value is computed as 0.8467 for the ANFIS model.

Comparison of NN for Fuzzy and ANFIS

The comparison results of NN for Fuzzy and ANFIS models for multi-criteria decision making problems are given in Table 4. The R-value and the MSE value for ANFIS were computed as 0.8467 and 0.0134, respectively. They were 0.7733 and 0.0193 for Golmohammadi's NN study. Because of higher R-value and lower MSE, ANFIS model gives the more precise results to the Supplier Score-Sc response than does Golmohammadi's NN study. Hence, the ANFIS model can be able to predict better than the Golmohammadi's

Table 4
Comparison of NN for Fuzzy and ANFIS models.

Performance	NN for fuzzy [14]	ANFIS
MSE	0.0193	0.0134
NMSE	0.4485	0.3750
MAE	0.1070	0.0857
Min. abs. error	0.0140	0.0073
Max. abs. error	0.2779	0.2806
R-value	0.7733	0.8467

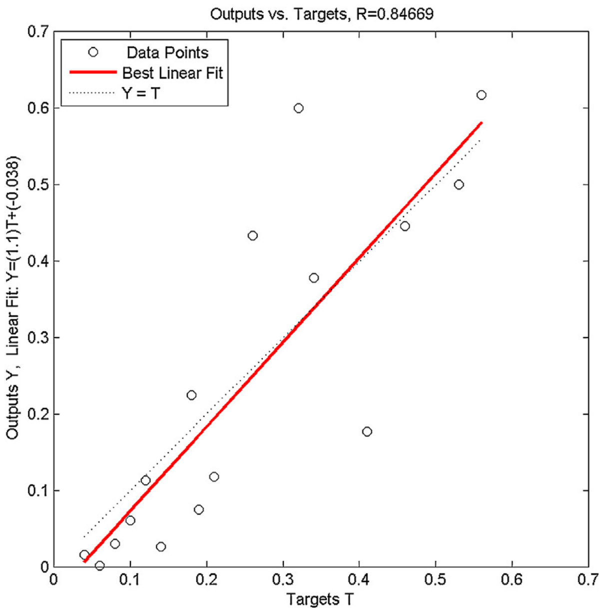

Fig. 9. *R*-value of output of ANFIS and target values of test data.

neural network application for fuzzy multi-criteria decision making problems.

Conclusion

As a result, supplier evaluation is a cumbersome work for most of the industrial engineers' operational area. Nowadays, importance of logistics increases. Firms have focused on customer satisfaction and reducing cost along with long-term contracts with credible suppliers. In order to do that, managers need to monitor the performance of the suppliers with an easy to use, dependable and applicable method. The designed ANFIS model proposes a better solution alternative in this area. The results of *R*-value and MSE for ANFIS at the end of 500 epochs were 0.8467 and 0.0134, respectively. They were 0.7733 and 0.0193 for the Golmohammadi's NN study in 1000 epochs. Hence, ANFIS can predict the Supplier Score-Sc with smaller error. Moreover, regression results show that the ANFIS model gives higher accuracy than Golmohammadi's NN study. As a result, the ANFIS model can be able to predict better than the Golmohammadi's neural network application for fuzzy multi-criteria decision making problems.

References

[1] W. Ho, X. Xu, P.K. Dey, Multi-criteria decision making approaches for supplier evaluation and selection: a literature review, Eur. J. Oper. Res. 202 (2010) 16–24.
[2] J.-S.R. Jang, C.-T. Sun, E. Mizutani, Neuro-fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Prentice Hall, Upper Saddle River, NJ, 1997.
[3] D. Golmohammadi, M. Mellat-Parast, Developing a grey-based decision-making model for supplier selection, Int. J. Prod. Econ. 137 (2012) 191–200.
[4] P. Pitchipoo, P. Venkumar, S. Rajakarunakaran, Fuzzy hybrid decision model for supplier evaluation and selection, Int. J. Prod. Res. 51 (2013) 3903–3919.
[5] G. Büyüközkan, An integrated fuzzy multi-criteria group decision-making approach for green supplier evaluation, Int. J. Prod. Res. 50 (2011) 2892–2909.
[6] A.W. Labib, A supplier selection model: a comparison of fuzzy logic and the analytic hierarchy process, Int. J. Prod. Res. 49 (2011) 6287–6299.
[7] F. Arikan, A fuzzy solution approach for multi objective supplier selection, Exp. Syst. Appl. 40 (2013) 947–952.
[8] S.I. Omurca, An intelligent supplier evaluation, selection and development system, Appl. Soft Comput. 13 (2013) 690–697.
[9] D. Dalalah, M. Hayajneh, F. Batieha, A fuzzy multi-criteria decision making model for supplier selection, Exp. Syst. Appl. 38 (2011) 8384–8391.
[10] S. Önüt, S.S. Kara, E. Işik, Long term supplier selection using a combined fuzzy MCDM approach: a case study for a telecommunication company, Exp. Syst. Appl. 36 (2009) 3887–3895.
[11] R.-H. Lin, An integrated model for supplier selection under a fuzzy situation, Int. J. Prod. Econ. 138 (2012) 55–61.
[12] M. Zeydan, C. Çolpan, C. Çobanoğlu, A combined methodology for supplier selection and performance evaluation, Exp. Syst. Appl. 38 (2011) 2741–2751.
[13] A. Amindoust, S. Ahmed, A. Saghafinia, A. Bahreininejad, Sustainable supplier selection: a ranking model based on fuzzy inference system, Appl. Soft Comput. 12 (2012) 1668–1677.
[14] D. Golmohammadi, Neural network application for fuzzy multi-criteria decision making problems, Int. J. Prod. Econ. 131 (2011) 490–504.
[15] D. Golmohammadi, R.C. Creese, H. Valian, J. Kolassa, Supplier selection based on a neural network model using genetic algorithm, IEEE Trans. Neural Netw. 20 (2009) 1504–1519.
[16] A.F. Güneri, T. Ertay, A. Yücel, An approach based on ANFIS input selection and modeling for supplier selection problem, Exp. Syst. Appl. 38 (2011) 14907–14910.
[17] A. Yücel, A.F. Güneri, A weighted additive fuzzy programming approach for multi criteria supplier selection, Exp. Syst. Appl. 38 (2011) 6281–6286.
[18] M.-L. Tseng, R.-J. Lin, Y.-H. Lin, R.-H. Chen, K. Tan, Close-loop or open hierarchical structures in green supply chain management under uncertainty, Exp. Syst. Appl. 41 (2014) 3250–3260.
[19] A. Saghaei, H. Didehkhani, Developing an integrated model for the evaluation and selection of six sigma projects based on ANFIS and fuzzy goal programming, Exp. Syst. Appl. 38 (2011) 721–728.
[20] M. Sedighi, K. Keyvanloo, J. Towfighi, Modeling of thermal cracking of heavy liquid hydrocarbon: application of kinetic modeling, artificial neural network, and neuro-fuzzy models, Ind. Eng. Chem. Res. 50 (2011) 1536–1547.
[21] B. Abbasi, H. Mahlooji, Improving response surface methodology by using artificial neural network and simulated annealing, Exp. Syst. Appl. 39 (2012) 3461–3468.
[22] J.S.R. Jang, Self-learning fuzzy controllers based on temporal backpropagation, IEEE Trans. Neural Netw. 3 (1992) 714–723.
[23] J.S.R. Jang, ANFIS: adaptive-network-based fuzzy inference system, IEEE Trans. Syst. Man Cybern. 23 (1993) 665–685.
[24] J.-B. Sheu, A hybrid neuro-fuzzy analytical approach to mode choice of global logistics management, Eur. J. Oper. Res. 189 (2008) 971–986.