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An approach based on ANFIS input selection and modeling for supplier selection problem

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ABSTRACT

Supplier selection is a key task for firms, enabling them to achieve the objectives of a supply chain. Selecting a supplier is based on multiple conflicting factors, such as quality and cost, which are represented by a multi-criteria description of the problem. In this article, a new approach based on Adaptive Neuro-Fuzzy Inference System (ANFIS) is presented to overcome the supplier selection problem. First, criteria that are determined for the problem are reduced by applying ANFIS input selection method. Then, the ANFIS structure is built using data related to selected criteria and the output of the problem. The proposed method is illustrated by a case study in a textile firm. Finally, results obtained from the ANFIS approach we developed are compared with the results of the multiple regression method, demonstrating that the ANFIS method performed well.

1. Introduction

Supplier selection plays an important role in the success of a company's strategic goals. Changing customer preferences, public procurement regulations, and new organizational forms with more decision-makers make the purchasing function more complex and important for companies in today's environment (De Boer, Labro, & Morlacchi, 2001). In addition, performing the purchasing function effectively and building strong and reliable partnerships with suppliers ensures that the company is more competitive in the market. An adequate method with appropriate selection criteria is necessary for a company to achieve a competitive advantage.

In practice, supplier selection includes several tangible and intangible factors. Weber et al. reviewed and classified 74 articles which have appeared in the literature since 1966 (Weber, Current, & Benton, 1991). The study categorized these articles with respect to the 23 criteria of Dickson's study. These criteria were originally based on a questionnaire sent to purchasing agents and managers from the United States and Canada. Dickson concluded that quality, delivery, and performance history are the three most important criteria. On the other hand, Weber and his colleagues noted that 47 of the 74 articles (64%) discussed more than one criterion. The two main articles that address the supplier selection criteria structure describe a multi-criteria view of the problem. The review of selection criteria based on various articles is shown in Table 1.

Several methods for supplier selection have appeared in literature, including approaches based on fuzzy logic. The main reason for a fuzzy logic approach is the need to handle vagueness and ambiguity in the problem. Researchers try to build effective models that not only consider quantitative aspects but also convert human judgments about qualitative criteria into meaningful results.

For the first time in a fuzzy supplier selection problem, Amid et al. present an asymmetric approach that enables decision makers to assign different weight for each criterion (Amid, Ghodsypour, & OBrien, 2006). Their fuzzy multi-objective linear model has the capability to capture the fuzziness of the problem and order quantities can easily be assigned to each supplier under various constraints. Chen et al. presented a fuzzy TOPSIS approach by applying trapezoidal fuzzy numbers to assess the importance level of each criterion and ratings of alternative suppliers with regard to selected criteria (Chen, Lin, & Huang, 2006). In this model, a closeness coefficient is defined to determine the ranking order of all alternative suppliers by calculating the distances to fuzzy positive and negative ideal solutions (Chen, 2000). Chan and Kumar implemented a Fuzzy Extended Analytic Hierarchy Process (FEAHP) model that includes four hierarchies for a global supplier selection problem (Chan & Kumar, 2007). The study also discusses the risk factors related to a global view of the problem. Bevilacqua et al. integrated the fuzzy logic approach with a Quality Function Deployment method for a supplier selection problem in a medium to large industry that manufactures complete clutch couplings (Bevilacqua, Ciarapica, & Giacchetta, 2006). In this model, alternative suppliers are ranked according to their fuzzy suitable index values. Kwong et al. introduced a combined scoring method with

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Table 1
Supplier selection criteria research.

Selection criteria	A	B	C	D	E	F	G	H	I
After sales service	X		X				X		
Amount of past business	X		X	X					
Attitude	X								
Communication system	X		X						
Conflict resolution					X				
Delivery	X	X	X			X	X	X	
Desire for business	X								
Ease of communication		X		X				X	
Economy				X					
Financial position	X	X	X	X	X	X			X
Flexibility and response to changes		X		X		X		X	X
Geographical location	X			X					
Impression and skill	X								X
Labor relations record	X								
Management and organization	X					X			X
Operating controls	X								
Packaging ability	X								
Performance history	X			X					
Political stability				X					
Price	X	X		X			X	X	
Procedural compliance and discipline	X					X			
Production facilities and capacity	X	X	X	X		X	X		X
Quality	X	X	X	X	X	X		X	X
Reciprocal arrangements	X		X						
Relationship closeness		X			X				
Reputation and position in industry	X	X							
Technical capability and technology	X	X	X	X	X	X	X		X
Terrorism				X					
Training aids	X								
Warranties and claim policies	X						X		

A. Dickson (1966); B. Lee (2009); C. Haq and Kannan (2006); D. Chan and Kumar (2007); E. Chen et al. (2006); F. Liu and Hai (2005); G. Xia and Wu (2007); H. Ghodsypour and O'Brien (1998); I. Yahya and Kingsman (1999).

a fuzzy expert systems approach to perform supplier assessment (Kwong, Ip, & Chan, 2002). In the case study, existing supplier assessment forms are used to assign the score of each individual supplier. Then obtained scores are used as inputs to build fuzzy if-then rules. Finally, the designed fuzzy expert system is implemented in the C programming language. In another study, Carrea and Mayorga applied a Fuzzy Inference System (FIS) approach to a supplier selection problem for new product development (Carrera & Mayorga, 2008). Their model includes 16 variables categorized in four groups and each group has an individual output. MATLAB FIS Editor is used to define rules and solve the problem. The proposed FIS system uses Gaussian and Bell membership functions to define the shape of both input and output variables. Ohdar et al. and Famuyiwa et al. also applied a Fuzzy Inference System approach to the supplier selection problem using the MATLAB FIS editor (Famuyiwa, Monplaisir, & Nepal, 2008; Ohdar & Ray, 2004). The main point of the Fuzzy Inference System approach is to determine fuzzy if-then rules from experts' opinions. ANFIS, unlike FIS, automatically produces adequate rules with respect to input and output data, and takes advantage of the learning capability of neural networks.

Many researchers and academicians concentrate on a fuzzy logic approach for the supplier selection problem, but not much attention is given to fuzzy logic with neural networks. Nassimbeni and Battain applied the ANFIS approach to evaluate the contribution that suppliers have on product development (Nassimbeni & Battain, 2003). The three inputs of model are product concept and functional design, product structural design and engineering, and process design and engineering. These inputs are used to evaluate suppliers and the sum of the weighted score of experts' ratings corresponding to 15 selected criteria taken as output for the model. The data for 12 suppliers were used to instruct the neuro-fuzzy system, and data from the other four was used to test the results. In this article, output depends on subjective judgment of experts and focuses on supplier evaluation in a New Product Development (NPD) environment. We also discuss the topic of selecting a membership function type.

There have been no prior applications of the neuro-fuzzy approach to the supplier selection problem and with respect to this fact a new model based on ANFIS is developed. For the first time in a supplier selection problem, ANFIS is used for both selection of criteria and developing the model of the problem. The model output is defined to be the share of each supplier's sales. We also discuss selection of the number and type of membership functions. After the construction of the database, the model has two main stages: ANFIS input selection is executed first, and then the ANFIS model is built with respect to the related input/output data pattern.

The paper is organized as follows: the next section introduces the basics of ANFIS. Section 3 includes a literature review of ANFIS. In Section 4, we present the algorithm for the model we developed. Section 5 includes a case study of the model. Finally, we present our conclusions in the last section.

2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Jang first introduced the ANFIS method by embedding the Fuzzy Inference System (FIS) into the framework of adaptive networks (Jang, 1993). An adaptive network is a network structure consisting of a number of nodes connected through directional links. The outputs of these adaptive nodes depend on modifiable parameters pertaining to these nodes. The learning rule specifies how these parameters should be updated to minimize error. On the other hand, FIS is a framework based on fuzzy set theory and fuzzy if-then rules. The structure of FIS has three main components: a rule base, a database, and a reasoning mechanism. The rule base contains fuzzy if-then rules. For example, one rule might be "if price is low, then supplier's rating is high," where low and high are linguistic variables. The database defines the membership functions applied in fuzzy rules and the reasoning mechanism performs the inference procedure (Jang, Sun, & Mizutani, 1997).

Assume that the FIS has two inputs, x and y, and one output, z. In addition, the rule base of the FIS contains two fuzzy if-then rules, similar to the rule types described by Takagi and Sugeno (1983):

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_2 and Y is B_2 then $f_2 = p_2x + q_2y + r_2$.

When $f(x,y)$ is a first-order polynomial as shown above, then the model is called a first-order Sugeno fuzzy model.

ANFIS architecture is shown in Fig. 1 where each node within the same layer performs functions of the same type. If a node's parameter set is not empty, then its node function depends on the parameter values; a square is used to represent this kind of adaptive node. On the other hand, if a node has an empty parameter set, then its function is fixed; a circle is used to denote this type of fixed node. The architecture is composed of five layers:

Layer 1: Every node i in this layer is a square node with a node function.

$$O_i^1 = \mu_{A_i}(x) \quad (1)$$

where x is the input to node i, A_i is the linguistic label, and O_i^1 is the membership function of A_i. Parameters in this layer are defined as premise parameters.

Layer 2: Circle nodes in this layer multiply the incoming signals and send the product out. This represents the firing strength of a rule.

$$\omega_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,2 \quad (2)$$

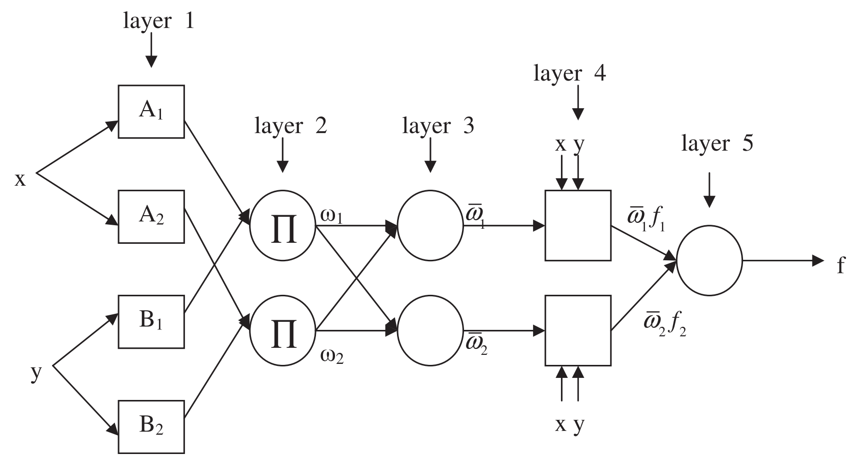


Fig. 1. Adaptive neuro-fuzzy inference system structure.

Layer 3: Every node in this layer, labeled in Fig. 1 with *N*, calculates the average ratio of *i*th rule's firing strength.

$$\bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2 \tag{3}$$

Layer 4: Every node *i* in this layer is a square node with a node function.

$$O_i^4 = \bar{\omega}_i f_i = \bar{\omega}_i(p_i x + q_i y + r_i) \tag{4}$$

where $\bar{\omega}_i$ is the output of layer 3 and parameters p_i, q_i and r_i will be referred to as consequent parameters.

Layer 5: The node in this layer computes the overall output as the summation of all incoming signals:

$$O_i^5 = \sum_i \bar{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \tag{5}$$

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 (Jang et al., 1997).

3. ANFIS literature review

The ANFIS method has been widely used in literature for different problems. In these studies, researchers and academicians take the advantage of hybrid learning structure of ANFIS compared to other neural network oriented studies (Ertay & Çekyay, 2005; Lee, 2008; Lee, Booth, & Alam, 2005; Lin, Tseng, Chou, & Chen, 2008; Moradkhani, Hsu, Gupta, & Sorooshian, 2004; Tchaban, Griffin, & Taylor, 1998). Wang and Elhag applied ANFIS for bridge risk assessment (Wang & Elhag, 2008). They used a dataset consisting of 506 bridge maintenance projects provided by the British Highways Agency. They split this data into a training dataset, consisting of 390 projects, and a testing dataset, consisting of 116 projects. Their model includes four inputs and each input has two generalized bell-shaped membership functions. The results obtained from ANFIS outperformed those from an Artificial Neural Network method. In another article, Malhotra and Malhotra applied ANFIS to differentiate good and bad credit (Malhotra & Malhotra, 2002). Their model has three inputs: the ratio of total payments to total income, the ratio of total debt to total income, and credit rating. Compared to the multiple discriminant analysis approach, the ANFIS model achieved better performance for assessing the bad loans. Polat and Gunes presented an integrated method that has two stages for diagnosis of diabetes disease (Polat & Güneş, 2007). In the first stage, Principal Component Analysis (PCA) is used to reduce the number of criteria from 8 to 4. In the second stage, ANFIS is applied to the selected criteria. This model is more accurate than the other various methods applied in literature. In another study, Çaydaş et al. also applied ANFIS with the PCA method to decrease the total number of inputs (Çaydaş, Hasçalık, & Ekici, 2009). They developed a model to predict surface roughness and white layer thickness in a wire electrical discharge machining process. Atsalakis and Valavanis applied ANFIS to create a forecasting system that predicts the next day's trend for a stock (Atsalakis & Valavanis, 2009). Their model has three inputs and one output. For each input, three Gaussian combination membership functions are used instead of bell shaped, Gaussian or triangular functions because they minimize root mean square error (RMSE). On average, the model reached 63.21% forecasting accuracy for three different approximately 60 day periods in the testing dataset. Quah applied three soft-computing models to a Dow Jones Industrial Average (DJIA) stock selection problem: Multi-Layer Perceptrons (MLP), ANFIS, and general growing and pruning radial basis function (GGAP-RBF) Quah, 2008. Huang et al. used ANFIS to differentiate between normal and glaucomatous eyes (Huang, Chen, & Huang, 2007). Ayata et al. investigated the potential use of natural ventilation as a passive cooling system in new building designs in Turkey by applying a simulation package program called FLUENT with ANFIS (Ayata, Çam, & Yıldız, 2007). First, data needed to develop an ANFIS model of the problem is formed by FLUENT. Then, two separate ANFIS models are presented to predict indoor average and maximum air velocities using the simulated data. Azamathulla et al. applied ANFIS to predict the bed load for moderately sized rivers in Malaysia (Azamathulla et al., 2009). A total of 346 sets of bed load data, obtained from four different rivers, are used to build the ANFIS structure. Results obtained from the constructed model are compared with a regression method; ANFIS performed well with a better accuracy rate. Baylar et al. used ANFIS to predict air entrainment rate and aeration efficiency of weirs by applying three inputs to two different ANFIS models (Baylar, Hanbay, & Özpolat, 2008). In a related study, model performance of multi-nonlinear and linear regression was compared; ANFIS produced better results than related regression models. Kannathal et al. applied ANFIS to classify heart abnormalities and a total of 600 datasets for 10 different cardiac states were used to build the model (Kannathal, Lim, Acharya, & Sadasivan, 2006). The model included three inputs, and a generalized bell-shaped membership function was selected because it performed better than other membership functions. The ANFIS model yielded better accuracy than an Artificial Neural Network (ANN) method.. Yuan et al. proposed an ANFIS model for a radar/infrared system and recommended ANFIS for its high speed real-time computation feature to compute sensor confidence degrees (Yuan, Dong, & Wang, 2009).

4. Structure of proposed model

Jang presented input selection for neuro-fuzzy algorithms using ANFIS and tested the method on two real world problems: the nonlinear regression problem of automobile gas mileage prediction, and nonlinear system identification using Box and Jenkins gas furnace data (Jang, 1996). When applying ANFIS, too many inputs cause many parameters for training and this makes the system complicated, diminishing its applicability. To handle this considerably important issue, ANFIS input selection method is applied to the problem.

An algorithm of the model based on ANFIS for dealing with supplier selection is expressed in Fig. 2. Steps 1–3 can be defined as the preparation process for building the database for the model. Steps

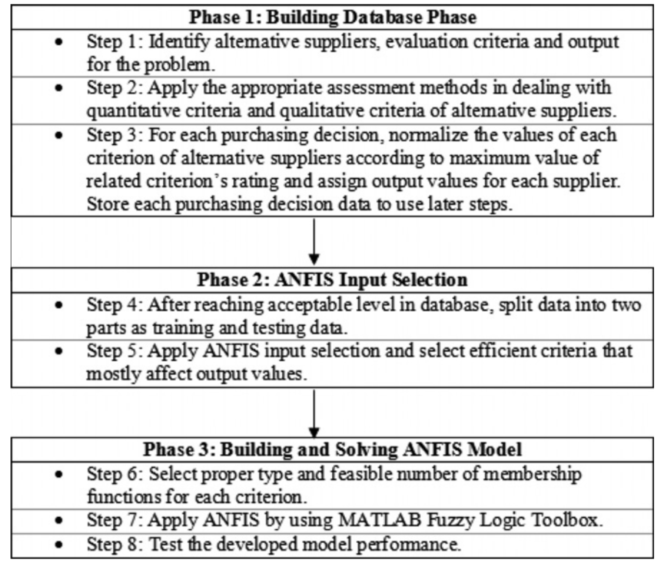


Fig. 2. Algorithm based on ANFIS for supplier selection problem.

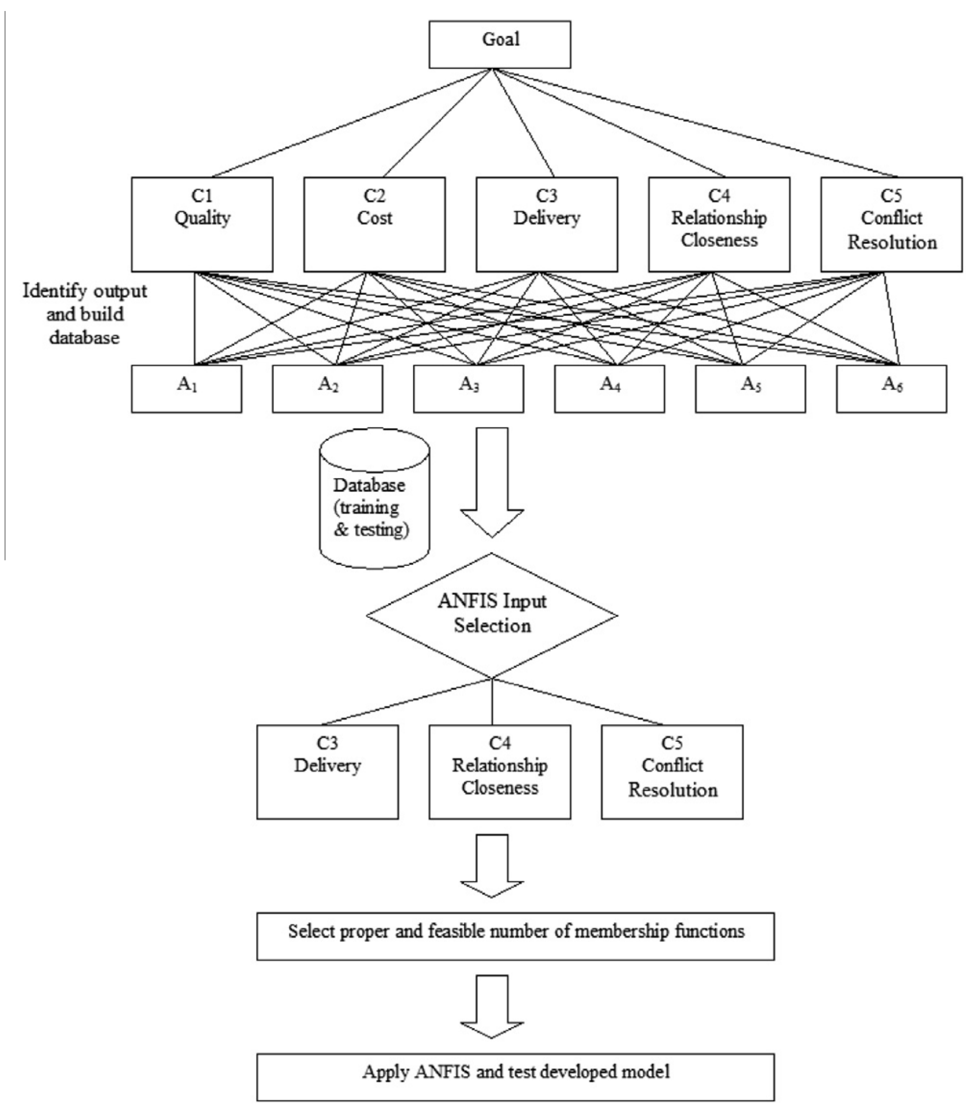


Fig. 3. Hierarchical structure of decision problem.

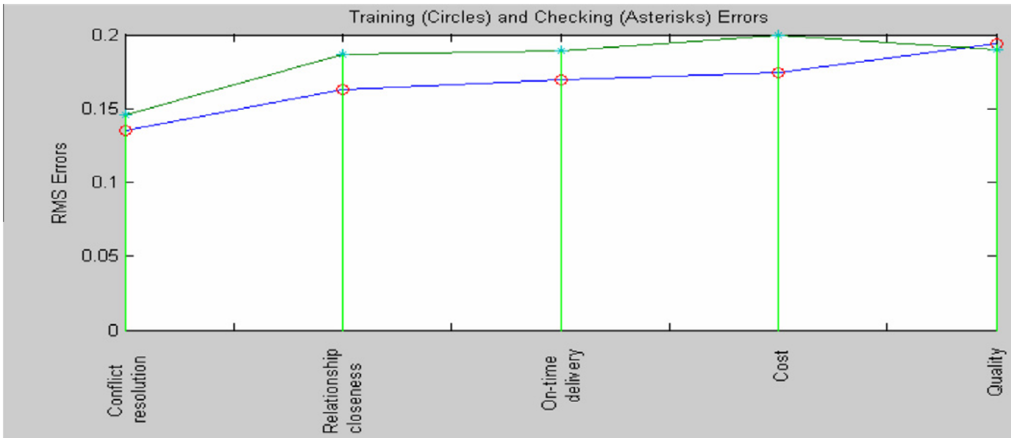


Fig. 4. Input selection for problem.

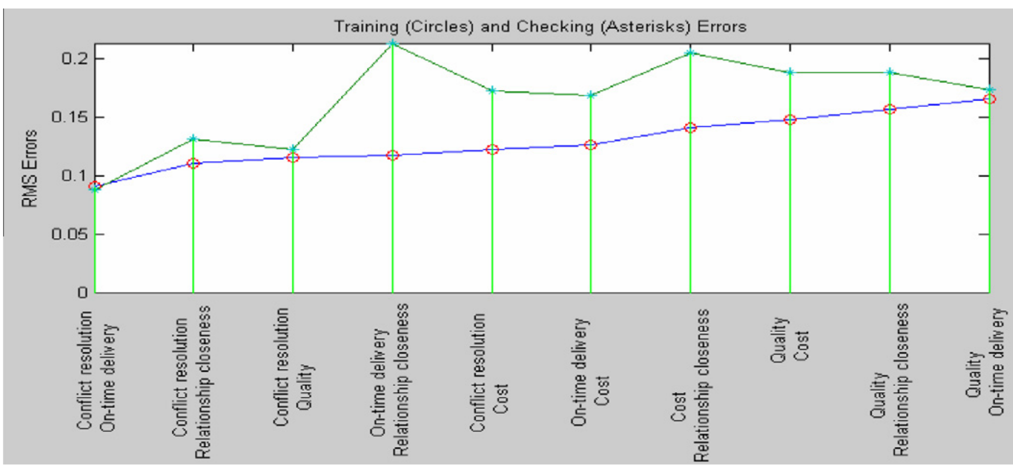


Fig. 5. Two inputs combination.

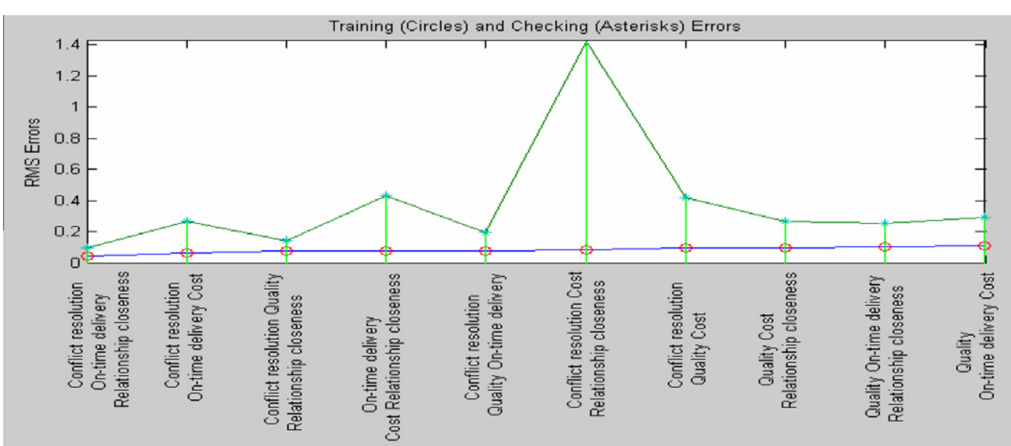


Fig. 6. Three inputs combination error level.

4–5 are applied to execute ANFIS input selection. Finally, Steps 6–8 are used to build the ANFIS structure and solve the model. After accomplishing these steps sequentially, a model that reflects the decision pattern for evaluating suppliers is formed for decision-makers.

5. Case study

This section represents application of the model based on ANFIS for supplier selection and tests its performance against the Multiple Linear Regression method. In this case study, a textile company

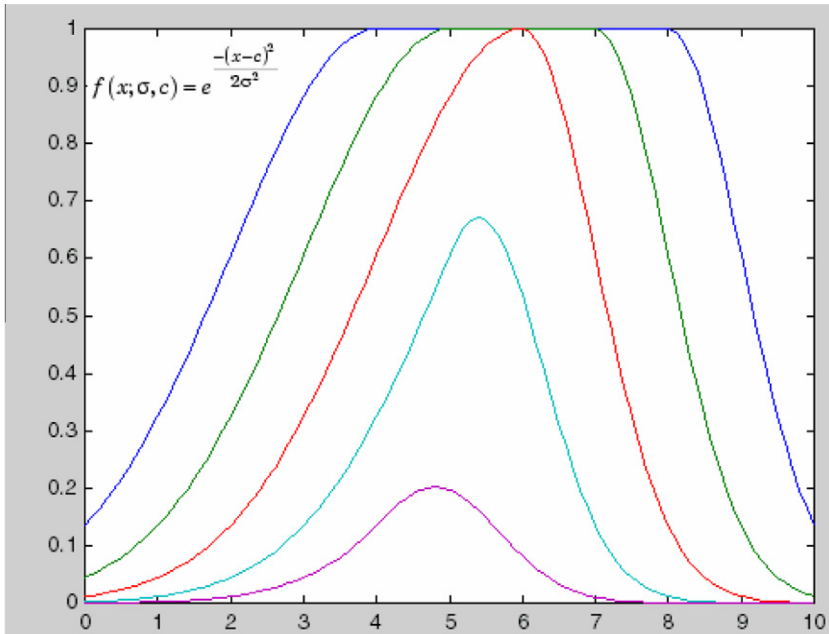


Fig. 7. Gaussian combination membership function.

desires to select suitable supplier(s) for its purchasing decision regarding a main product that affects the production process considerably. The company is established in Istanbul and specializes in the dyed and printed fabrics industry. With a 1000 tonne manufacturing capacity per month and 100 employees, the firm exports its products to five different countries located in Europe and Asia. The hierarchical structure of the decision problem is shown in Fig. 3. Each phase and step of the algorithm is presented in individual subsections.

5.1. Building database phase

This is the first phase of the algorithm and includes three steps. In the first step, alternative suppliers and supplier selection criteria are identified. Then, in the second step, the methods to evaluate criteria are proposed. The final step of this phase is the construction of the database.

Step 1: Six alternative suppliers (A_1, A_2, A_3, A_4, A_5, A_6) and five criteria are selected by decision-makers to evaluate alternatives:

- Quality.
- Cost.
- On-time delivery.
- Relationship closeness.
- Conflict resolution.

Criteria are selected based on published literature research and experts' opinions. Weber et al. mentioned that quality, delivery, and cost are the three most important criteria that interest researchers and practitioners (Weber et al., 1991). In addition, articles based on the textile industry considered these three criteria in several applications (Araz, Ozfirat, & Ozkarahan, 2007; Su, Dyer, & Gargeya, 2009; Teng & Jaramillo, 2005). On the other hand, decision-makers of companies emphasized the importance of a relationship with the supplier. To meet this requirement, relationship closeness and conflict resolution are taken into consideration as other criteria. Finally, in order to present a measurable and objective model, sales share is taken as the output for the problem.

Step 2: In this step, appropriate assessment methods to deal with quantitative criteria and qualitative criteria should be selected. To achieve this, qualitative criteria such as on-time delivery, relationship closeness, and conflict resolution are ranked on a scale from 1 to 10. Real data is applied to quantitative criteria such as quality and cost. For the quality criterion, defect rate of each alternative supplier is taken for assessment.

Step 3: In the gathering data process, the values for each criterion for alternative suppliers are normalized by the maximum values. Phase 1 is completed with 76 cases that occurred over an 8 month period. At this point, data is adequate for executing Phase 2, the ANFIS input selection.

5.2. ANFIS input selection

This phase consists of two steps. ANFIS input selection is implemented in the MATLAB environment. The most effective inputs are determined to build the final ANFIS model of the problem.

Step 4: Data is randomly split into two groups: 57 cases for training and 19 cases for testing data.

Step 5: To achieve input selection, the "exhsrch" command is used. This command performs a comprehensive search within

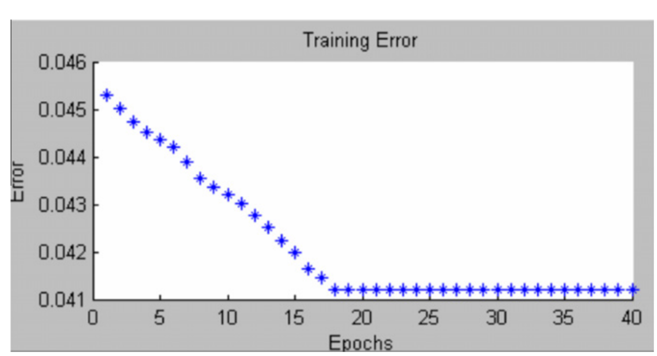


Fig. 8. Gaussian combination training error.

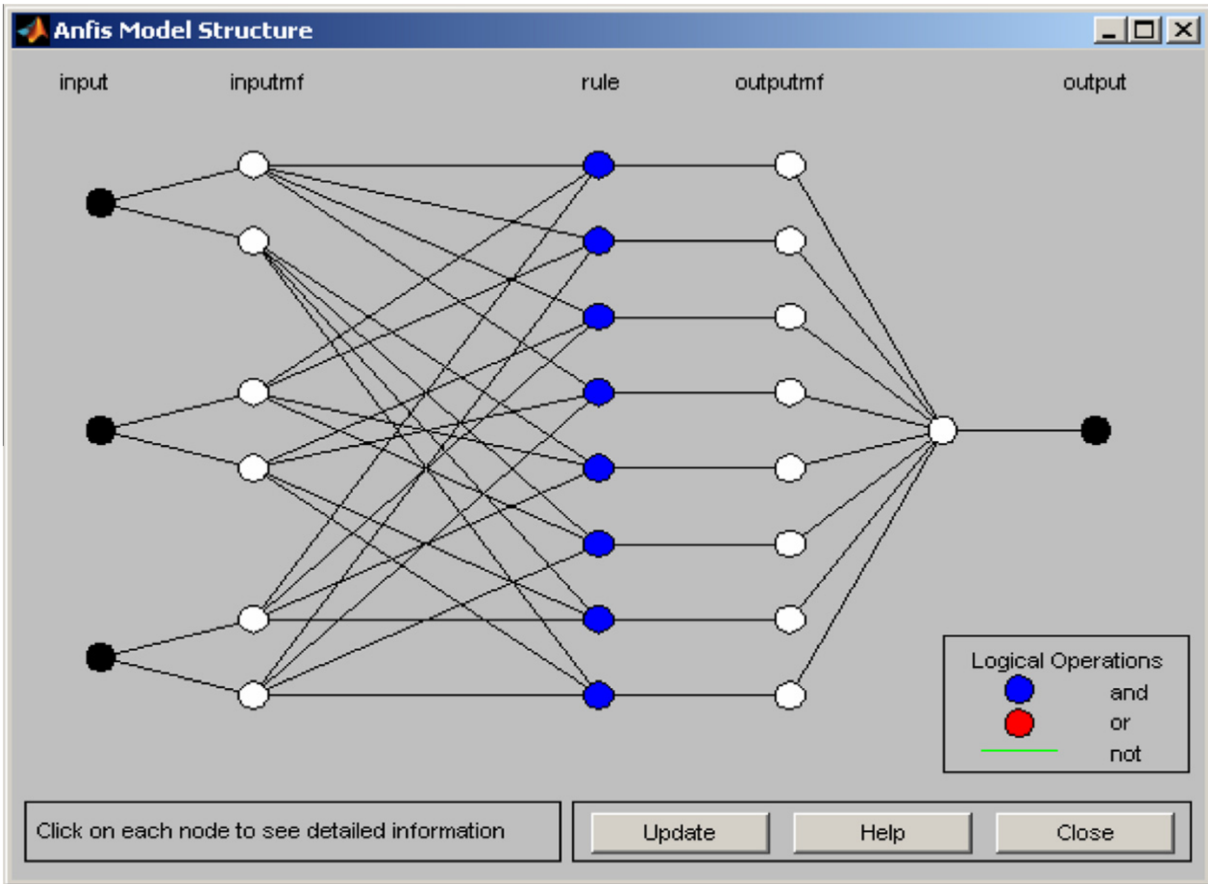


Fig. 9. ANFIS structure of problem.

the available inputs to select the set of inputs that most influence the output. exhsrch (1, trn_data, test_data, input_name) command is executed to find the most influential input that affects the output value. trn_data and test_data correspond to training data and testing data and input_name contains the list of all inputs. After execution of the command, conflict resolution is found to be the most effective input in the problem, as shown in Fig. 4.

To calculate two inputs combination error values, "1" is replaced with "2" in the exhsrch command arguments. Conflict resolution and on-time delivery inputs are returned as the most effective inputs and output error is decreased from 0.1355 to 0.0909 as illustrated in Fig. 5.

Next, a combination of three inputs is tried. The results identify conflict resolution, on-time delivery, and relationship closeness as the most influential inputs, with a 50% improvement in error value (Fig. 6). These three inputs are selected as a final decision due to input numbers applied in many articles and point that ANFIS gives better solution with a simple structure. At this point, Phase 2 is complete for the problem.

Unselected inputs, such as quality and cost, are the most widely used criteria in various studies in literature, and this point may arouse interest. Selected inputs are discussed and experts from the company agree that the content of selected inputs reflects the strategy of company with regard to product purchasing activity.

5.3. Building and solving ANFIS model

The MATLAB ANFIS editor is used to complete the last phase, which consists of three steps. We determine a feasible number of membership functions, and the ANFIS model is built in the first two steps. In the last step, the developed model performance is tested by applying training and testing data.

Step 6: Because the number of data elements should be greater than the number of modified parameters, two membership functions are chosen for each input in the model. If three membership functions are assigned to each input, the editor gives a warning about the fact that modifiable parameters exceed the dataset.

The ANFIS editor presents eight different types of membership functions for decision-makers to use in problems: Triangular, Trapezoidal, Generalized bell, Gaussian curve, Gaussian combination, Π-shaped, Difference between two sigmoid functions, and Product of two sigmoid functions. In the model, each type is tested individually, similar to other studies (Atsalakis and Valavanis, 2009; Kannathal et al., 2006). As illustrated in Fig. 7, a Gaussian combination membership function is chosen to train the input/output data pattern because it minimizes the RMSE (Fig. 8).

Step 7: After determining the number and type of membership functions, the ANFIS model is structured as illustrated in Fig. 9. A hybrid learning algorithm is applied to the model, and the training dataset is trained for 40 epochs. Forty epochs are adequate for the model because the minimal checking error occurs by about epoch 18.

Step 8: After training, the rule structure of the model is obtained, as illustrated in Fig. 10. The rule viewer displays a roadmap of the whole fuzzy inference process and allows decision-makers to easily change input values and obtain output values. In Fig. 10, each rule is a row of plots and each column is a variable. When the user changes input values by moving the red lines, the system produces output values automatically, as seen in last column of the

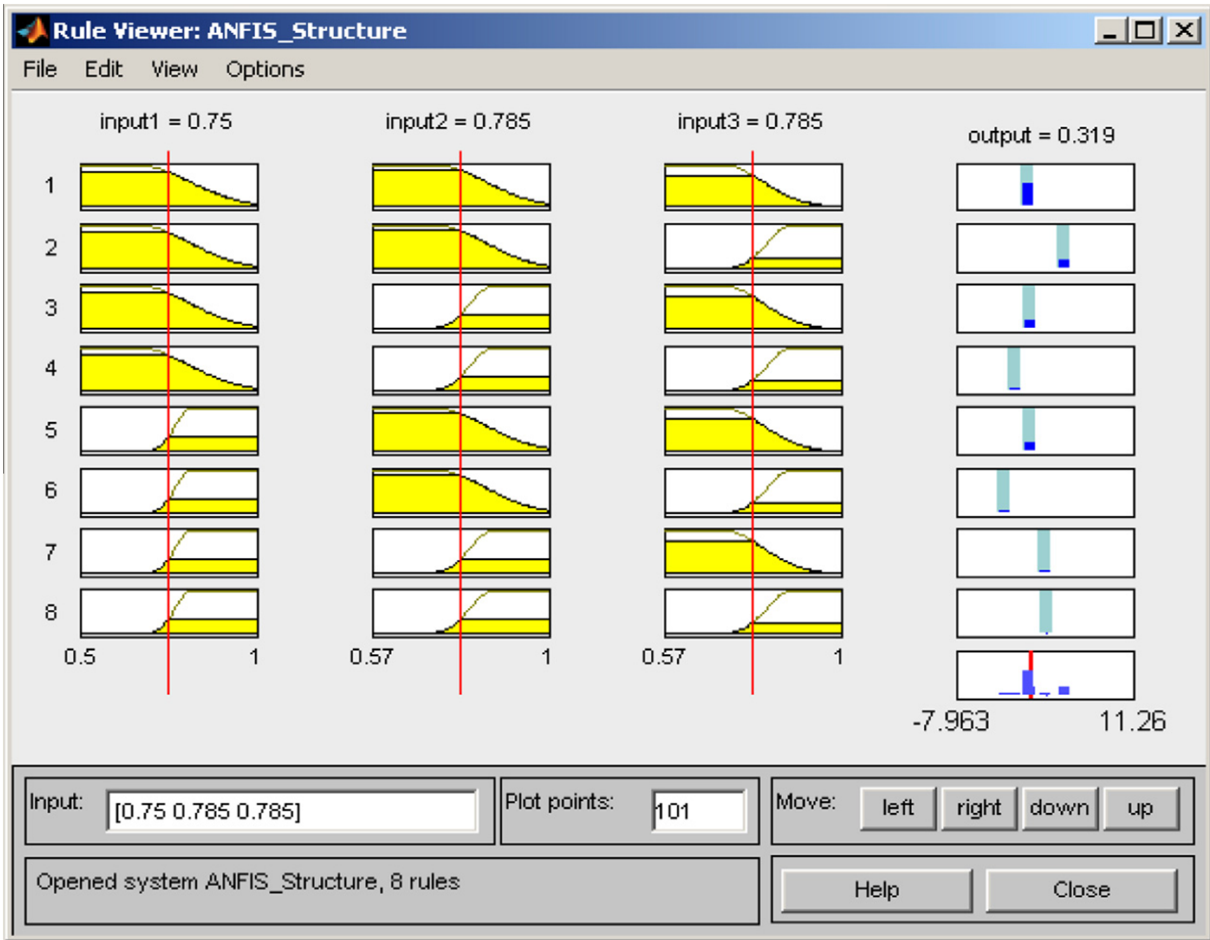


Fig. 10. ANFIS rule structure.

figure. As two membership functions are assigned for each input, the model presents 8 (2^3) different rules to produce the output value. When the rule structure is analyzed, the output value increases parallel to results obtained from the input selection phase. Conflict resolution is the most effective input, and integration of conflict resolution with on time delivery is more important than integration with relationship closeness. If "Average" and "High" linguistic values are assigned for the membership functions of each input, the rule structure is formed as shown in Fig. 11.

Then testing data and training data are used to test the model performance. Fig. 12 presents the comparison of real values and corresponding output values proposed by the ANFIS model. FIS outputs are plotted with asterisk ($*$) symbols, and data is plotted as plus (+) symbols. The plot demonstrates a correspondence between the FIS output and the data, indicating that the ANFIS model we have developed is accurate.

In this problem, sales share is taken as the output, and for each purchasing decision, the sum of the share of all suppliers should equal 1. Therefore, training and testing data ANFIS model results are already normalized.

To show efficiency of the model, the Multiple Linear Regression (MLR) method is applied to the problem using Excel. Coefficients obtained from MLR are expressed in Table 2. Table 3 represents the comparison of error values of the two methods.

RMSE and MAPE are the most commonly used measures of accuracy for developed models. The formulae of RMSE and MAPE are:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{6}$$

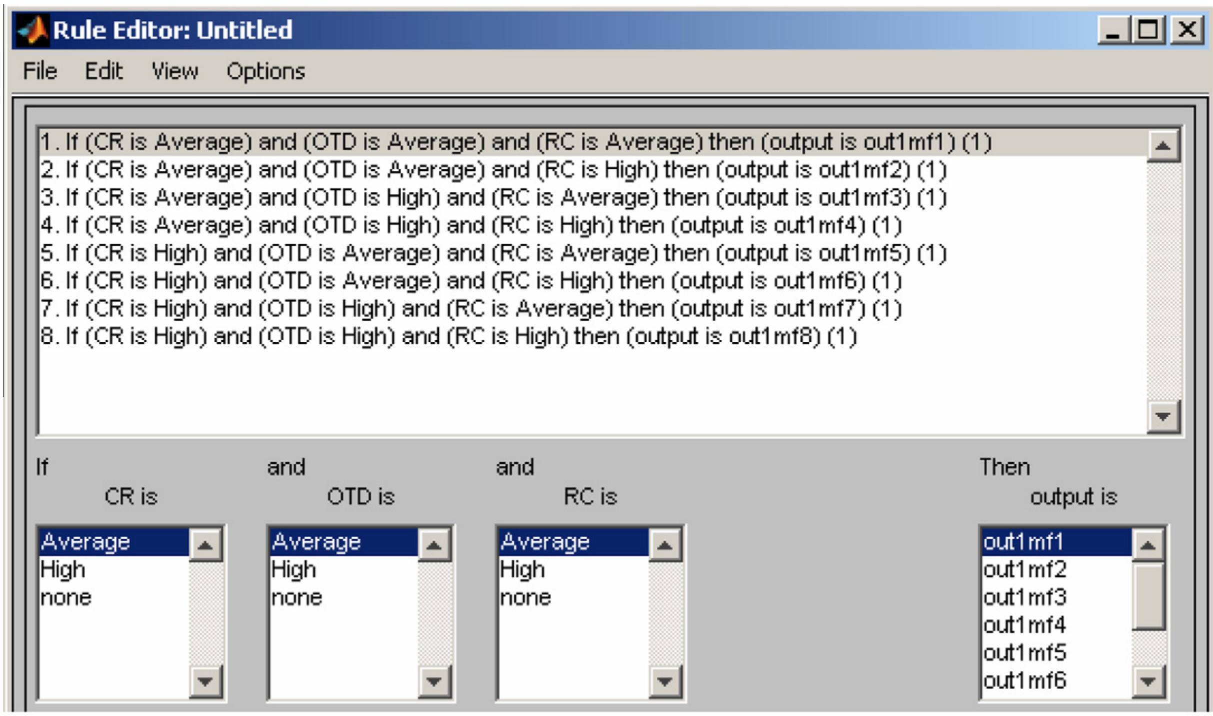
$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{7}$$

where n is total number of observations, A_t is actual value and F_t is forecasted value produced by model.

When the MAPE values are considered, ANFIS has significantly better accuracy rates than MLR (86% vs. 49%) in training data and 74% vs. 44% in testing data. Also, RMSE values of the ANFIS model are lower, indicating better performance than the MLR model. As a result, the ANFIS model we have developed provides decision-makers with an effective structure for analysis of new purchasing decisions.

As mentioned above, the company works with six different suppliers to purchase product. For instance, only 4 of 6 existing suppliers are available to purchase the product in a certain period, and the company decides to work with a new supplier instead of the existing ones. Table 4 includes the normalized criteria values of the existing four suppliers. The last column presents the output values, which are the normalized sales share values of each supplier, calculated from the ANFIS model results.

When a new supplier is integrated into the purchasing decision, sales share values of existing suppliers are decreased drastically as seen in Table 5.



CR: Conflict resolution OTD: On-time delivery RC: Relationship closeness

Fig. 11. Rule structure.

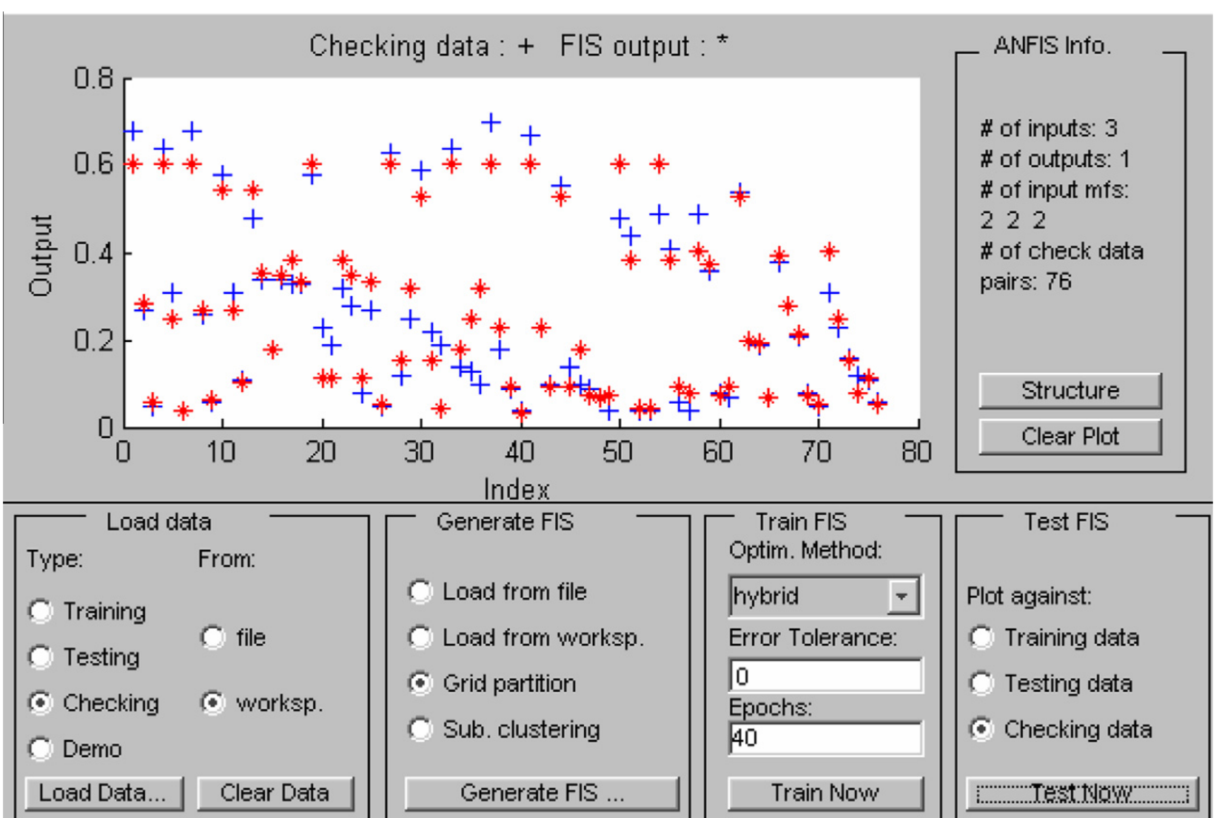


Fig. 12. Developed model and actual output values comparison.

Table 2
Coefficient values for MLR.

	Coefficients
Intercept	−1.47
Conflict resolution	0.69
On-time delivery	0.78
Relationship closeness	0.55

Table 3
Comparison of ANFIS model and multiple linear regression.

Model	Training data		Testing data	
	Root Mean Squared Error (RMSE)	Mean Absolute Percentage Error (MAPE)	Root Mean Squared Error (RMSE)	Mean Absolute Percentage Error (MAPE)
ANFIS	0.037	0.140	0.080	0.262
MLR	0.075	0.510	0.130	0.556

Table 4
Example of a purchasing decision with four suppliers.

Supplier	Conflict resolution	On-time delivery	Relationship closeness	Sales share (%)
Supplier 1	1.00	0.71	1.00	41
Supplier 2	0.86	0.86	1.00	13
Supplier 3	0.57	1.00	1.00	39
Supplier 4	0.57	0.86	0.86	6

Table 5
Contribution of new supplier to the example.

Supplier	Conflict resolution	On-time delivery	Relationship closeness	Sales share (%)
Supplier 1	1.00	0.71	1.00	28
Supplier 2	0.86	0.86	1.00	9
Supplier 3	0.57	1.00	1.00	27
Supplier 4	0.57	0.86	0.86	4
Supplier 5	1.00	0.86	0.86	31

6. Conclusion

In today's global and competitive environment, firms should build an effective supplier base and select adequate partnerships by applying solid analytical techniques. In this paper, we present a new analytical technique, based on the ANFIS model, for supplier selection decision-making. After constructing the database, the model consists of two main stages: input selection with ANFIS, and building the ANFIS model using selected inputs from previous stage. To evaluate the efficiency of the model, MLR is applied to the same data; the ANFIS model we present outperformed the MLR according to the metrics of RMSE and MAPE. The ANFIS model we propose takes advantage of the learning capability of neural networks to build a useful analytic structure for decision-making related to supplier selection.

From the point of view of a company, this structure can be easily applied to future purchasing decisions. To apply this strategy, decision makers from the company assign weightings for each assessment criteria for each alternative supplier. Then, the ANFIS system calculates output values that model the sales share of each supplier. Finally, the company can purchase items based on the obtained results. This decision support system facilitates the purchasing and decision making process of the company. This improved decision-making process provides a competitive advantage for the company, helping it to compete in the textile marketplace.

The ANFIS model we have developed is robust with respect to the probable types of changes in the business. For example, if a new supplier enters consideration, or if the company decides to discontinue its relationship with an existing supplier, the ANFIS model will still work with the same criteria structure. On the other hand, if experts decide to incorporate a new criterion, the model loses efficiency because its method of producing results depends on application of historical data. If the company anticipates that the criteria structure will change in the future, the database structure should be constructed with consideration for these planned changes.

For future work, other criteria reducing methods, such as clustering analysis, principal component analysis, linear discriminant analysis, and independent component analysis, may be applied with ANFIS for the supplier selection problem. However, the input selection phase we presented in this paper is also based on ANFIS. This is preferred because it presents a quick and straightforward method for input selection and a comprehensive solution that contains ANFIS in the implementation stages. If the problem includes multiple outputs, extended versions of ANFIS exist, such as Coactive neuro-fuzzy inference system (CANFIS) and multiple ANFIS (MANFIS). Finally, integration of ANFIS with linear programming may be considered as a topic for future research in problems with various constraints such as capacity and budgeting.

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