TECHNOLOGICAL AND ECONOMIC DEVELOPMENT OF ECONOMY
ISSN 2029-4913 / eISSN 2029-4921

2017 Volume 23(1): 178–195
doi: 10.3846/20294913.2016.1189461

NONLINEAR GENETIC-BASED MODEL FOR SUPPLIER SELECTION: A COMPARATIVE STUDY

Alireza FALLAHPOUR[a], Atefeh AMINDOUST[b],
Jurgita ANTUCHEVIČIENĖ[c], Morteza YAZDANI[d]

[a]*Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur, Malaysia*
[b]*Department of Industrial Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Isfahan, 8514143131, Iran*
[c]*Department of Construction Technology and Management, Vilnius Gediminas Technical University, LT-10223 Vilnius, Lithuania*
[d]*Department of Business Management, Universidad Europea de Madrid, Madrid, Spain*

Received 01 July 2015; accepted 25 November 2015

Abstract. Evaluation and selection of candidate suppliers has become a major decision in business activities around the world. In this paper, a new hybrid approach based on integration of Gene Expression Programming (GEP) with Data Envelopment Analysis (DEA) (DEA-GEP) is presented to overcome the supplier selection problem. First, suppliers' efficiencies are obtained through applying DEA. Then, the suppliers' related data are utilized to train GEP to find the best trained DEA-GEP algorithm for predicting efficiency score of Decision Making Units (DMUs). The aforementioned data is also used to train Artificial Neural Network (ANN) to predict efficiency scores of DMUs. The proposed hybrid DEA-GEP is compared to integrated approach of Artificial Neural Network with Data Envelopment Analysis (DEA-ANN) to support the validity of the proposed model. The obtained results clearly show that the model based on GEP not only is more accurate than the DEA-ANN model, but also presents a mathematical function for efficiency score based on input and output data set. Finally, a real-life supplier selection problem is presented to show the applicability of the proposed hybrid DEA-GEP model.

Keywords: Gene Expression Programming (GEP), Artificial Neural Network (ANN), Data Envelopment Analysis (DEA), supplier selection.

JEL Classification: C44, C61.

Introduction

Modern day's business environment is frequently distinguished by increasing intricacy, ambiguity, unsteadiness and unpredictability. Thus, organizations must take each and every opportunity to advance their operational performance to stay competitive in the world-

Corresponding author Jurgita Antuchevičienė
E-mail: *jurgita.antucheviciene@vgtu.lt*

Routledge
Taylor & Francis Group

wide marketplace by appropriately selecting its trading partners. Supply chain management (SCM) is a process that covers raw material procurement, production of finished products and distributing the finished good to consumers through distributors and retailers. In a supply chain network, supplier evaluation and selection is a deliberated task because of high complications with several conflicting, commensurable, ordinal and cardinal factors involved in the decision making process. In this network, organizations are forced to harmonize their purchasing activities in order to gain advantage. In managing purchasing activities proficiently, supplier evaluation and selection plays a crucial role and has become a very fundamental component for viable benefits of any organization (Rezaei 2015). In the concept of SCM, supplier is as the first echelon, followed by manufacturer, distributor, retailer and, finally, end customer. Thus, selecting proper suppliers plays a significant role in firms and industries as this influence the overall performance of a SCM (Omurca 2013; Amindoust *et al.* 2012). Indeed, suitable suppliers significantly help in alleviating unnecessary costs, improving the operations and increasing customer satisfaction (Arikan 2013). Therefore, the issue of supplier selection has attracted a lot of research attention. In this study, a new model is proposed by integrating genetic-based artificial intelligence (AI) technique with non-parametric approach in supplier selection.

Supplier selection is a multi-criteria decision making (MCDM) process (Bhattacharya *et al.* 2010; Yazdani *et al.* 2016) which becomes more complicated with conflicting criteria such as quality, cost, delivery and service (Omurca 2013; Humphreys *et al.* 2003; Guneri *et al.* 2009). Thus, great attention has been received from practitioners and scholars over the past few decades. Many conceptual methods including individual methods and hybrid methods have been proposed to select the best suppliers.

Integrated approach of Artificial Neural Network with Data Envelopment Analysis (DEA-ANN) is one of the hybrid methods which is used as a useful method for analyzing supplier's performance (Fallahpour *et al.* 2014). Data Envelopment Analysis (DEA) as a non-parametric method is widely used to help decision makers in determining the relative efficiency of homogeneous Decision Making Units (DMUs). Although, DEA does not require strict assumption, it has some weaknesses as a mathematical method (Santin 2008). DEA is very sensitive to the presence of the outliers and statistical noise (Bauer 1990). In addition, it requires huge computer resources in terms of memory and central processing unit (CPU) time while using large data set (Emrouznejad, Shale 2009). In order to solve the problems with DEA, Wu *et al.* (2006) put forward that Artificial Neural Network (ANN) can overcome the limitations of DEA. Wang (2003) demonstrated that ANN under concavity constraints can be used to explore the efficiency frontiers on the basis of collected data.

Although ANN overcomes complexity non-linear relationship, ANN is a black box system (Alavi *et al.* 2011; Moghassem, Fallahpour 2011). Thus, the main disadvantage of ANN is the lack of the estimative function for the dependent variable using independent variables. Furthermore, ANN cannot determine an accurate approximation of the correct relationship between dependent and independent variables in comparison with other existing AI techniques (Mehr *et al.* 2013; Fallahpour *et al.* 2016).

This paper aims to overcome the aforementioned limitations of DEA and weaknesses of ANN through combining DEA with a robust AI technique called Gene Expression Programming (GEP). The main purpose of this paper is to provide a mathematical model for calculating suppliers' efficiency and classifying them. There is the first attempt to integrate DEA with GEP in supplier selection.

The proposed model is implemented in a garment company. In order to validate the DEA-GEP model, the model was evaluated from four different aspects. In order to demonstrate the accuracy of the model for both the efficiency computing and classification in training, results obtained by the model were compared with the actual efficiency and classification. To validate the accuracy of the model in estimation for both the efficiency and the classification, untrained data set was used and compared the results obtained by the model with the actual efficiency and classification. To evaluate the power of the model as an intelligent-based model, ANN was used as a powerful tool in modelling and compared the result derived from GEP-based model with the computed results derived from ANN-based model for both training and estimation (testing). Since DEA works based on inputs and outputs, the model was evaluated in terms of recognizing the inputs from the outputs by parametric analysis. For further verification of the ability of the model in calculating suppliers' efficiency and suppliers' classification, data set of year the next year was employed as an unseen and untrained data and the results were compared with the actual results.

The rest of this paper is organized as follows. Section 1 includes the related literature on supplier selection. Section 2 provides a brief overview of the utilized techniques and the methodology proposed in this paper. The case study, results and discussion are presented in Section 3. The Conclusions are presented in the last section.

1. Literature review

This section provides brief overview on the criteria used in supplier evaluation and the approaches proposed for selecting suitable suppliers.

1.1. Supplier selection criteria

As mentioned earlier, supplier selection is a multiple criteria problem and selecting appropriate criteria is one of the main steps of supplier evaluation and selection (Büyüközkan, Çifçi 2011). Dickson (1966) gathered 23 different criteria which were selected by 273 American and Canadian purchasing agents and managers in 1966. The author ranked the criteria and showed that the most widely used criterion is quality, followed by delivery, performance history, warranties and claim policies, production facilities and capacity and price (cost). Recently, Ho *et al.* (2010) conducted a review on supplier selection according to 78 papers published between 2000 and 2008. The authors reported that the most widely adopted criteria for supplier selection are quality, delivery, price (or cost), manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment respectively. Chang *et al.* (2011) presented top 10 criteria that received most attention based on the literature as proposed in Table 1.

Table 1. Top 10 criteria used in the literature of supplier selection

Criteria	I	II	III	IV	V	VI	VII	VIII	IX
Cost	*		*		*		*		
Delivery	*	*	*	*	*		*		
Flexibility		*			*				
Lead time								*	
Production capability									*
Quality	*	*	*	*	*	*			
Reaction to demand change									*
Delivery reliability								*	
Service									*
Technical capability	*	*	*	*			*		

Notes: I: Dickson (1966), II: Noorul Haq, Kannan (2006), III: Lee (2009), IV: Liu, Hai (2005), V: Ghodsypour, O'Brien (1998), VI: Chen *et al.* (2006), VII: Xia, Wu (2007), VIII: Kreng, Wang (2005), IX: Wang, Hu (2005)

1.2. Supplier selection techniques

A suitable supplier plays a significant role in achieving competitive advantage and reducing the purchasing cost in any firm. Therefore, various methods have been proposed regarding the selection of appropriate suppliers by academics and practitioners. Chai *et al.* (2013) divided the approaches into individual approaches and integrated approaches. They categorized the individual approaches to supplier selection into three parts: I) Multi-Criteria Decision Making (MCDM) methods such as Analytic Hierarchy Process (AHP), Analytic Network Process (ANP) (Ignatius *et al.* 2016) Elimination and Choice Expressing Reality (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Yazdani, Payam 2015) Decision Making Trial and Evaluation Laboratory (DEMATEL), Simple Multi Attribute Rating Technique (SMART); II) Mathematical Programming (MP) including Data Envelopment Analysis (DEA), Linear Programming (LP), Non-Linear Programming (NLP), Multi Objective Programming (MOP), Goal Programming (GP), Stochastic Programming (SP). III) Artificial Intelligence (AI) approaches including Genetic Algorithm (GA), Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Adaptive Neuro Fuzzy Inference System (ANFIS). The integrated approaches were classified into integrated approaches, integrated ANP, integrated uncertain decision approaches and integrated DEA.

DEA as a non-parametric method has been successfully used in selecting suppliers based on their efficiency ratings (Liu *et al.* 2000). Several models of DEA have been proposed to improve the process of supplier selection such as (Saen 2007a; Mirhedayatian *et al.* 2014) (Note that some researchers considered DEA as an individual method (Ho *et al.* 2010) and several researchers assume that it is a kind of Mathematical Programming model (Chai *et al.* 2013; Vahdani *et al.* 2012). One of the approaches that has recently received great attention is AI techniques such as ANFIS (Güneri *et al.* 2011), ANN (Wei *et al.*

1997), SVM (Vahdani *et al.* 2012). In the literature fuzzy set theory has been considered as a technique to convert qualitative data to quantitative data and also applied to MCDM techniques (Chen *et al.* 2006) and MP techniques (Amid *et al.* 2006).

Although a lot of individual methods have been proposed, each individual method has its own disadvantage in decision making (Vahdani *et al.* 2012). Therefore, to improve the evaluation process of suppliers, researchers have combined these approaches together. In recent years integrated methods have been commonly applied to supplier selection such as combination of AHP–DEA approach to assess and select slightly non-homogeneous suppliers (Saen 2007b). In that paper, AHP was employed to find the relative weight of suppliers that had missing value. Afterward, DEA was used to calculate the efficiency. Demirtas and Ustun (2008) integrated ANP with Multi-Objective Mixed Integer Linear Programming (MOMILP) to deal with both tangible and intangible factors in selecting the most appropriate suppliers and determining the best quantities among selected suppliers to maximize the total value of purchasing and minimize the budget and defect rate. In the first part, ANP and AHP were deployed to consider both tangible and intangible factors. Then, the weights calculated by them were used as coefficients in the first objective function of the MOMILP model. At last, the model was solved by ε-constraint and Reservation Level driven Tchebycheff Procedure (RLTP).

In recent years, combination of DEA and ANN has been widely used for selecting the best suppliers by combining DEA and ANN (as an AI approach) techniques such as Çelebi, Bayraktar (2008), Kuo *et al.* (2010), Nourbakhsh *et al.* (2013), etc. For example, Ozdemir and Temur (2009) conducted a study using DEA and Multi Layered Perceptron (MLP) ANN in a German iron and steel industry. They categorized 24 suppliers according to six criteria (input/output), namely material quality, discount on amount, discount on cash, payment term, delivery time and annual revenue (considered as an output). After getting the result by input oriented DEA, an ANN (MLP) was constituted to predict the efficiency rating of the suppliers. Wu (2009) used a DEA-ANN model to evaluate as well as select the best suppliers. To show the predictive power of the model, a five-fold cross-validation was carried out. Finally, the result obtained by DEA-ANN was compared with DEA-Decision Tree (DT) model. The study concluded that DEA-ANN is more accurate than DEA-DT.

The current study is aimed at not only achieving a mathematical function for suppliers' efficiency, but also enriching the literature of supplier selection by introducing a new genetic-based approach with high training power called GEP. As a robust technique, GEP can improve the idea of combining DEA and AI technique in decision making, especially in supplier selection.

2. Proposed DEA-GEP model

To design the proposed DEA-GEP model, compare it with DEA-ANN model, and measure the performance of the two mentioned models, some basic concepts must be considered. These concepts are discussed in the next sub-sections and finally the description of the proposed model is presented through three stages in Chapter 2.5.

2.1. Data Envelopment Analysis (DEA)

Performance measuring is an essential duty for a DMU to find its weaknesses so that subsequent improvements can be made. Charnes *et al.* (1978) developed DEA as a mathematical programming technique for calculating the relative performance of decision-making units (DMUs) in terms of the observed operation practice in a sample of comparable DMUs. A frontier comprising best performers is determined by DEA. The maximum efficiencies are constrained to 1. Based on DEA, DMUs are divided into two parts, efficient and inefficient. DEA involves the solution of a linear programming problem to fit a non-stochastic, nonparametric production frontier based on the actual input–output observations in the sample. There are two important basic models, namely Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC). Assume that there are n DMUs, ($DMU_j : j = 1,2, ..., n$) which apply m inputs ($x_i : i = 1,2, ..., m$) to create s outputs ($y_r : r = 1,2, ..., s$). The input oriented efficiency of a particular DMU0 under the assumption of variable returns to scale (VRS), can be obtained from the following linear programs (input-oriented BCC model) (Banker *et al.* 1984):

$$\begin{aligned} \min Z_o &= \theta - \varepsilon.\vec{l}s^-, \qquad (1)\\ \text{s.t.}\ \ & Y\lambda - s^+ = Y_o,\\ & \theta X_o - X\lambda - s^- = 0,\\ & \vec{l}\,\lambda = 1,\\ & \lambda, s^+, s^- \geq 0, \end{aligned}$$

where s^+ and s^- are the slacks in the system.

n linear programming problems of the above form must be solved for performing a DEA analysis. A DMU is termed efficient if and only if the optimal value θ is equal to 1 and all the slack variables are 0.

For more information, there are over 3000 papers and several books about this technology.

2.2. Artificial Neural Network (ANN)

MLP is a feed forward-based architecture of ANN which is usually trained with Back Propagation (BP) learning algorithm (Gandomi, Alavi 2011). There are at least three layers in a MLP network. The first layer is the input layer, the second layer is the hidden layer and the last layer is the output layer. There are number of processing units and each of them is fully interconnected with weighted connections to units in the subsequent layer. Each of these layers has several processing units and each unit is fully interconnected with weighted connections to units in the subsequent layer. There are a number of nodes in every layer. Every input is multiplied by the interconnection weights of the nodes (Mirzahosseini *et al.* 2011).

At the end, the result (h_j) is as Eq. (2):

$$h_j = f\left(\sum_i x_i w_{ij} + b\right), \qquad (2)$$

where f is motivation function (e.g. Linear, Sigmoid or Hyperbolic tang), x_i is the activation of ith hidden layer node and w_{ij} is the weight of the connection joining the jth neuron in a layer with the ith neuron in the previous layer, and b is the bias for the neuron.

2.3. Gene Expression Programming (GEP)

Koza (1992) first invented Genetic Programming as an extension of Genetic Algorithm (GA), inspired of Darwinian evolutionary theory, which automatically generates mathematical models. The basic difference between the GA and GP approaches is that the GA represents the solution as a string of numbers and the GP represents the solution as a computer programs (mathematical model) (Mollahasani *et al.* 2011; Güllü 2014; Zhao *et al.* 2012; Rashed *et al.* 2012; Moghassem *et al.* 2012). There are tree type of GP known as tree-based GP, linear-based GP and graph-based GP (Fig. 1) (Luo, Zhang 2012). Linear-based GP has been received much attention among them.

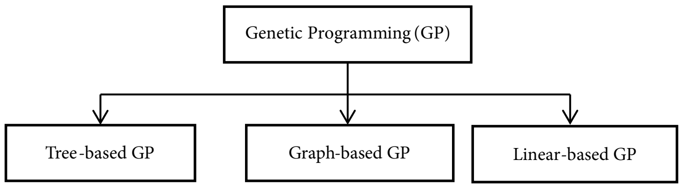

Fig. 1. Different types of GP

GEP as a robust linear GP-based approach was introduced by Ferreira (2001). GEP requires five elements: function set, terminal set, fitness function, control parameters, and termination condition to develop a model. In the GEP algorithm, in order to present solutions of problems, fixed length of character strings are performed, which then proposed like Expression Trees (ETs) of different sizes and shapes. Due to multi-genic nature of GEP, more complicated programs composed of number of subprograms will be allowed to be generated during the evolutionary process (Mollahasani *et al.* 2011). A GEP gene includes a several of symbols which are components from function or terminal sets like {+, _, ×, /, cos} and the terminal set like {*a, b, c,* –4} (Alavi, Gandomi 2011a; Alavi *et al.* 2013). A typical GEP gene is as bellow:

$$+.\times.\cos.a.-.+.+.\times b.a.c.-4.b.a. \tag{3}$$

The proposed expression is called Karva notation or K-expression, which can be illustrated as an ET (Mollahasani *et al.* 2011; Alavi *et al.* 2013). Figure 2 shows the expression tree of the above sample gene.

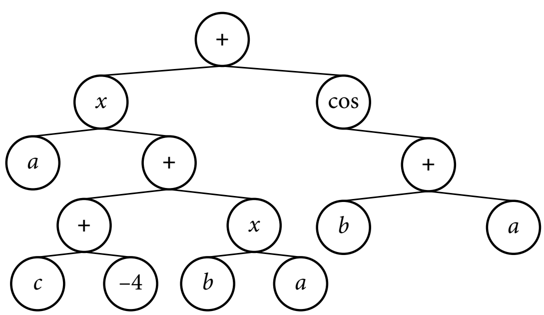

Fig. 2. Sample of Expression Trees (ETs)

The transformation process is created from the start position in the K-expression, which corresponds to root of the ET, and reads through the string one by one (Alavi *et al.* 2011). The mentioned GEP gene can be represented in a mathematical equation as:

$$a((c-4)-(b\times a))+\cos(a+b). \tag{4}$$

There are four steps in the GEP (Ferreira 2001):

1. Creating individual for the initial population randomly.
2. Creating chromosomes like ET and assessing fitness of the individuals.
3. Choosing the most appropriate individuals based on their fitness to generate with modification.
4. Reiteration the aforementioned process to find a solution.

The copied individuals into the next generation are determined according to fitness by roulette wheel. This guarantees the survival and cloning of the best individual to the next generation. Using various combinations of genetic operators, variation in the population is introduced. These operators include crossover, mutation and rotation. The rotation operator is applied to rotate two subparts of an element sequence in a genome with respect to a randomly chosen point (Ferreira 2001; Alavi *et al.* 2011). This can also significantly reshape the ETs. For example, the following gene rotates the first five elements of gene (1) to the end:

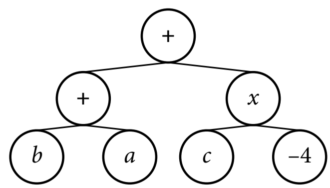

Fig. 3. An example of ET

$$+.+.\times b.a.c-4.b.a.+.\times.\cos.a.-. \tag{5}$$

The solution function is built using only the first seven elements $(b+a)+(c\times-4)$, with the corresponding expression illustrated in Figure 3.

2.4. Performance measures

In this study, for evaluating of capabilities of models, Mean-Squared Error (MSE), Root MSE (RMSE) and Mean Absolute Error (MAE) are used as the criteria between the experimental and predicted measures:

$$\mathrm{MSE}=\frac{1}{n}\sum_{1}^{n}\left(t_{i-}o_i\right)^2; \tag{6}$$

$$\mathrm{RMSE}=\sqrt{\frac{\sum_1^n\left(t_i-o_i\right)^2}{n}}; \tag{7}$$

$$\mathrm{MAE}=\frac{1}{n}\sum\left(t_i-o_i\right)^2, \tag{8}$$

where t is the experimental value, o is the predicted value and n is total number of data.

2.5. The proposed model

In this paper, the BCC model is used for classifying the suppliers. Figure 4 illustrates the conceptual model for supplier selection using DEA, GEP and ANN.

It generally contains two sections. Section 1 applies DEA to calculate the DEA score given to each supplier. After obtaining suppliers' efficiency, the calculated DEA scores are used to derive the class for each supplier, typically classified as efficient and inefficient clusters. Module 2 utilizes supplier performance-related data to train GEP and ANN and apply the trained models to new suppliers for testing. If the performance measures of the prediction are sufficiently good, the process stops, if not, the process is continued. Figure four depicts the proposed hybrid model.

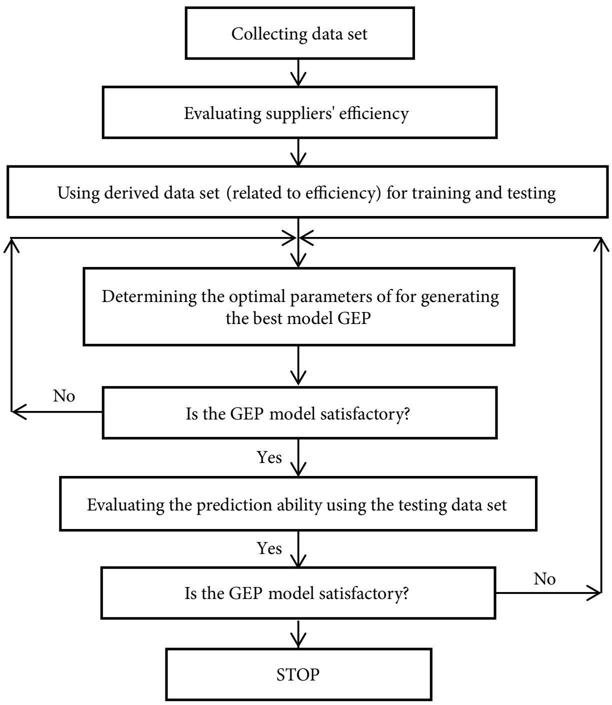

Fig. 4. The hybrid model for supplier selection

3. Case study

In order to evaluate the applicability of the integrated model, this section presents findings from its implementation in a sample company (the company's name is not disclosed for privacy reasons). The company is a garment manufacturer that produces women's underwear. The staffing capacity is 700 employees. In order to fill its daily order of more than 400 000 garments, it engages the services of 100 suppliers. Company policy demands suppliers to hold certification in the following: ISO9001 (quality management systems) (Sampaio *et al.* 2009), ISO14001 (environmental management systems) (Bansal, Hunter 2003) and ISO10002 (customer management systems) (Hughes, Karapetrovic 2006).

3.1. Data

The referred collected data utilized 4 input variables that show the capabilities of the suppliers to generate 2 output factors that show the performance outcomes of the suppliers in the evaluation process (Table 2).

The Inputs and Outputs are as follows.

Inputs:

- Number of Personnel (NP);
- Transportation Equipment Capacity (ton) (TEC);
- Warehouse Capacity (m^3) (WC);
- Advertisement Cost (AC).

Outputs:

- Number of Dairy Shops (NDS);
- Total Sale Revenue (2010-2011) (TSR).

3.2. Implementation and discussion

DEA not only calculates the efficiency measure of each supplier but also classifies it into efficient and inefficient group. In this survey, BCC model is used to get the efficiency measure of each supplier. The outcome of BCC model is divided into two parts, training set and prediction set to combine with GEP and ANN. Prediction (testing) part has been presented in Table 2, rows 19–24. In this research LINGO 11 Software was used.

Table 2. Related data for candidate suppliers

Supplier's number	NP	TEC	WC	AC	NDS	TSR	BCC model
1	8	13	20	330	175	3489	0.677
2	8	6.8	12	171	150	4256	1
3	4	8.5	35	239	122	5205	1
4	3	3.5	10	86	92	1522	0.999
5	3	1.7	14	29	75	1526	0.785
6	2	1.7	10	15	62	1928	1
7	14	13.8	70	175	410	12673	1
8	3	3.4	30	16	110	1985	1
9	4	5.2	30	210	144	3897	0.937
10	3	5.2	400	8	75	1565	1
11	4	5.2	44	34	86	2030	0.618
12	8	10.4	100	208	172	6066	0.742
13	3	3.4	20	57	80	2314	0.774
14	5	8.5	50	69	73	2081	0.429
15	8	11.9	70	164	172	5790	0.732
16	3	5.1	40	87	140	2375	0.971

End of Table 2

Supplier's number	NP	TEC	WC	AC	NDS	TSR	BCC model
17	2	3.5	30	34	67	1057	0.999
18	2	1.7	10	160	160	1967	1
Data set for testing							
19	4	10.4	50	54	75	2169	0.560
20	15	13.6	100	30	310	6643	1
21	11	12.1	25	202	395	5758	1
22	3	5.2	30	17	72	1176	0.880
23	4	5.1	40	187	173	3967	0.962
24	3	3.4	30	46	62	2488	0.833

3.2.1. Parameters design of ANN

In this paper, Neuro Solutions 5 software is used for implementing ANN. In this study, the multi-layer Perceptron with error backpropagation learning algorithm is applied. Other parameters of ANN are as follows:

- The number of training epochs: 926;
- Momentum: 0.7;
- Activation functions: Tanh (x);
- Number of hidden layer: 2;
- Number of neurons in each hidden layer: 4.

The performance measures for training and testing are presented in Table 3. Note that in this ANN, the inputs and outputs mentioned in 3.1 are used as input units.

Table 3. Performance measures (DEA-ANN)

Training data		Testing data	
MSE	0.022	MSE	0.007
RMSE	0.148	RMSE	0.085
MAE	0.167	MAE	0.052

3.2.2. Parameters design of GEP

As it was indicated in 3.1, multi input and multi output are used for determining the efficiency of DMUs. Like ANN, the efficiency scores are given GEP to find the best trained algorithm for prediction. Many different parameters of GEP have been chose for getting the best structure. It is worthy to know that there is no exact method to find the optimized parameters in GEP, generally in intelligent-based models (Emrouznejad, Shale 2009). Consequently, several runs must be done to find the best structure (Mousavi *et al.* 2014). The parameters used in the GEP model are presented in Table 4. It should be mentioned that the parameters of GEP in Table 4 are set based on the data set we have collected from the real case study. In a case of new data set, the parameters of GEP must be changed.

The performance measures for training and testing are presented in Table 5.

Table 4. GEP parameters

	Parameters	Value
Function set	Functions	×, +, –, power (x, y^*), e^y
Chromosome Structure	Chromosome	30
	Number of genes	4
	Head size	9
	Linking function	Addition
Fitness Function	MSE	
Genetic Operators	Mutation rate	0.044
	One-point recombination rate	0.2
	Two- point recombination rate	0.3
	Gene recombination rate	0.1
	Gene transportation rate	0.1
Numerical Constant	Constants per gene	2
	Data type	Floating Point
	Lower bound	–10
	Upper bound	+10

Table 5. Performance measures (DEA-GEP)

Training data		Testing data	
MSE	0.007	MSE	0.004
RMSE	0.085	RMSE	0.066
MAE	0.070	MAE	0.051

3.2.3. Presenting a mathematical function by GEP

Unlike ANN which has a black box (Alavi, Gandomi 2011b) GEP can present a mathematical function. In fact, GEP presents a function between efficiency score and the inputs and the outputs of BCC model. The function generated by the GEP algorithm in prediction of efficiency is shown in Eq. (9):

$$y = \frac{x_5 - 1.08}{x_2 + x_5} + \frac{x_5}{\left(x_6 - x_4 - x_2\right) - \left(x_4 \times x_2\right)} + \frac{2 \times x_1}{x_3 - x_5} . \quad (9)$$

In the above equation x_1, x_2, ..., x_6 called as below respectively:

- Number of Personnel (NP) = x_1;
- Transportation Equipment Capacity (ton) (TEC) = x_2;
- Warehouse Capacity (m^3) (WC) = x_3;
- Advertisement Cost (AC) = x_4;
- Number of Dairy Shops (NDS) = x_5;
- Total Sale Revenue (2010-2011) (TSR) = x_6;
- Efficiency score of each DMU = y.

As can be observed, the proposed equation by GEP, as a behavioural model, can be used for monitoring the suppliers' efficiency. Indeed, the proposed model is performed as a strategic model which helps the managers to evaluate the suppliers' efficiency for long-term. In addition, this model reduces the time of calculation of the efficiency process, because the managers only need to substitute the values of each of the criterion in the equation. This is notable that these kinds of models are always used for efficiency evaluation in the future. Therefore, the best supplier is the alternative which has the closest value to one.

In terms of the results obtained and compared the two hybrid models, it can be concluded that DEA-GEP is better than DEA-ANN. Tables 3 and 5 show that DEA-GEP in all the three performance factors is more accurate than DEA-ANN for training and testing. Also, it should be mentioned that, although the ANN-based model can predict the suppliers' efficiency accurately, however, the biggest problem we are dealing with in this model is the black box system. It means that the managers need a strong knowledge about the neural network to understand the relationship between the criteria (inputs/outputs) and the performance. On the other hand, not only the ANN-based model cannot help the managers but also might make them confuse.

To show the ranking power of the proposed GEP model, the real ranking calculated by DEA was compared with the ranking done by the proposed GEP model and the ANN model for the testing data set as the unseen and untrained data set. As can be seen (Table 6), the ranking conducted by GEP is more accurate than ANN, compared to the real ranking. By applying GEP, all the suppliers were ranked correctly, while by applying ANN, only two ranks were done correctly.

Table 6. The ranking of suppliers for testing data set

Supplier's number	DEA value	Real ranking	ANN-Based model: efficiency score	Ranking of ANN	GEP-Based Model: efficiency score	Ranking of GEP
19	0.54	5	0.51	5	0.59	5
20	1	1	0.79	4	1	1
21	1	1	1	1	1	1
22	0.88	3	0.86	2	0.84	3
23	0.96	2	1	1	0.96	2
24	0.83	4	0.83	3	0.77	4

Conclusions and future works

Supplier selection, as one of the main steps in success of firms' supply chain management, has received much attention from both academia and practitioners. As a multi criteria decision making issue, supplier evaluation and selection is a complicated process. Therefore, developing techniques which solve this problem for managers of organizations is very important.

In this study, two soft computing methods (GEP and ANN) are focused in the supplier selection problem.

For the first time, DEA is integrated with GEP to exploit the capabilities of the GEP approach and to enrich the supplier selection literature. First, the suppliers' efficiencies are obtained through applying BCC-DEA model. Then, the suppliers' related data are utilized to train GEP to find the best trained DEA-GEP algorithm for predicting efficiency score of DMUs.

Similar to the proposed GEP model, ANN is integrated with DEA (DEA-ANN) to support and validate the DEA-GEP model.

Applying three accuracy measures criteria including MSE, RMSE, and MAE, it is found that the GEP based model performs better than ANN integrated model.

Unlike the ANN approaches, which have "black box" characteristic, GEP can present a mathematical function for supplier selection. This mathematical function based on a set of data given by GEP model can be optimized to get the best solution for efficiency of each DMU. Accordingly, it can be considered as superiority of the DEA-GEP model to measure the efficiency scores of DMUs for future study.

Although the proposed model is accurate, however finding the optimized parameters of GEP, as stated earlier, is a trial and error process, and there is no guarantee to construct the GEP structure easily.

Also, using support vector machine (SVM), ANFIS and comparing them with the results of the current research is another suggestion for future work.

References

Alavi, A. H.; Aminian, P.; Gandomi, A. H.; Esmaeili, M. A. 2011. Genetic–based modeling of uplift capacity of suction caissons, *Expert Systems with Applications* 38(10): 12608–12618. http://dx.doi.org/10.1016/j.eswa.2011.04.049

Alavi, A. H.; Gandomi, A. H. 2011a. Prediction of principal ground–motion parameters using a hybrid method coupling artificial neural networks and simulated annealing, *Computers & Structures* 89(23): 2176–2194. http://dx.doi.org/10.1016/j.compstruc.2011.08.019

Alavi, A. H.; Gandomi, A. H. 2011b. A robust data mining approach for formulation of geotechnical engineering systems, *Engineering Computations* 28(3): 242–274. http://dx.doi.org/10.1108/02644401111118132

Alavi, A. H.; Gandomi, A. H.; Nejad, H. C.; Mollahasani, A.; Rashed, A. 2013. Design equations for prediction of pressuremeter soil deformation moduli utilizing expression programming systems, *Neural Computing and Applications* 23(6): 1771–1786. http://dx.doi.org/10.1007/s00521-012-1144-6

Amid, A.; Ghodsypour, S. H.; O'Brien, C. 2006. Fuzzy multiobjective linear model for supplier selection in a supply chain, *International Journal of Production Economics* 104(2): 394–407. http://dx.doi.org/10.1016/j.ijpe.2005.04.012

Amindoust, A.; Ahmed, S.; Saghafinia, A.; Bahreininejad, A. 2012. Sustainable supplier selection: a ranking model based on fuzzy inference system, *Applied Soft Computing* 12(6): 1668–1677. http://dx.doi.org/10.1016/j.asoc.2012.01.023

Arikan, F. 2013. A fuzzy solution approach for multi objective supplier selection, *Expert Systems with Applications* 40(3): 947–952. http://dx.doi.org/10.1016/j.eswa.2012.05.051

Banker, R. D.; Charnes, A.; Cooper, W. W. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science* 30(9): 1078–1092. http://dx.doi.org/10.1287/mnsc.30.9.1078

Bansal, P.; Hunter, T. 2003. Strategic explanations for the early adoption of ISO 14001, *Journal of Business Ethics* 46(3): 289–299. http://dx.doi.org/10.1023/A:1025536731830

Bauer, P. W. 1990. Recent developments in the econometric estimation of frontiers, *Journal of Econometrics* 46(1): 39–56. http://dx.doi.org/10.1016/0304-4076(90)90046-V

Bhattacharya, A.; Geraghty, J.; Young, P. 2010. Supplier selection paradigm: an integrated hierarchical QFD methodology under multiple–criteria environment, *Applied Soft Computing* 10(4): 1013–1027. http://dx.doi.org/10.1016/j.asoc.2010.05.025

Büyüközkan, G.; Çifçi, G. 2011. A novel fuzzy multi–criteria decision framework for sustainable supplier selection with incomplete information, *Computers in Industry* 62(2): 164–174. http://dx.doi.org/10.1016/j.compind.2010.10.009

Çelebi, D.; Bayraktar, D. 2008. An integrated neural network and data envelopment analysis for supplier evaluation under incomplete information, *Expert Systems with Applications* 35(4): 1698–1710. http://dx.doi.org/10.1016/j.eswa.2007.08.107

Chai, J.; Liu, J. N.; Ngai, E. W. 2013. Application of decision–making techniques in supplier selection: a systematic review of literature, *Expert Systems with Applications* 40(10): 3872–3885. http://dx.doi.org/10.1016/j.eswa.2012.12.040

Chang, B.; Chang, C. W.; Wu, C. H. 2011. Fuzzy DEMATEL method for developing supplier selection criteria, *Expert Systems with Applications* 38(3): 1850–1858. http://dx.doi.org/10.1016/j.eswa.2010.07.114

Charnes, A.; Cooper, W. W.; Rhodes, E. 1978. Measuring the efficiency of decision making units, *European Journal of Operational Research* 2(6): 429–444. http://dx.doi.org/10.1016/0377-2217(78)90138-8

Chen, C. T.; Lin, C. T.; Huang, S. F. 2006, A fuzzy approach for supplier evaluation and selection in supply chain management, *International Journal of Production Economics* 102(2): 289–301. http://dx.doi.org/10.1016/j.ijpe.2005.03.009

Demirtas, E. A.; Ustun, O. 2008. An integrated multiobjective decision making process for supplier selection and order allocation, *Omega* 36(1): 76–90. http://dx.doi.org/10.1016/j.omega.2005.11.003

Dickson, G. W. 1966. An analysis of vendor selection systems and decisions, *Journal of Purchasing* 2: 5–17.

Emrouznejad, A.; Shale, E. 2009. A combined neural network and DEA for measuring efficiency of large scale datasets, *Computers & Industrial Engineering* 56(1): 249–254. http://dx.doi.org/10.1016/j.cie.2008.05.012

Fallahpour, A.; Olugu, E. U.; Musa, S.N.; Khezrimotlagh, D.; Wong, K. Y. 2016. An integrated model for green supplier selection under fuzzy environment: application of data envelopment analysis and genetic programming approach, *Neural Computing and Applications*, 27(3): 707–725. http://dx.doi.org/10.1007/s00521-015-1890-3

Fallahpour, A.; Olugu, E. U.; Musa, S.N.; Khezrimotlagh, D.; Khezrimotlagh, S. Singh. 2014. Supplier selection under fuzzy environment: a hybrid model using KAM in DEA, in *Recent Developments in Data Envelopment Analysis and its Applications*, *Proceedings of the 12th International Conference of DEA*, 14–17 April 2014, Kuala Lumpur, Malaysia, 342–348.

Ferreira, C. 2001. Gene expression programming: a new adaptive algorithm for solving problems, *Complex Systems* 13(2): 87–129.

Gandomi, A. H.; Alavi, A. H. 2011. Applications of computational intelligence in behavior simulation of concrete materials, *Computational Optimization and Applications in Engineering and Industry* 359: 221–243. http://dx.doi.org/10.1007/978-3-642-20986-4_9

Ghodsypour, S. H.; O'Brien, C. 1998. A decision support system for supplier selection using an integrated analytic hierarchy process and linear programming, *International Journal of Production Economics* 56: 199–212. http://dx.doi.org/10.1016/S0925-5273(97)00009-1

Güllü, H. 2014. Function finding via genetic expression programming for strength and elastic properties of clay treated with bottom ash, *Engineering Applications of Artificial Intelligence* 35: 143–157. http://dx.doi.org/10.1016/j.engappai.2014.06.020

Güneri, A. F.; Ertay, T.; YüCel, A. 2011. An approach based on ANFIS input selection and modeling for supplier selection problem, *Expert Systems with Applications* 38(12): 14907–14917. http://dx.doi.org/10.1016/j.eswa.2011.05.056

Guneri, A. F.; Yucel, A.; Ayyildiz, G. 2009. An integrated fuzzy–lp approach for a supplier selection problem in supply chain management, *Expert Systems with Applications* 36(5): 9223–9228. http://dx.doi.org/10.1016/j.eswa.2008.12.021

Ho, W.; Xu, X.; Dey, P. K. 2010. Multi–criteria decision making approaches for supplier evaluation and selection: a literature review, *European Journal of Operational Research* 202(1): 16–24. http://dx.doi.org/10.1016/j.ejor.2009.05.009

Humphreys, P. K.; Wong, Y. K.; Chan, F. T. S. 2003. Integrating environmental criteria into the supplier selection process, *Journal of Materials Processing Technology* 138(1): 349–356. http://dx.doi.org/10.1016/S0924-0136(03)00097-9

Hughes, S.; Karapetrovic, S. 2006. ISO 10002 complaints handling system: a study, *International Journal of Quality & Reliability Management* 23(9): 1158–1175. http://dx.doi.org/10.1108/02656710610704258

Ignatius, J.; Rahman, A.; Yazdani, M.; Šaparauskas, J.; Haron, S. H. 2016. An integrated fuzzy ANP–QFD approach for green building assessment, *Journal of Civil Engineering and Management* 22(4): 551–563. http://dx.doi.org/10.3846/13923730.2015.1120772

Koza, J. R. 1992. *Genetic programming: on the programming of computers by means of natural selection.* Cambridge, MA, USA: MIT press.

Kreng, V. B.; Wang, I. C. 2005. Supplier management for manufacturer – a case study of flexible PCB, *The International Journal of Advanced Manufacturing Technology* 25(7–8): 785–792. http://dx.doi.org/10.1007/s00170-003-1808-6

Kuo, R. J.; Wang, Y. C.; Tien, F. C. 2010. Integration of artificial neural network and MADA methods for green supplier selection, *Journal of Cleaner Production* 18(12): 1161–1170. http://dx.doi.org/10.1016/j.jclepro.2010.03.020

Lee, A. H. 2009. A fuzzy supplier selection model with the consideration of benefits, opportunities, costs and risks, *Expert Systems with Applications* 36(2): 2879–2893. http://dx.doi.org/10.1016/j.eswa.2008.01.045

Liu, F. H. F.; Hai, H. L. 2005. The voting analytic hierarchy process method for selecting supplier, *International Journal of Production Economics* 97(3): 308–317. http://dx.doi.org/10.1016/j.ijpe.2004.09.005

Liu, J.; Ding, F. Y.; Lall, V. 2000. Using data envelopment analysis to compare suppliers for supplier selection and performance improvement, *Supply Chain Management: An International Journal* 5(3): 143–150.

Luo, C.; Zhang, S. L. 2012. Parse–matrix evolution for symbolic regression, *Engineering Applications of Artificial Intelligence* 25(6): 1182–1193. http://dx.doi.org/10.1016/j.engappai.2012.05.015

Mehr, A. D.; Kahya, E.; Olyaie, E. 2013. Streamflow prediction using linear genetic programming in comparison with a neuro–wavelet technique, *Journal of Hydrology* 505: 240–249. http://dx.doi.org/10.1016/j.jhydrol.2013.10.003

Mirhedayatian, S. M.; Azadi, M.; Saen, R. F. 2014. A novel network data envelopment analysis model for evaluating green supply chain management, *International Journal of Production Economics* 147: 544–554. http://dx.doi.org/10.1016/j.ijpe.2013.02.009

Mirzahosseini, M. R.; Aghaeifar, A.; Alavi, A. H.; Gandomi, A. H.; Seyednour, R. 2011. Permanent deformation analysis of asphalt mixtures using soft computing techniques, *Expert Systems with Applications* 38(5): 6081–6100. http://dx.doi.org/10.1016/j.eswa.2010.11.002

Moghassem, A.; Fallahpour, A.; Shanbeh, M. 2012. An intelligent model to predict breaking strength of rotor spun yarns using gene expression programming, *Journal of Engineered Fabrics & Fibers (JEFF)* 7(2): 1–10.

Moghassem, A.; Fallahpour, A. 2011. Processing parameters optimization of draw frame for rotor spun yarn strength using Gene Expression Programming (GEP), *Fibers and Polymers* 12(7): 970–975. http://dx.doi.org/10.1007/s12221-011-0970-y

Mollahasani, A.; Alavi, A. H.; Gandomi, A. H. 2011. Empirical modeling of plate load test moduli of soil via gene expression programming, *Computers and Geotechnics* 38(2): 281–286. http://dx.doi.org/10.1016/j.compgeo.2010.11.008

Mousavi, S. M.; Mostafavi, E. S.; Hosseinpour, F. 2014. Gene expression programming as a basis for new generation of electricity demand prediction models, *Computers & Industrial Engineering* 74: 120–128. http://dx.doi.org/10.1016/j.cie.2014.05.010

Noorul Haq, A.; Kannan, G. 2006. Design of an integrated supplier selection and multi–echelon distribution inventory model in a built-to-order supply chain environment, *International Journal of Production Research* 44(10): 1963–1985. http://dx.doi.org/10.1080/00207540500381427

Nourbakhsh, V.; Ahmadi, A.; Mahootchi, M. 2013. Considering supply risk for supplier selection using an integrated framework of data envelopment analysis and neural networks, *International Journal of Industrial Engineering Computations* 4(2): 273–284. http://dx.doi.org/10.5267/j.ijiec.2013.01.001

Omurca, S. I. 2013. An intelligent supplier evaluation, selection and development system, *Applied Soft Computing* 13(1): 690–697. http://dx.doi.org/10.1016/j.asoc.2012.08.008

Ozdemir, D.; Temur, G. T. 2009. DEA ANN approach in supplier evaluation system, *World Academy of Science, Engineering and Technology* 54: 343–348.

Rashed, A.; Bazaz, J. B.; Alavi, A. H. 2012. Nonlinear modeling of soil deformation modulus through LGP–based interpretation of pressuremeter test results, *Engineering Applications of Artificial Intelligence* 25(7): 1437–1449. http://dx.doi.org/10.1016/j.engappai.2011.11.008

Rezaei, J. 2015. A two–way approach to supply chain partner selection, *International Journal of Production Research* 53(16): 4888–4902. http://dx.doi.org/10.1080/00207543.2014.1003663

Saen, R. F. 2007a. Suppliers selection in the presence of both cardinal and ordinal data, *European Journal of Operational Research* 183(2): 741–747. http://dx.doi.org/10.1016/j.ejor.2006.10.022

Saen, R. F. 2007b. A new mathematical approach for suppliers selection: accounting for non–homogeneity is important, *Applied Mathematics and Computation* 185(1): 84–95. http://dx.doi.org/10.1016/j.amc.2006.07.071

Sampaio, P.; Saraiva, P.; Guimarães Rodrigues, A. 2009. ISO 9001 certification research: questions, answers and approaches, *International Journal of Quality & Reliability Management* 26(1): 38–58. http://dx.doi.org/10.1108/02656710910924161

Santin, D. 2008. On the approximation of production functions: a comparison of artificial neural networks frontiers and efficiency techniques, *Applied Economics Letters* 15(8): 597–600. http://dx.doi.org/10.1080/13504850600721973

Vahdani, B.; Iranmanesh, S. H.; Mousavi, S. M.; Abdollahzade, M. 2012. A locally linear neuro-fuzzy model for supplier selection in cosmetics industry, *Applied Mathematical Modelling 36*(10): 4714–4727. http://dx.doi.org/10.1016/j.apm.2011.12.006

Wang, S. 2003. Adaptive non–parametric efficiency frontier analysis: a neural–network–based model, *Computers & Operations Research* 30(2): 279–295. http://dx.doi.org/10.1016/S0305-0548(01)00095-8

Wang, S.; Hu, H. 2005. Application of rough set on supplier's determination, in *The Third Annual Conference on Uncertainty.* Springer, 256–262.

Wei, S.; Zhang, J.; Li, Z. 1997. A supplier–selecting system using a neural network, *IEEE, International Conference in Intelligent Processing Systems* 1: 468–471.

Wu, D. D.; Yang, Z.; Liang, L. 2006. Using DEA–neural network approach to evaluate branch efficiency of a large Canadian bank, *Expert Systems with Applications* 31(1): 108–115. http://dx.doi.org/10.1016/j.eswa.2005.09.034

Wu, D. 2009. Supplier selection: a hybrid model using DEA, decision tree and neural network, *Expert Systems with Applications* 36(5): 9105–9112. http://dx.doi.org/10.1016/j.eswa.2008.12.039

Xia, W.; Wu, Z. 2007. Supplier selection with multiple criteria in volume discount environments, *Omega* 35(5): 494–504. http://dx.doi.org/10.1016/j.omega.2005.09.002

Yazdani, M.; Hashemkhani Zolfani, S.; Zavadskas, E. K. 2016. New integration of MCDM methods and QFD in the selection of green suppliers, *Journal of Business Economics and Management 17*(6): 1097–1113. http://dx.doi.org/10.3846/16111699.2016.1165282

Yazdani, M.; Payam, A. F. 2015. A comparative study on material selection of microelectromechanical systems electrostatic actuators using Ashby, VIKOR and TOPSIS, *Materials & Design* 65: 328–334. http://dx.doi.org/10.1016/j.matdes.2014.09.004

Zhao, L.; Wang, L.; Cui, D. W. 2012. Hoeffding bound based evolutionary algorithm for symbolic regression, *Engineering Applications of Artificial Intelligence* 25(5): 945–957. http://dx.doi.org/10.1016/j.engappai.2012.04.005

Alireza FALLAHPOUR is Master, received from Islamic Azad University of Iran in 2010. Now he is research assistant at University of Malaya (UM) and is studying for his doctorate of mechanical engineering at UM, Malaysia. Research interests: supply chain management, intelligent approaches and multiple criteria decision making.

Atefeh AMINDOUST is Doctor at the Islamic Azad University, Najafabad branch, Iran. Her research interests include supply chain management, decision making and fuzzy logic.

Jurgita ANTUCHEVIČIENĖ is Doctor, Professor at the Department of Construction Technology and Management, Vilnius Gediminas Technical University, Vilnius, Lithuania. She is a member of EURO Working Groups Multicriteria Decision Aiding and OR in Sustainable Development and Civil Engineering, Editorial Board member of three international research journals. Her research interests include sustainable development, construction business management and investment, multiple criteria analysis, decision-making theories and decision support systems.

Morteza YAZDANI, is a PhD scholar in business and economic at Universidad Europea de Madrid, Spain. His main research interest is application of multi criteria decision making in different fields of knowledge as material science, supply chain management and also strategic planning. He has published papers in some international journals as *International Journal of Strategic Decision Science, Expert Systems with Applications, Materials & Design, Journal of Civil engineering and management, International Journal of Business* and *Systems Research and International Journal of Logistics Research*.