Comparison of ANFIS and FAHP-FGP methods for supplier selection

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Abstract

Purpose – In the contemporary global market, supplier selection represents a crucial process for enhancing firms' competitiveness. This is a multi-criteria decision-making problem that involves consideration of multiple criteria. Therefore this requires reliable methods to select the best suppliers. The purpose of this paper is to examine and propose appropriate method for selecting suppliers.

Design/methodology/approach – ANFIS and fuzzy analytic hierarchy process-fuzzy goal programming (FAHP-FGP) are new methods for evaluating and selecting the best suppliers. These methods are used in this study for evaluating suppliers of dairy industries and the results obtained from methods are compared by performance measures such as Mean Squared Error, Root Mean Squared Error, Normalized Root Men Squared Error, Mean Absolute Error, Normalized Root Men Squared Error, Minimum Absolute Error and R^2.

Findings – The results indicate that the ANFIS method provides better performance compared to the FAHP-FGP method in terms of the selected suppliers scoring higher in all the performance measures.

Practical implications – The proposed method could help companies select the best supplier, by avoiding the influence of personal judgment.

Originality/value – This study uses the well-structured method of the fuzzy Delphi in order to determine the supplier evaluation criteria as well as the most recent ANFIS and FAHP-FGP methods for supplier selection. In addition, unlike most other studies, it performs the selection process among all available suppliers.

Keywords Supplier selection, Fuzzy Delphi method, Adaptive Neuro-fuzzy inference system (ANFIS), Fuzzy analytic hierarchy process (FAHP), Fuzzy goal programming (FGP)

Paper type Research paper

1. Introduction

Today companies need to take advantage of any opportunity to increase their ability for competing with their rivals (Jadidi *et al.*, 2015). They strive to achieve excellence in delivering high quality and low cost products and services to their customers by improving the efficiency of their supply chain system to gain competitive advantages (Moghaddam, 2015). The structure of a supply chain generally consists of a combination of potential suppliers, distributors, retailers and customers (Hugos, 2011). In most supply chains the supplier selection is a prominent task for most companies because the purchasing costs account for more than 50 percent of all companies' internal expenses (Aissaoui *et al.*, 2007). Supplier selection is a multi-criteria decision-making problem that involves consideration of several distinct and sometimes conflicting interrelated criteria. Therefore this requires reliable methods to cope with this complexity. There exist in the literature many approaches to the topic of supplier selection, most of them are multi-criteria decision-making methods (Orji and Wei, 2015) with the obvious disadvantage of high volume of calculations needed in order to carry out pair comparisons. In addition to that, they are not usually effective or even applicable in uncertain conditions (Karbasian *et al.*, 2011). In order to overcome the mathematical complexity and the high volume of calculation needed, other methods have been developed in the recent years. Among them

Kybernetes
Vol. 45 No. 3, 2016
pp. 474-489

0368-492X
DOI 10.1108/K-09-2014-0195

are the fuzzy neural network (FNN), which are able to go through the supplier selection process with high accuracy in lesser time. They have got the ability to solve complex problems as well as the uncertain ones saving the experience of the professional individuals (Boer *et al.*, 2001). Fuzzy analytic hierarchy process-fuzzy goal programming (FAHP-FGP) is a new method for supplier selection too. Due to these reasons these methods have been chosen for this study. Prior to that and in order to determine the evaluation criteria, the fuzzy Delphi method (FDM) has been utilized here to provide the input for the supplier selection methods mentioned.

2. Literature review

Earlier studies on supplier selection focussed on identifying the criteria used to select suppliers. Dickson (1966) is one of the first people who worked on supplier selection. He identified 23 important and functional criteria in supplier selection. Weber *et al.* (1991) identified the most common criteria were: quality, delivery time, price, geographical state and the supplier's capabilities.

Many different methods have been used for supplier selection, which can be traced back to 1968. Some of them (Setak *et al.*, 2012) have been presented below:

(1) mathematical programming model: linear programming, goal programming, etc;

(2) multiple attribute decision-making (MADM) methods: analytic hierarchy process, analytic network process, etc;

(3) fuzzy set theory: fuzzy, fuzzy MADM methods and fuzzy mathematical programming;

(4) intelligence approaches: ANN, FNN, etc;

(5) statistical/probabilistic approaches: categorical method, uncertainty analysis, etc; and

(6) hybrid approaches.

Each one of the above-mentioned methods possesses its own pros and cons. For instance, MADM methods are the simple ones, but they are highly dependent upon the personal judgments. Moreover, the majority of its methods do not take into consideration the interrelationships among the criteria. When this kind of internal dependency exists, the validity of these methods would be questionable. Among other disadvantages associated with these methods would be the high volume of calculations needed for performing pair comparisons and their incapability to produce valid results in uncertain conditions (Karbasian *et al.*, 2011; Ozkan and Inal, 2014). Mathematical programming methods also contain disadvantages in regards to dealing with qualitative criteria. As Pal *et al.* (2013) states: "These methods need a certain level of arbitrary ideals and cannot conform to the mental characteristics of the decision makers. Moreover, these methods involve complex and heavy mathematical calculations." Likewise the Fuzzy set theory is also a complex method since understanding the logic of its outputs is very difficult as it allows the simultaneous functioning of precise and obscure variables (Vahdani *et al.*, 2012). Artificial intelligence methods, especially FNN, have a lot of advantages that take away the need for complex formalization of the decision-making process. Since these methods automatically learn from historical data, they do not need to determine the weights of the criteria, therefore they are not dependent upon the individuals' mental judgments, and can easily learn the non-linear relationships among independent and dependent variables. When the number of criteria or options is higher in a complex and uncertain situation, these methods have a better performance in comparison to traditional methods and most importantly, they have the ability to conform to the new knowledge (Boer *et al.*, 2001; Kuo *et al.*, 2010; Saghaei and Didehkhani, 2011). Some studies conducted in the field of supplier selection have made use FGP and FNN methods which will be mentioned.

Kumar *et al.* (2004) have used the FGP method in auto parts industry for selecting best suppliers among the four whom the company had worked with. Lee *et al.* (2009) have used FAHP for selecting suitable criteria then they have used FGP for selecting best suppliers in TFT-LCD industry. Kuo *et al.* (2010) have used PSO based on FNN for qualitative data and a decision integration model for quantitative data, then have used fuzzy knowledge decision to achieve the optimal decision in Laptop Computer Company. Keskin *et al.* (2010) have used the Fuzzy ART method for clustering all the suppliers based on the criteria in automotive manufacturing company. Guneri *et al.* (2011) have used the ANFIS method for supplier selection in a textile firm, select the best suppliers among the six whom the company had worked with. This study has also compared the results obtained using the ANFIS method with ones from multi-variable regression method. Subsequently it has been illustrated that ANFIS provides a better performance. Khalili-Damghani *et al.* (2013) have applied ANFIS in order to select suppliers in a wire harness firm. They evaluated five suppliers with whom the company had worked previously. They have also determined the optimal purchase volume using the FGP method. Ozkan and Inal (2014) used ANFIS for supplier selection. They did not carry out the proposed method in a certain case. They used the NN for the Fuzzy method using the same data and compared the results of both methods. The results indicated the better performance of the ANFIS method. Sivrikaya *et al.* (2015) have applied GP in order to select suppliers in textile industry. They determined evaluation criteria based on the FAHP method and evaluated seven suppliers with whom the company had worked previously. They did not compare this method with other methods.

3. Methodology

The case studied here is a dairy product producer (Zarrin Ghazal Co). For this study, all the suppliers of raw milk in the region, which included 60 industrial cow herders, are considered as the statistical population and the entire population is surveyed. The supplier evaluation criteria are determined using FDM method and supplier selection process is carried out using ANFIS and FAHP-FGP methods. The output of methods is evaluated and critically compared using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Maximum Absolute Error (Ma AE), Minimum Absolute Error (Mi AE), Normalized Root Men Squared Error (NRMSE) and R^2.

4. Case study and analysis

Zarrin Ghazal Co. is the producer of ice cream with the commercial brand of Daity and dairy products with the commercial brand of Apada. This company can be considered a pioneer in the Iranian dairy industry. In the dairy market it offers more than 100 types of products and it needs the supply of 400 tons of raw milk on a daily basis. Due to its competitive position and its market share, the supplier selection and evaluation is of a crucial importance.

4.1 Selecting the important criteria

In the first step, the suppliers' selection criteria will be determined. In order to realize this objective the FDM is used.

4.1.1 FDM. FDM was proposed by Ishikawa *et al.* (1993) to overcome the issue of membership functions in regard to "the (un)attainable period with a high degree" in a fuzzy set. It was derived from the traditional Delphi technique and fuzzy set theory. Noorderhaven (1995) indicated that applying the FDM to the group decision making, can solve the fuzziness of common understanding of expert opinions. This study applied the triangular membership functions and the fuzzy theory in order to do so.

The FDM steps are as follows:

(1) Consider all the possible criteria that may affect the order in which the suppliers would be selected. Ask for experts opinions using a questionnaire to specify the importance of each evaluation criteria. As the human judgment is often vague and cannot be necessarily associated with a numerical order, the analyst must select the appropriate linguistic terms. Its goal would be to integrate the opinions of all the experts consulted, to eliminate the less influential criteria. The most common linguistic terms which can be employed in the questionnaire are: very low, low, medium low, medium, medium high, high, and very high.

(2) Set up triangular fuzzy numbers (Figure 1). Calculate the evaluation value of the triangular fuzzy number of each criteria given by the experts. This study has utilized the geometric mean model of mean general model proposed by Klir and Yuan (1995) for FDM to figure out the common understanding of a group decision. The computing formula is illustrated as follows.

Assuming the evaluation value of the significance of the j element given by the expert i of the total of n experts is $\tilde{w}_{ij} = (a_{ij}, b_{ij}, c_{ij})$; $i = 1, 2, \ldots, n$; $j = 1, 2, \ldots, m$. Then the fuzzy weighting $\tilde{w}_j$ of the j element is $\tilde{w}_j = (a_j, b_j, c_j)$; $j = 1, 2, \ldots, m$. In which:

$$a_j = \mathrm{Min}\{a_{ij}\}, \quad b_j = \frac{1}{n}\sum_{i=1}^{n} b_{ij}, \quad c_j = \mathrm{Max}\{c_{ij}\}$$

(3) Defuzzification: use simple center of gravity method to defuzzify the fuzzy weight $\tilde{w}_j$ of each alternate element to a definite value of S_j as stated below:

$$S_j = \frac{a_j + b_j + c_j}{3}, \quad j = 1, 2, \ \ldots \ , m$$

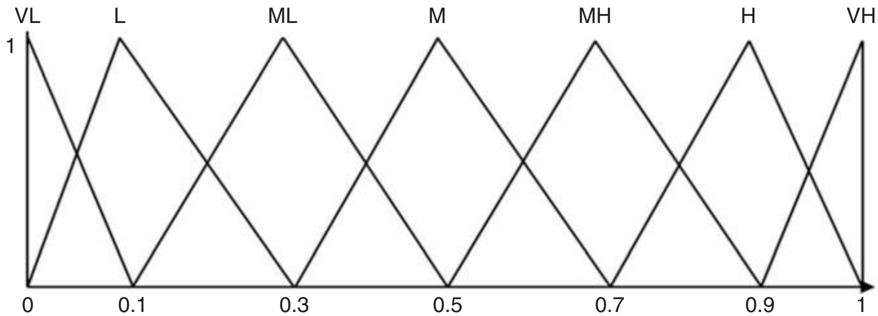

Figure 1.
Linguistic scale for fuzzy Delphi

(4) Screen evaluation indexes: finally, proper criteria can be screened out from numerous criteria by setting the threshold α. The principle of screening is as follows: if $S_j \geqslant \alpha$, then No. j factor is the evaluation index. If $S_j < \alpha$, then delete No. j factor.

For this study a questionnaire has been designed incorporating an extensive number of criteria. Each expert consulted, was asked to prioritize the criteria using the qualitative scale of very low to very high.

After allocating triangular fuzzy numbers, $\tilde{w}_j$, to each one of the important criteria selected by the experts, the S_j of each criteria was calculated and was compared to the threshold level of α. The results are presented in Table I. Based on the expert opinions, the α figure was set at 0.7.

As illustrated in Table I, quality, delivery, production capacity, price, geographical location, commitment, and transportation services have been selected as the most influential in the supplier selection process.

4.2 Suppliers evaluation

To run the suppliers selection process, 60 industrial dairy firms have been considered. These included suppliers whom the company had worked with previously, as well as some new suppliers.

The data used for evaluation was a combination of the experts' opinions and some formal data acquired from related national authorities. The following describes the evaluation method deployed for each criterion.

Quality (C_1): the criterion for evaluating quality is the amount of microbial load in each ml of raw milk. The lower figures show higher quality.

Table I.
Fuzzy Delphi results

	Criterion	(a_j, b_j, c_j)	S_j
1.	Quality (Dickson, 1966)	(0.7, 0.98, 1)	0.89
2.	Delivery (Dickson, 1966)	(0.7, 0.96, 1)	0.88
3.	Performance history (Dickson, 1966)	(0, 0.2, 0.5)	0.23
4.	Production capacity (Dickson, 1966)	(0.5, 0.84, 1)	0.78
5.	Price (Dickson, 1966)	(0.7, 0.92, 1)	0.87
6.	Financial position (Dickson, 1966)	(0, 0.26, 0.7)	0.32
7.	Procedural compliance (Dickson, 1966)	(0.1, 0.42, 0.7)	0.40
8.	Communication system (Dickson, 1966)	(0, 0.34, 0.7)	0.34
9.	Reputation and position in industry (Dickson, 1966)	(0.1, 0.42, 0.9)	0.47
10.	Desire for business (Dickson, 1966)	(0.1, 0.46, 0.9)	0.48
11.	Management and organization (Dickson, 1966)	(0, 0.34, 1)	0.44
12.	Operating controls (Dickson, 1966)	(0.1, 0.58, 1)	0.56
13.	Attitude (Dickson, 1966)	(0.3, 0.66, 1)	0.65
14.	Impression (Dickson, 1966)	(0.1, 0.54, 0.9)	0.51
15.	Labor relations record (Dickson, 1966)	(0.3, 0.68, 1)	0.66
16.	Geographical location (Dickson, 1966)	(0.7, 0.96, 1)	0.88
17.	Amount of past business (Dickson, 1966)	(0, 0.48, 0.9)	0.46
18.	Reliability (Kannan and Tan, 2002)	(0, 0.66, 1)	0.55
19	Process improvement (Kannan and Tan, 2002)	(0.1, 0.6, 1)	0.56
20.	Commitment (Kannan and Tan, 2002)	(0.7, 0.98, 1)	0.89
21.	Transportation services (Rouyendegh and Saputro, 2014)	(0.5, 0.9, 1)	0.80

Delivery (C_2): the performance of the supplier in delivering the milk on time is evaluated by the Likert spectrum.

Production Capacity (C_3): evaluated by the daily production capacity of the supplier in tons per day.

Price (C_4): evaluated by the price of 1 kg of raw milk.

Geographical location (C_5): evaluated by the distance between the suppliers location and the company in km.

Commitment (C_6): how committed the supplier is to the terms of the contract and its responsibilities. This criterion is also evaluated based on Likert spectrum.

Transportation services (C_7): does the supplier own transportation vehicles which deliver the raw milk.

The data gathered then were normalized using the linear method.

4.3 Supplier selection using adaptive-network-based Fuzzy inference system method

ANFIS is a feed-forward neural network with each layer being a part of the Neuro-fuzzy system which has been developed by Jang *et al.* (1997). The main difference between FNNs with ANNs is that the weights of the FNNs are defined based on fuzzy principles and they are not pre-determined. In the FNN, two partitions are used, namely, grid partition and cluster subtraction. In grid partition, the input data are divided into different equal parts and by increasing the number of divisions, the number of factors is increased exponentially which means when the number of inputs are high, the network training process can last up to several hours or even days. In cluster subtracting, the input data are divided based on their influence radius. In this case, the number of linear and non-linear factors is significantly reduced, which speeds up the network training process. Since there are seven inputs in this study, if the grid method is used for optimizing the parameters, the number of rules will be enormous and the grid would not be able to respond accordingly. The cluster subtracting method is utilized in order to select suppliers using FNN. The hybrid optimization method is used here and the training epochs are considered to be 60 ones. The range of influence is varied from 0.1 to 0.7 and the optimal model is determined accordingly. In the ANFIS method, at first the data are divided by the user into three categories of training, test and check. Then, the data are loaded into MATLAB R2014a, and the predictions are carried out:

(1) the total number of data: 66;

(2) training data (70 percent): 46;

(3) test data (15 percent): 10;

(4) checking data (15 percent): 10; and

(5) the information for ANFIS is as follows.

ANFIS info:

- number of nodes: 723;
- number of linear parameters: 357;
- number of non-linear parameters: 612;
- total number of parameters: 969;
- number of training data pairs: 46;

- number of checking data pairs: 10; and
- number of fuzzy rules: 42.

4.4 Supplier selection using FAHP and FGP model

4.4.1 FAHP. The aim of any FAHP method is to priories ranking of alternatives. FAHP method as the decision support system to help decision makers making better choices both in relation to tangible criteria and intangible criteria (Tang and Lin, 2011).

The process of applied FAHP is listed as follows.

Step 1: building the hierarchical structure.

First was to build the hierarchical structure. The hierarchical structure was described as follows. The goal was placed at the top of hierarchy, and the general criteria were placed at second level. The secondary sub-criteria with respect to each dimension were placed at third level.

Step 2: building the pair-wise comparison matrix.

By the second questionnaires gathered from selected experts, we obtained the relative importance of paired criteria factors at level n + 1 under the evaluation of criteria at level n by individual experts' opinions, and the pair-wise comparison matrix was accordingly conducted.

Step 3: calculating triangular fuzzy numbers.

Concerning the relative importance of each individual evaluation construct in pair-wise comparison matrix, triangular fuzzy number was calculated to integrate all experts' opinions. It can be used to present the fuzziness of all experts' opinions with respect to the relative importance of paired factors:

$$\tilde{a}_{ij} = \left(\alpha_{ij}, \beta_{ij}, \delta_{ij}\right)$$

where $\tilde{a}_{ij}$ is the triangular fuzzy number; α_{ij} the minimum of the jth subcriterion subordinated to the ith general criterion; β_{ij} the geometric mean of the jth subcriterion; and δ_{ij} the maximum of the jth subcriterion subordinated to the ith general criterion.

Step 4: building the fuzzy positive reciprocal matrix.

After triangular fuzzy numbers were solved to represent the fuzziness of experts' opinions, the fuzzy positive reciprocal matrix A can be further built:

$$A = \left[\tilde{a}_{ij}\right] \quad \tilde{a}_{ij} = \left[\alpha_{ij}, \beta_{ij}, \delta_{ij}\right]$$

Step 5: calculating the fuzzy weights of fuzzy positive reciprocal matrix.

Through the following formulas, the positive reciprocal geometric mean Z_i of triangular fuzzy numbers and the fuzzy weight $\overline{W}_i$ can be obtained:

$$Z_i = [\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \ldots \times \tilde{a}_{in}]^{1/n}, \quad \forall_i$$

$$\overline{W}_i = Z_i \otimes (Z_1 \oplus Z_2 \oplus \ldots + Z_n)^{-1}$$

$$\tilde{a}_1 \otimes \tilde{a}_2 \cong \left(\alpha_1 \times \alpha_2, \beta_1 \times \beta_2, \delta_1 \times \delta_2\right)$$

$$\tilde{a}_1 \oplus \tilde{a}_2 \cong (\alpha_1+\alpha_2, \beta_1+\beta_2, \delta_1+\delta_2)$$

$$Z_1^{-1} = (\delta_1^{-1}, \beta_1^{-1}, \alpha_1^{-1})\ldots$$

$$\tilde{a}_1{}^{1/n} = \left\{\alpha_1^{1/n}, \beta_1^{1/n}, \delta_1^{1/n}\right\}\ldots$$

Step 6: defuzzification.

Since the weights of all evaluation criteria were fuzzy values, it was necessary to compute a non-fuzzy value by the process of defuzzification. The defuzzified weight W_i can be obtained:

$$W_i = \frac{W_{\alpha i} + W_{\beta i} + W_{\delta i}}{3}$$

where $W_{\alpha i}$ the right-end value of the fuzzy weight; $W_{\beta i}$ the value of the fuzzy weight with the degree of membership as 1; and $W_{\delta i}$ the left-end value of the fuzzy weight.

Step 7: normalization.

In order to effectively compare the relative importance among evaluation criteria, we normalized the obtained weights using the following formula:

$$NW_i = \frac{W_i}{\sum_{i=1}^{n} W_i}$$

4.4.2 FGP. Zimmermann (1978) adopted fuzzy version of the linear programming model as:

$$cx \tilde{\leqslant} z_0, Ax \tilde{\leqslant} b, x \tilde{\geqslant} 0$$

where Z_0 expresses aspiration level of the decision maker. Zimmermann (1978) defined membership function of minimization objective as demonstrated below, where z_l^+ and z_l^- represents maximum and minimum values of related objective, respectively:

$$\mu_{zl}(x) = \begin{cases} 1 & for\ z_l \geqslant z_l^+ \\ (z_l(x) - z_l^- / (z_l^+ - z_l^-) & for\ z_l^- \leqslant z_l(x) \leqslant z_l^+ \\ 0 & for\ z_l \leqslant z_l^- \end{cases}$$

The linear membership function for the fuzzy constraint is defined as:

$$\mu_{gr}(x) = \begin{cases} 1 & for\ g_r(x) \leqslant b_r \\ (1 - (g_r(x) - b_r)/d_r & for\ b_r \leqslant g_r(x) \leqslant b_r + d_r \\ 0 & for\ g_r(x) \geqslant b_r + d_r \end{cases}$$

where d_r is the subjectively chosen constant of admissible violation of the rth inequalities constraints. Subsequently, the weighted additive model for supplier selection problem is expressed as follows (Yucel and Fuat, 2011):

$$\max \sum_{j=1}^{q} w_j \lambda_j + \sum_{r=1}^{h} \beta_r \gamma_r$$

s.t.:

$$\lambda_j \leqslant \mu_{zj}(x) \quad j = 1, 2, \ldots, q, \quad (for\ all\ objective\ functions)$$

$$\gamma_r \leqslant \mu_{gr}(x) \quad r = 1, 2, \ldots, h, \quad (for\ fuzzy\ constrints)$$

$$g_p(x) \leqslant b_p \quad p = h+1, \ldots, m, \quad (for\ deterministic\ constrints)$$

$$\lambda_j, \gamma_r \in [0.1].$$

$$\sum_{j=1}^{q} w_j + \sum_{r=1}^{h} \beta_r = 1, \quad w_j, \quad \beta_r \geqslant 0.$$

$$x_i \geqslant 0, \quad i = 1, 2, \ldots, n.$$

where $\mu_{zj}(x)$ and $\mu_{gr}(x)$ are membership functions of each objective and fuzzy constraint. The w_j and b_j are the relative importance of fuzzy goals and constraints. In this research adopted from FAHP in summation, computational procedure and algorithm of the presented model is as follows:

The multi-objective linear formulation of this case is presented as min Z_1, Z_3, Z_4 and max Z_2, Z_5, Z_6:

$$Z_1 = 0.111X_1 + 0.143X_2 + 1X_3 + \cdots + 0.5X_{10}$$

$$Z_2 = 0.921X_1 + 0.961X_2 + 0.934X_3 + \cdots + 0.956X_{10}$$

$$Z_3 = 1X_1 + 0.5X_2 + 1X_3 + \cdots + 0.5X_{10}$$

$$Z_4 = 0.1X_1 + 0.1X_2 + 1X_3 + \cdots + 0.85X_{10}$$

$$Z_5 = 0.4X_1 + 0.8X_2 + 0.3X_3 + \cdots + 0.75X_{10}$$

$$Z_6 = 0.75X_1 + 1X_2 + 1X_3 + \cdots + 1X_{60}$$

s.t.:

$$X_1 + X_2 + X_3 + \ldots + X_{60} = 100$$

$$X_i \leqslant 1$$

$$X_i \geqslant 0, \quad 1, 2, \ \ldots \ , 10.$$

Three objective functions $Z_1, Z_2, \ldots, Z_6$ are respectively net quality, delivery, price, geographical location, commitment and transportation services goals. X_i is the number of units purchased from ith supplier and g_i is production capacity. Upper and lower bounds demonstrated in Table II, are used to construct membership functions as below:

$$(a)\ \mu_{z1}(x) = \begin{cases} 1 & z_1 \leqslant 50 \\ \frac{150 - z_1}{50} & 100 \leqslant z_1 \leqslant 150 \\ 0 & z_1 \geqslant 100 \end{cases}$$

$$(b)\ \mu_{z2}(x) = \begin{cases} 1 & z_2 \geqslant 100 \\ \frac{z_2 - 10}{90} & 10 \leqslant z_2 \leqslant 100 \\ 0 & z_2 \leqslant 10 \end{cases}$$

$$(c)\ \mu_{z3}(x) = \begin{cases} 1 & z_3 \leqslant 50 \\ \frac{150 - z_3}{50} & 100 \leqslant z_3 \leqslant 150 \\ 0 & z_3 \geqslant 100 \end{cases}$$

$$(d)\ \mu_{z_4}(x) = \begin{cases} 1 & z_4 \leqslant 50 \\ \frac{150 - z_4}{50} & 100 \leqslant z_4 \leqslant 150 \\ 0 & z_4 \geqslant 100 \end{cases}$$

$$(e)\ \mu_{z5}(x) = \begin{cases} 1 & z_5 \geqslant 100 \\ \frac{z_5 - 10}{90} & 10 \leqslant z_5 \leqslant 100 \\ 0 & z_5 \leqslant 10 \end{cases}$$

Criteria and constraint	Weights	$\mu = 0$	$\mu = 1$	$\mu = 0$
Quality	0.259	–	100	150
Delivery	0.291	10	100	–
Geographical location	0.012	–	100	150
Price	0.015	–	100	150
Commitment	0.205	10	100	–
Transportation services	0.095	10	100	–
Demand	0.123	10	100	150

Table II. The data set for membership functions

$$(f)\,\mu_{z6}(x) = \begin{cases} 1 & z_6 \geqslant 100 \\ \frac{z_6 - 10}{90} & 10 \leqslant z_6 \leqslant 100 \\ 0 & z_6 \leqslant 10 \end{cases}$$

$$(g)\ \mu_{gd}(x) = \begin{cases} \frac{d(x) - 10}{90} & 10 < d(x) < 100 \\ \frac{150 - d(x)}{50} & 100 \leqslant d(x) < 150 \\ 0 & d(x) \leqslant 10, \quad d(x) \geqslant 100 \end{cases}$$

Applying membership functions and the final weights obtained from Table II, fuzzy multi-objective linear structure of the numerical example is expressed as follows:

$$\max 0.259\lambda_1 + 0.291\lambda_2 + 0.012\lambda_3 + 0.015\lambda_4 + 0.205\lambda_5 + 0.095\lambda_6 + 0.123\gamma_1$$

s.t.:

$$\lambda_1 \leqslant \frac{150 - 0.111X_1 + 0.143X_2 + 1X_3 + \cdots + 0.5X_{10}}{50}$$

$$\lambda_2 \leqslant \frac{0.921X_1 + 0.961X_2 + 0.934X_3 + \cdots + 0.956X_{10} - 10}{90}$$

$$\lambda_3 \leqslant \frac{150 - (1X_1 + 0.5X_2 + 1X_3 + \cdots + 0.5X_{10})}{50}$$

$$\lambda_4 \leqslant \frac{150 - (0.1X_1 + 0.1X_2 + 1X_3 + \cdots + 0.85X_{10})}{50}$$

$$\lambda_5 \leqslant \frac{0.4X_1 + 0.8X_2 + 0.3X_3 + \cdots + 0.75X_{10} - 10}{90}$$

$$\lambda_6 \leqslant \frac{0.75X_1 + 1X_2 + 1X_3 + \cdots + 1X_{60} - 10}{90}$$

$$\gamma_1 \leqslant \frac{150 - (X_1 + X_2 + X_3 + \ldots + X_{10})}{50}$$

$$\gamma_1 \leqslant \frac{(X_1 + X_2 + X_3 + \ldots + X_{10}) - 10}{90}$$

$$X_i \leqslant 1$$

$$x_i \geqslant 0, \quad i = 1, 2, \ldots, 10$$

$$\lambda_j, \gamma_r \in [0.1]$$

In this method the data have been normalized. Microsoft Excel Solver is used to solve the problem.

4.5 Comparative results

In order to carry out a more reliable comparison, the real data of the ten suppliers recently working with the company are used as the test data (Table III) and their outputs are compared based on the performance measures, presented in below in accordance to Vahdani *et al.* (2012) and Ozkan and Inal (2014) findings. As the data have been normalized, the values presented in Table IV almost are figures between 0 and 1. Logically the best network would be the one generating results with minimum MSE, RMSE, NRMSE, Ma AE, Mi AE and MAE, having at the same time, the highest R^2 value:

$$MSE = \frac{\sum_{i=1}^{n} \left(p_i - \hat{p}_i\right)^2}{N}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(p_i - \hat{p}_i\right)^2}{N}}$$

$$NRMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(p_i - \hat{p}_i\right)^2}{\sum_{i=1}^{n} p_i^2}}$$

$$Ma\,AE = \max\left|p_i - \hat{p}_i\right|$$

C_1	C_2	C_3	C_4	C_5	C_6	C_7	Actual	ANFIS	FAHP-FGP
0.111	1	0.1	0.921	0.4	0.75	1	0.300	0.230	0.1777
0.143	0.5	0.1	0.961	0.8	1	1	0.580	0.650	0.0003
1	1	1	0.934	0.3	1	1	0.994	0.985	0.7354
0.077	1	1	0.985	0.9	0.75	1	0.350	0.400	0.0003
0.067	0.75	0.2	0.975	1	0.75	1	0.180	0.200	0.0000
0.059	0.5	1	0.917	1	0.75	1	0.199	0.150	0.0000
0.053	0.5	0.8	0.97	0.8	0.5	0	0.014	0.089	0.0000
0.059	1	0.2	0.943	0.2	0.75	1	0.222	0.240	0.1445
0.053	0.75	0.75	1	0.3	0.75	0	0.060	0.074	0.0000
0.5	0.5	0.85	0.956	0.2	1	1	0.550	0.478	0.6354

Table III. Test data and their outputs in methods and actual

	MSE	RMSE	NRMSE	Ma AE	Mi AE	MAE	R^2
ANFIS	0.0026	0.0515	0.1159	0.0750	0.009	0.0446	0.9662
FAHP-FGP	0.0629	0.2508	0.7943	0.5796	0.014	0.1926	0.6155

Note: Comparing the outputs of the methods using performance measures

Table IV. Comparing results of two methods

$$Mi\,AE = \min\left|p_i - \hat{p}_i\right|$$

$$MAE = \frac{\sum_{i=1}^{n}\left|p_i - \hat{p}_i\right|}{N}$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(p_i - \bar{p}_i\right)\left(\hat{p}_i - \bar{\hat{p}}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(p_i - \bar{p}_i\right)^2 \sum_{i=1}^{n}\left(\hat{p}_i - \bar{\hat{p}}_i\right)^2}}$$

In which p_i is the real output; $\hat{p}_i$ is the output predicted by the network; n is the number of the data; $\bar{p}_i$ is the mean of real outputs and $\bar{\hat{p}}_i$ is the mean for the predicted outputs.

In Figure 2, the R^2 curves and the network solutions are compared against the real test data.

Based on the value of performance measures and comparison of the solutions generated by the networks against the real solutions from the test data, it has been concluded that the ANFIS method seems to have a better performance compared to the

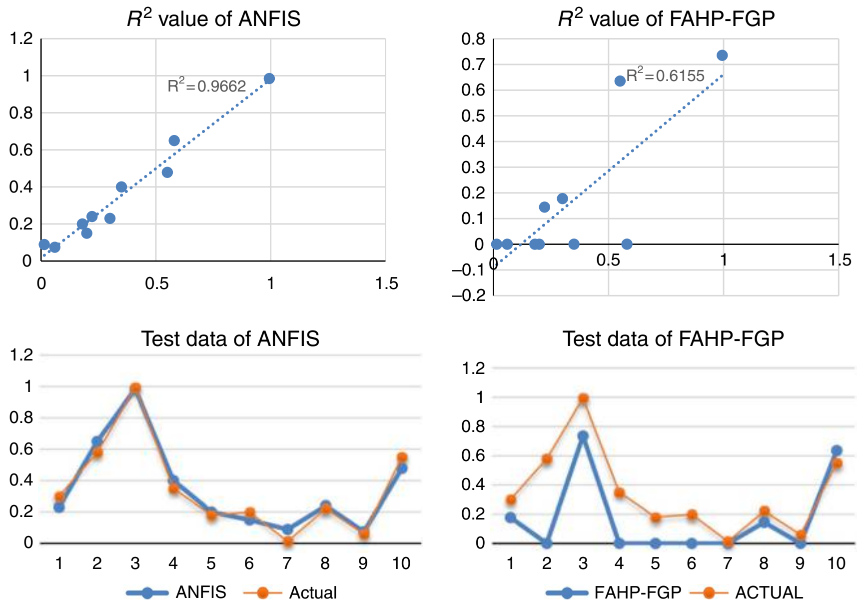

Figure 2. Comparative results of test data and R^2 value

Table V. The information of selected supplier

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	ANFIS	FAHP-FGP
A_{19}	0.077	1	0.05	0.909	0.018	1	1	0.230	0.850
A_{29}	0.143	1	0.75	0.943	0.011	1	1	0.985	0.802
A_{48}	0.053	0.75	0.04	0.917	0.038	0.75	1	0.172	0.685
A_{60}	1	1	0.3	0.934	0.167	1	1	0.800	0.685
A_{26}	0.111	1	0.095	0.921	0.029	1	1	0.800	0.219
A_{30}	0.143	1	0.8	0.947	0.01	1	1	0.985	0.000

FAHP-FGP method for all the performance measures. Moreover, as illustrated in Figure 2, its solutions were closer to the real solutions.

Finally the data for potential suppliers were entered in both networks. Table V presents the suppliers with the highest output score as the selected best suppliers in a way that their combined production capacity reaches 400 tons per day which is the daily raw milk needed by the company. As it can be seen, FAHP-FGP's results are almost similar to the results of ANFIS, with the two suppliers out of four being the same. This method has selected the suppliers A_{19} and A_{48} instead of A_{26} and A_{30} chosen by other method. This simply means these inputs have scored higher in the most criteria, using FAHP-FGP, compared with the supplier A_{19} and A_{48}.

5. Conclusion

The cost and quality of acquiring the raw material have significant effect on the quality and the price of the products, and subsequently on the overall success of the business (Lin *et al.*, 2009). Therefore suppliers are the vital sources of organization, and better supplier selection helps improving the products (Rajesh and Ravi, 2015). Supplier selection is a decision-making process based on multiple criteria. The decision maker should determine a solution based on different and conflicting criteria (Golmohammadi and Mellat-Parast, 2012). In this study the ANFIS and FAHP-FGP methods, which are recently applied to the supplier selection process have been utilized to select the best suppliers and FDM method has been used to determine the criteria. The seven criteria chosen, using this method, are quality, price, production capacity, geographical location, delivery time, commitment and transportation service. This study has been carried out in Zarrin Ghazal Co., which is the producer of dairy products. Due to the nature of the raw material, this company uses (raw milk) which is highly sensitive to conditions under which it is stored and transported, therefore selecting the right supplier is of outmost importance. As illustrated in literature review none of the previous studies mentioned, has had a case study in the food industry. Moreover, contrary to some the other studies, all the potential suppliers have been considered here, not only the ones with whom the company had previously worked with. Studies have shown that in 50 percent of the cases, organizations that only consider their current suppliers in the process of evaluation and selection, can lose their chances of selecting the best suppliers (Dyer and Chu, 2000). The ANFIS network which have been deployed here was trained by historical data. The information regarding the last ten suppliers which worked with the company were used as the test data in order to enhance the evaluation of the networks' predictions. Then, the values for performance measures were calculated for the test data using all two methods and the results were compared. The findings indicate ANFIS generates better results compared to the FAHP-FGP, ANFIS achieving better scores in the all of the performance measures. The results are in conformity with the results of the study carried out by Guneri *et al.* (2011), Khalili-Damghani *et al.* (2013) and Ozkan and Inal (2014). They have also concluded that ANFIS achieves better performance in the supplier selection process.

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