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ORIGINAL ARTICLE

A hybrid model for supplier selection: integration of AHP and multi expression programming (MEP)

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Abstract Supplier evaluation and selection is a complicated process which deals with conflicting attributes such as quality, cost. To mitigate the computational complexity, intelligent-based techniques have gained much popularity. But the main shortcoming of the existing models in this regard is to be a black box system. In this paper, we aim to combine analytical hierarchy process with multi-expression programming to both introduce a new evolutionary approach in the field of supplier evaluation and selection and cope with the earlier problem. To show the validity of the model, statistical test was carried out. The finding showed that the proposed model is accurate and acceptable for using in the evaluation process.

Keywords Supplier selection · Black box · Multi-expression programming · AHP · Supply chain management

1 Introduction

Supplier evaluation and selection is a critical issue for achieving success in any manufacturing industry. Multi-criteria decision making (MCDM) as the main approach of decision-making theory has been successfully used to solve this problem [1, 2]. Due to the presence of conflicting factors such as quality, cost, assessing and selecting the proper suppliers is a very complex problem. Therefore, numerous solo and integrated models have been presented in this area.

One of the most attractive techniques for suppliers' performance evaluation is artificial intelligence (AI)-based techniques [3, 4]. Increasingly, academics are exploring neural-based techniques such as artificial neural network (ANN) [5] and adaptive neuro fuzzy inference system (ANFIS) [6] as the reliable approaches for supplier evaluation and selection. AI models as computer-aided techniques can predict suppliers' performance based on the historical data set.

One of the integrated neural-based methods which recently received much attention is combination of analytical hierarchy process (AHP) and ANN for assessing suppliers' performance [5, 7]. Although this model is robust and accurate in performance evaluation, it has some limitations. Although AHP is useful in decision making, it cannot handle vagueness. In addition, ANN is a powerful tool in pattern recognition, but it is unable to propose an explicit mathematical model. In order to overcome the aforementioned problems, this paper is aimed at integrating fuzzy AHP and fuzzy preference programming (FPP) with multi-expression programming (MEP).

The main contributions of this model are:

- A new genetic-based model is introduced in the field of supplier selection.
- A genetic decision model on the basis of the relationship of a set of input and output is developed in a unique manner to forecast the performance.
- A new pairwise comparison model for weight calculations and performance values is performed for a MEP model.
- Historical data set is used in assessment and modeling.

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The rest of the model is presented as follows: Sect. 2 provides literature review related to supplier selection. Section 3 provides information about the techniques and the proposed model. Case study is presented in Sect. 4. Model performance evaluation is given in Sect. 5. Finally, conclusion is presented in Sect. 6.

2 Literature

Since a proper supplier has crucial influence on the performance of SCM, various models have been proposed in this area. The literature reports that it can be categorized into seven main parts such as multi-attribute decision making (MADM) like TOPSIS, AHP, ANP, ; mathematical modeling including linear programing, integer programing, nonlinear modeling; data envelopment analysis (DEA); fuzzy set theory (FST); artificial intelligence (AI) such as ANFIS, ANN, SVM; statistical/probabilistic approaches; hybrid techniques.

Each category possesses its own advantages and disadvantages. MADM is easy to use, but the results are almost based on decision makers' opinion. For example, different weights could be given to the different criteria by the experts. Mathematical programming technique is an accurate model, but it is unable to take into account qualitative criteria. In the mathematical models, finding the accurate model for decision makers is so difficult. DEA method does not use any assumption in efficiency evaluation, but it is very sensitive to homogeneity. Most of the other categories do not consider the interactions among the various factors and also cannot effectively consider risk and uncertainty in estimating the supplier's performance [3].

Among the aforementioned techniques, predictive AI models have been received much attention from the academics and practitioners. One of the benefits of AI methods in contrast with other approaches is that they do not need assumption in the decision-making process. Moreover, AI methods provide predictive models based on the historical data set. This feature is very useful for decision making [5]. Generally, the literature reports that AI techniques can handle better with complexity and imprecision than previous approaches [8].

With respect to the literature, there are three main predictive AI-based models for supplier evaluation and selection including: pure AI-based model (such as ANN-based models, ANFIS-based model, SVM-based models, and FIS-based models); DEA–AI models (such as DEA–SVM, DEA–ANN) and AHP–AI (AHP–ANN, AHP–ANFIS) models.

Kuo et al. [9] proposed an intelligent supplier decision support system which is able to consider both the quantitative and qualitative criteria. The model enables decision makers to deal with quantitative data such as profit and productivity. Guneri et al. [6] proposed a predictive ANFIS-based model in supplier selection in a textile industry. A 1–10 numeric scale was applied to rate the criteria. After collecting the data set, three most effective criteria on the performance were selected and a predictive ANFIS-based model was proposed to estimate the suppliers' performance. Golmohammadi [7] proposed a neural-based structure for decision making and selecting the best suppliers. After defining the evaluative criteria, using AHP pairwise comparison the data set was collected. Then, the collected AHP-based data set was divided into two parts for training the ANN model and testing its prediction ability. In order to improve the model, mathematical models were defined for measuring each criterion. Afterwards, the same operation was done with the new collected data set. Ozkan and Inal [10] improved the model proposed by Golmohammadi [5] and presented an ANFIS-based model for supplier selection. They highlighted that their model is more accurate than the proposed neural network model. Fallahpour et al. [11] combined DEA with ANFIS to evaluate suppliers' performance. They concluded that the proposed integrated model is more accurate model compared to other models. This paper is aimed at extending Golmohammadi's model by combining AHP with MEP.

3 Methodology

In this part, an overview about AHP and MEP is given. Then, the proposed model is explained.

3.1 Analytical hierarchy process (AHP)

Saati proposed AHP as a useful and flexible decision-making model which can be used for both qualitative and quantitative attributes. As the attributes are determined and the weights are computed by pairwise comparison matrix, similar procedure can be applied to calculate the weight of the alternatives. The pairwise comparison matrix of alternatives is structured based on attribute. The result is a new reciprocal square matrix for each criterion, with its corresponding eigenvector. The procedure is repeated for all attributes, and the number of each alternative and criterion is obtained. Afterwards, the score of each alternative is multiplied by the weight of the corresponding attribute. At the end, all the numbers for an alternative are summed up to find the overall score, and the final calculation results show the importance of each alternative [12, 13]. The alternatives are then ranked according to their calculated values. Generally, problems associated with AHP are split into three parts [14]:

Table 1 Range for attributes measuring

Very poor (VP)	$1 \leq W \leq 2$
Poor (P)	$2 \leq W \leq 3$
Poor medium (PM)	$3 \leq W \leq 4$
Medium (M)	$4 \leq W \leq 6$
Medium good (MG)	$6 \leq W \leq 7$
Good (G)	$7 \leq W \leq 8$
Very good (VG)	$8 \leq W \leq 9$

1. Structuring the problem; evaluation of local priorities; determination of global priorities. The main feature of AHP is pairwise comparisons which enable decision makers to obtain the best decision. Practically, AHP includes the following steps:
2. Forming the defined attributes hierarchically.
3. Generating judgment matrix using pairwise comparison.
4. Computing a priority vector to weight the components of the matrix.
5. Determining global priorities by gathering all local priorities with the application of a simple weighted sum.
6. At the end, the eigenvalue is performed to evaluate the strength of the consistency ratio of the comparative matrix and identify whether to accept the information.

In order to measure the rate of the criteria and suppliers' performance, 1–9 scale (Saaty scale) is used (see Table 1). The mathematical process starts by normalizing and obtaining the relative weights for each matrix. The relative weights are given by the right eigenvector (W) corresponding to the largest eigenvalue ($\lambda_{\max}$), as:

$$A_W = \lambda_{\max} W \tag{1}$$

3.2 Multi-expression programming (MEP)

Oltean and Dumitrescu [15] presented MEP as an extension of genetic programming (GP). MEP performs linear chromosomes for solution encoding [16]. MEP is able to encode multiple computer programs of a problem in a single chromosome [16]. After checking the fitness of the programs, the best one is selected to propose the chromosome. MEP is not as complex as other GP such as gene expression programming (GEP). MEP begins by generating a random population of individuals. MEP applies the following stages to create the best solution:

1. Choosing two parents using a binary tournament procedure and recombining them with a fixed crossover probability;
2. Gaining two offspring by the recombination of two parents;
3. Mutating the offspring and replacing the worst individual in the current population with the best of them.

Number of the MEP genes per chromosome is constant and determines the length of the chromosome. A terminal (an element in the terminal set T) or a function symbol (an element in the function set F) is encoded by each gene. A gene that encodes a formulation consists of pointers toward the function arguments. Function parameters always have indices of lower values than the position of that function itself in the chromosome. The first symbol in a chromosome must be a terminal symbol as stated by the proposed representation scheme [17].

3.3 Methodology

This paper is aimed at proposing hybrid AHP–MEP model to cope with the earlier-mentioned problems associated with the previous intelligent-based model. To this end, the following steps should be carried out (see Fig. 1):

Step 1 Collecting the importance of each criterion for suppliers (alternatives) by pairwise comparison (using AHP),

Step 2 Collecting the suppliers' performance (scores) by pairwise comparison (using AHP),

Step 3 Dividing the gathered data set into twofold for training (pattern recognition) and testing (prediction evaluation),

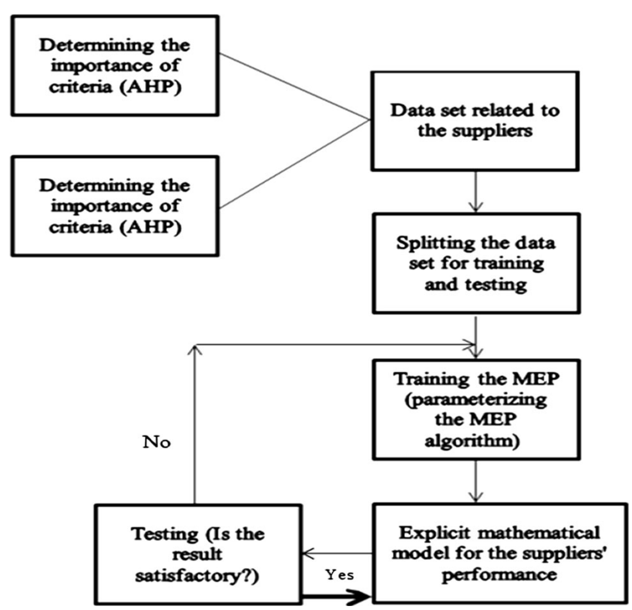

Fig. 1 Methodology of the model

Step 4 Assessing the model using statistical test and other AI-based models.

In order to evaluate the accuracy of the model, mean square error (MSE) and mean absolute error (MAE) are used in training and testing stages.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(h_i - O_i)^2}{n} \tag{2}$$

$$\mathrm{MAE} = \frac{1}{n}\left|\sum_{1}^{n}(h_i - o_i)\right| \tag{3}$$

where h_i and O_i are, respectively, the real and predicted performance scores for the *ith* performance, $\overline{h_i}$ and $\overline{o_i}$ are, respectively, the average of the real and predicted performance scores, and n is the number of suppliers.

4 Case study

To show the feasibility and application of the proposed model, a real-life supplier selection problem from a textile company of Iran is considered (the company name is not disclosed for privacy reasons) which produces open-end (OE) yarn. Its staff strength is 500. It works with 33 suppliers to fill its daily order. Therefore, there is a great need to evaluate the suppliers' performance.

4.1 Determining the supplier selection criteria

The first echelon in evaluating the suppliers' performance includes determining and defining the evaluation attributes. In this study, based on the literature and experts' opinion, five criteria were selected and applied to the textile factory. The five criteria are quality, delivery, technology, cost, and flexibility. Table 2 shows the definition of each criterion.

4.2 Rating each attribute and suppliers' performance score

As said earlier, AHP-based pairwise comparison is used to gather the data set. Three experts have been selected to rate the determined criteria and the suppliers' performance. The experts have PhD degree in long-fiber spinning, weft knitting, and non-woven knitting. Each of them has more than 10 years of experience in the textile industry. For this research, they were asked to rate the selected criteria and the suppliers' performance based on the 1–9 Saaty scale (Table 1). Next, pairwise comparison is performed for obtaining suppliers' performance scores. Table 3 illustrates the collected data set.

4.3 Training MEP (mathematical model) and testing

The gathered data set was divided into twofolds for training and testing (50 % for training and 50 % for testing). In the training, MEP was run to find a computer program that connects the criteria to the performance. The best model was chosen considering the lowest statistical errors (shown in Sect. 5).

4.3.1 Parameters of the predictive MEP-based algorithm, the mathematical equation of the suppliers' performance evaluation and statistical measures in both the training and testing process

Since there is no exact rule to find the optimum parameters in MEP (AI-based) techniques [21], for finding the best structure of MEP several runs were conducted. Table 4 provides the best parameters of MEP predictive algorithm. To find the optimized MEP-based model, there are some important parameters which should be structured very well.

Table 2 Selection criteria for evaluating the suppliers' performance

Criteria	Definition
Quality	The excellence ability of supplied materials to meet or exceed purchasers' expectations. In order to evaluate this criterion, quality certification and standards are very important [18]. This attribute has positive impact on the suppliers' efficiency, and with increasing QM, the suppliers' efficiency increases
Delivery (D)	This looks at the on-time delivery. As this criterion increases, supplier's performance is better
Technology	This mainly focuses on the range of material supplied and modernity of the machinery. This factor has a direct relationship with efficiency
Cost (C)	This covers the final cost of the goods and transportation [19]. A supplier is termed as "the more efficient supplier" whose total cost is lower than other competing suppliers
Flexibility (F)	Rate of response to change [20]. With increasing this attribute, the supplier's performance increases

Table 3 First data set

Inputs					Output
Q	D	T	P	F	Performance
3	6	3.5	4	1.5	0.05
3.5	3.5	6	6	1.5	0.05*
3	4	5	4	7	0.07
7	6	4.5	6	3	0.10*
6.5	6.5	6.5	6.5	5.5	0.11
5	4	5.5	4	5	0.11*
5	6	6	5.5	2.5	0.12
3.5	5	6	6.5	3.5	0.13*
5.5	4.5	6	4.5	7	0.15
5	6.5	3.5	3.5	8	0.16*
5.5	6.5	5.5	7	5.5	0.19
5	7	5.5	7	5.5	0.19*
4	6	7	5	9	0.19
2	6.5	2	8	4	0.22*
5.5	7.5	5.5	3.5	7.5	0.23
5	7	9	4.5	5	0.23*
4	4	7	6.5	6	0.25
6	6.5	8	4.5	5	0.27*
4	5.5	7	8	4	0.28
5	6.5	8	5	6	0.30*
7	8	7	4.5	2.5	0.34
6.5	7.5	6.0	6.5	3	0.36*
6	7	9	7	8	0.42
7	8	7	6	3	0.44*
8.5	8	7.5	2.5	7.5	0.46
7	6.5	7	5	8	0.47*
6	7	6	5	6	0.48
7.5	6	7	5.5	8	0.49*
7.5	7.5	9	3	4.5	0.59
8	9	8	4	5	0.59*
8.5	7	6.5	4	7	0.61
8	9	8	5	4	0.61*
8	8	8.5	6	4	0.64

* These are the testing data set

Table 4 Optimal parameters of MEP

Parameters	Setting
Population size	500–2000
Chromosome length	90 genes
Number of generations	500
Number of tournament	4
Crossover probability	0.5, 0.9
Crossover type	Uniform
Mutation probability	0.01
Terminal set	Problem input

$$P = \sin(x_T + x_Q - 18.5) + \left[\cos\left(\cos\left(\mathrm{Ln}\left(x_P - \frac{x_Q}{x_T} + 1.26\right)\right)\right)\right]^3 + \left[\sin\left(\sin\left(\cos\left(e^{\frac{x_F}{x_Q}}\right)\right)\right)\right] + \left[\frac{0.075}{(0.93x_D - x_P - x_T - x_Q + 0.075)}\right]$$

The remaining 50 % of the data set is used for evaluating the predictive ability of the model. In the training, the MSE, MAE, and R are 0.002, 0.013, and 0.963, respectively. In the testing stage, MSE, MAE, and R are 0.007, 0.043, and 0.912, respectively. Figure 2 shows the accuracy of the model for both training and testing.

5 Performance evaluation

To assess the performance of the model, Smith [22] defined the following circumstances:

- If a model gives $|R| > 0.8$, a strong correlation exists between the predicted and real values.
- If a model gives $0.2 < |R| < 0.8$, a correlation exists between the predicted and real values.
- If a model gives $|R| < 0.2$, a weak correlation exists between the predicted and real values.

In all conditions, the error values (e.g., MSE) should be at the minimum [23]. The derived results show that the MEP models provide very precise predictions for both the training and testing data sets.

6 Conclusion

Suppliers' performance evaluation as a common MCDM problem has received much attention from academics and practitioners. In today's competitive world, companies have concentrated on customer satisfaction and decreasing price with long-term contracts with reliable suppliers. Consequently, a robust and applicable method is needed to ease monitoring suppliers' performance for managers.

Over the recent decade, combining AHP with ANN has gaining popularity. Although ANN is very powerful in model prediction, its major drawback is the black box system. Therefore, in this paper, a new evolutionary technique, namely MEP, was introduced to solve the earlier-mentioned problem.

Generally, it could be concluded that the proposed model (AHP–MEP) is very powerful and precise in suppliers' performance evaluation. The main limitation of the proposed model is that while increasing the number of criteria and alternative (supplier) the burden of computational complexity is increased.

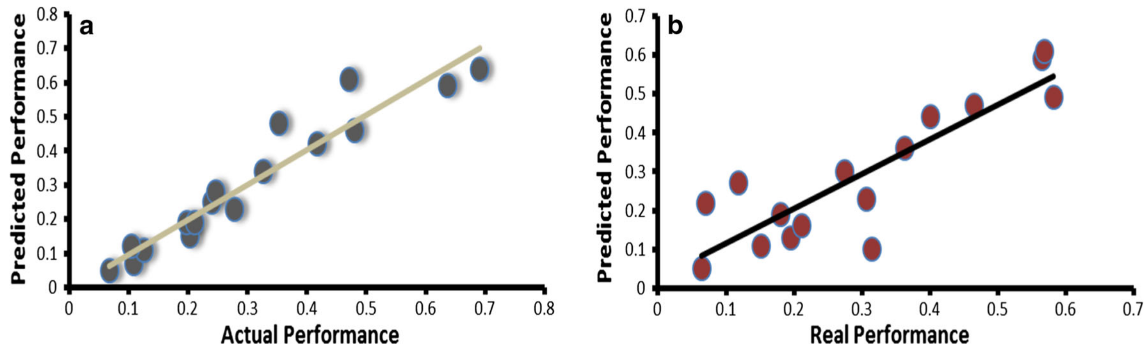

Fig. 2 Actual versus predicted suppliers' performance scores using the GEP model **a** training data, **b** testing

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