Iranian Journal of Management Studies (IJMS) *http://ijms.ut.ac.ir/*
Vol. 11, No. 2, Spring 2018 *Print ISSN: 2008-7055*
pp. 209-241 *Online ISSN: 2345-3745*
DOI: *10.22059/ijms.2018.237965.672750*

An Intelligence-Based Model for Supplier Selection Integrating Data Envelopment Analysis and Support Vector Machine

Alireza Fallahpour[1], Nima Kazemi[2*], Mohammad Molani[3], Sina Nayeri[4], Mojtaba Ehsani[1]

1. *Department of Management, Farvardin Institute of Higher Education, Qaemshahr, Mazandaran, Iran*
2. *Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur, Malaysia*
3. *Innovation and Management Research Center, Ayatollah Amoli Branch, Islamic Azad University, Amol, Iran*
4. *Department of Industrial Engineering, Babol Noshirvani University of Technology, Babol, Iran*

(Received: July 17, 2017; Revised: March 30, 2018; Accepted: April 8, 2018)

Abstract

The importance of supplier selection is nowadays highlighted more than ever as companies have realized that efficient supplier selection can significantly improve the performance of their supply chain. In this paper, an integrated model that applies Data Envelopment Analysis (DEA) and Support Vector Machine (SVM) is developed to select efficient suppliers based on their predicted efficiency scores. In the first step, fuzzy linguistic variables are changed to crisp data as initial dataset for DEA. Actual efficiency scores are then calculated for each Decision Making Unit (DMU) using CCR-DEA model. Afterwards, suppliers' performance-related data are used for training SVM-DEA model. A numerical example representing an actual case is provided to indicate the applicability of the model.

Keywords

Supplier selection, support vector machine, data envelopment analysis, supplier efficiency, artificial intelligence.

∗ **Corresponding Author, Email**: nimakzm@gmail.com

Introduction

One of the main objectives of Supply Chain Management (SCM) is to organize and coordinate flow of raw materials and components from different suppliers to manufacturers, aiming at manufacturing the products that meet customers' expectations (Pagell & Wu, 2017; Fallahpour et al., 2017a; Fallahpour et al., 2017b; Panda et al., 2017). Effective SCM strategies can be established by implementing responsible and efficient purchasing and supply rules. A preliminary step in this regard would be to ensure that suppliers are successfully selected (Kumar et al., 2017; Panda et al., 2017). This process is named as Supplier Selection Process (SSP). An appropriate SSP is important for designing and operating SCMs efficiently. A proper SSP may lead to a long-term and close relationship between a purchaser and supplier, which might ensure a successful SCM (Kazemi et al., 2015a; Liu et al., 2018; de Boer & de Boer, 2017). This highlights the fact that in today's competitive market, suppliers have an invaluable influence on the success of manufacturing industries (GüNeri et al., 2011; Kazemi et al., 2014; Gupta & Barua, 2017; Luthra et al., 2017). In order to handle a SSP, decision-makers should employ an appropriate approach and proper criteria for the problem. SSP is known as a typical multi-criteria decision making process, which consists of multiple factors, parameters and conflicting criteria. A widespread interest from both academics and practitioners has recently been given to the SSP (Karsak & Dursun, 2016; Montanari et al., 2017; Zimmer et al., 2016; Keshavarz Ghorabaee et al., 2017; Wetzstein et al., 2016).

Over the years, several methods have been proposed which are summarized in seven main categories as mathematical programming, multiple attribute decision making, fuzzy set theory, intelligent approaches, statistical or probabilistic methodologies, hybrid approaches and other exciting methods (Vahdani et al., 2012). Each category possesses its own specific merits and demerits. The inability of traditional methods to produce a realistic solution in SSP has become a critical concern for managers and experts. As a superior alternative approach, Multi Criteria Decision Makings (MCDMs) are simple methods, although highly dependent on human judgments (PrasannaVenkatesan & Goh, 2016). Mathematical programming encounters significant problems when considering qualitative factors and requires arbitrary aspiration levels (Modak et al., 2016b; Modak et al., 2016a). In addition, it cannot accommodate subjective attributes. Most of the other categories do not consider the interactions among the various factors and also cannot effectively realize risk and uncertainty in determining the supplier's performance (Önüt et al., 2009; He et al., 2017).

Fuzzy set theory, as one of the most widely used techniques for modelling uncertainty, is recognized as an appropriate tool that can simplify decision making process (Shekarian et al., 2017; Kazemi et al., 2016a). Fuzzy set theory has been integrated into various MCDM models to furnish the possibility of describing uncertainty quantitatively (Kazemi et al., 2016b; Chou & Chen, 2017; Kazemi et al., 2015b; Shekarian et al., 2014; Ehsani et al., 2017; De & Mahata, 2017).

On the other hand, it can be seen that DEA, as a non-parametric approach, has been utilized to assess the suppliers' efficiency and ranking (Ignatius et al., 2016). Although DEA determines the efficiency of suppliers, it assumes that collected data accurately reflects all relevant input and output variables that describe the evaluation process. In practice, this is a restrictive assumption given that gathering complete information of all relevant inputs and outputs may not be feasible. Moreover, implementing DEA for large dataset with many inputs and outputs needs huge computer resources in terms of memory and CPU time (Emrouznejad & Shale, 2009; Fallahpour et al., 2016). In order to overcome the mentioned problems, researchers have established integrated models.

In order to overcome the mentioned problems derived from DEA, researchers tried to combine DEA with Artificial Intelligence (AI) to predict the efficiency score and to take the advantages of the strengths of various methods, or complement their weaknesses (Misiunas et al., 2016; Vlahogianni et al., 2016; Modhej et al., 2017; Saberi et al., 2016). AI based models, including artificial and fuzzy neural networks, have widely been utilized in the field of supplier selection (Fallahpour et al., 2017a; Fallahpour et al., 2017b; Kuo et al., 2010). In addition, AI based models have some priorities over other approaches as, for example, they do not need a complicated decision making process. This type of models can tackle complexity and uncertainty of decision making process better since in comparison with MCDM methods, they do not require experts' opinions. The AI methods provide the actual trade-off based on the learning from the experts or cases in the past (Fallahpour et al., 2016).

Despite knowing the merits of integrated algorithm, shortcomings among existing researches make it reasonable to create a selection model based on an intelligent approach in a fuzzy environment. All in all, in this study, an integrated DEA-SVM (Support Vector Machine) model is presented to identify the best supplier for textile mills. To the best of our knowledge, there is not any study that analyzed SSP by using jointly DEA and SVM approaches in textile industry. Hence, this study presents an integrated DEA and AI approaches to demonstrate the advantages of using both DEA and AI approaches in combination. The reminder of the paper is as follows: The second section includes the literature review. Third section will explain the methodology and the proposed model. In Section 4, the implementation of the model, results and discussion are interpreted. Finally, the conclusion is presented in Section 5.

Literature Review

Academic societies and research groups believe that integrated or hybrid supplier selection structures enhance the synergy of the study and improve efficiency of the extracted results (Fallahpour et al., 2017b). Demirtas and Üstün (2008) introduced an integrated multi-objective decision process that used analytical network process to rank suppliers considering tangible and intangible variables. They also developed a Multi-Objective Mixed Integer Linear Programming (MOMILP) to allocate the optimum order quantities to the selected suppliers. Liao and Kao (2011) addressed an integrated Fuzzy

Technique Approach for Order Preference by Similarity to Ideal Solution (F-TOPSIS) and Multi-Choice Goal Programming (MCGP) to solve SSP.

Mokhtari et al. (2013) used fuzzy Delphi, fuzzy Analytical Hierarchy Process (AHP) and fuzzy VIKOR in the supplier selection process in textile industry. The authors aimed to model a highly reliable and acceptable standard for supplier selection in textile mills. Fuzzy Delphi was exploited to derive five essential criteria, while fuzzy AHP and VIKOR were used to weight those criteria and select the best suppliers, respectively. Integration of fuzzy logic and TOPSIS again appeared in Yayla et al. (2012), where the authors selected the appropriate supplier in the garment industry.

Non-parametric approaches like DEA are more flexible and do not assume any functional form. In common, traditional approaches for estimating empirical production functions aimed at measuring the technical efficiency can be divided in two types. Stochastic frontier analysis imposes a parametric model whose parameters can be adjusted through the empirical dataset. This approach draws up a linear piecewise convex production frontier through the efficient decision-making units (DMU) (Santin, 2008). DEA technique aids decision makers in grouping alternatives into efficient and inefficient ones (Wu, 2009). Some researchers have pointed out some close connections between DEA and MCDM (Amin et al., 2006; Azadeh et al., 2008; Tavana et al., 2016b; Mousavi-Nasab & Sotoudeh-Anvari, 2017). Some of them have focused on the similarity between the notion of efficiency in DEA and MCDM, although practically the two approaches are different in measuring efficiency (Opricovic, 2016; Yousefi & Hadi-Vencheh, 2016; Verma & Puri, 2017). In DEA, the efficient frontier is built as the envelope of all the decision-making units included in the sample. Efficiency is measured in relative terms by comparing each unit with the others in the same sample (Ghasemi et al., 2015). But, in MCDM, efficiency is measured in absolute terms. In a MCDM problem, the decision-maker faces a number of constraints which determine the feasible set. Therefore, by exploring the feasible set it is possible to determine what solutions are efficient without any comparison across DMUs (Andre et al., 2010). The usefulness of DEA has been shown in supplier selection area. For instance, Mohammady Garfamy (2006) conducted a DEA approach for supplier selection. Azadeh et al. (2016) developed an integrated approach based on experimental design and computer simulation for supplier selection. The authors applied DEA to assess suppliers based on different criteria in a closed loop supply chain. Recently, there has been an exponential growth in the number of publications related to theory and applications of DEA, and it has attracted supply chain investigators in supplier evaluation and selection programs. Emrouznejad and Yang (2018) presented a comprehensive review on the application of DEA to different fields.

Although DEA has been applied in several studies including supplier selection, there are still some drawbacks which make it infeasible to apply it in some cases. DEA assumes that the collected data accurately reflect all the relevant input and output variables which describe the evaluation process. In practice, this is a restrictive assumption (Oum et al., 2013). However, in DEA the number of inputs and outputs included in the model defines the number of constraints. As the number of constraints increases, the efficiency scores of Decision Making Units (DMUs) will also increase and more suppliers tend to lie on or to be close to the frontier (Hanafizadeh et al., 2014). In order to overcome the limitations associated with homogeneity and accuracy of the assumptions of DEA, AI techniques were introduced recently to assist in estimating the efficiency frontiers for decision makers. It has been demonstrated that AI techniques can assist model developers in finding data envelopes, which are based on the entire dataset rather than on some extreme data points from which uncertain information has been lost (Kanal & Lemmer, 2014).

One of the popular areas of research in supplier selection has been to integrate Artificial Intelligence (AI)-based models and MCDM models in different areas of SSPs. GüNeri et al. (2011) proposed a predictive ANFIS-based model for both criteria selection and performance evaluation of supplier, and proposed the applicability of their model in textile industry. Vahdani et al. (2012) a linear neuro-fuzzy model for supplier assessment in cosmetic industry. The models was developed and implemented in two different stages: Selecting appropriate criteria for assessing the suppliers and then evaluating performance of suppliers using the developed model. Fallahpour et al. (2016) integrated the so called Kourosh and Arash Method (KAM), DEA and Genetic Programming (GP) for a green supplier selection.

Model and Methodology

In the following, the developed model for supplier selection using DEA-SVM will be presented, including three steps. In the first step, by using GMIR method, linguistic variables are changed to crisp data as initial dataset for DEA. In the second step, DEA will be used to classify suppliers into efficient and inefficient groups based on the computed efficiency scores. In the last step, SVM will be applied as a classification or regression module, which presents supplier performance-related information to train AI model and employ the trained predictor to new suppliers. In Step 3, the objective is to address the classification or the regression problem, which involves the development of a relationship between the classes and the criteria. To establish such a functional relationship, it is necessary that the prediction error between the priori efficiency and predicted efficiency values is minimized. In the following sub-sections, three main elements of the developed model will be discussed in detail.

Fuzzy Set Theory

In the real world, there are many qualitative criteria for evaluating suppliers' performance, which usually rely on subjectivity, ambiguity and vagueness. In other words, exact data are insufficient for supplier selection. Fuzzy Set Theory (FST) was introduced by Zadeh (1965) and is a useful approach for measuring qualitative and vague concepts. In this paper, triangular fuzzy numbers were exploited to evaluate the suppliers' performance.

A fuzzy set is defined by means of its membership function $f_{A(x)}$ shown in Figure 1 and based on the following definitions.

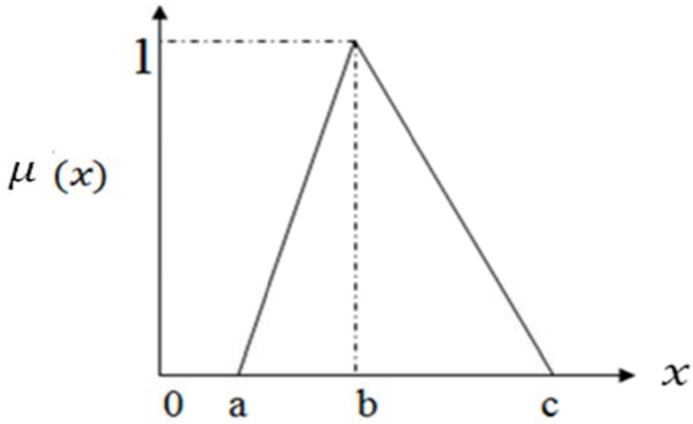

Figure 1. Triangular fuzzy number

Definition 1. Assume $\widetilde{A}$ is a fuzzy set in a universe of discourse X and membership function $\mu_{\widetilde{A}}(x)$ describes it .This function is related to each element x, where x belongs to the interval [0, 1]. The function value $\mu_{\widetilde{A}}(x)$ is termed as the degree of membership of x in $\widetilde{A}$ (Kazemi et al., 2010).

Definition 2. The fuzzy set $\widetilde{A}$ is both normal and convex. By normality, it is meant that:

$$\exists x \in X, \quad \mu_{\widetilde{A}}(X) = 1 \tag{1}$$

And by convex, it is meant that:

$$\forall x_1 \in X, \ \forall x_2 \in X, \ \forall \alpha \in [0,1],$$

$$\mu_{\widetilde{A}}(\alpha x_1 + (1-\alpha)x_2) \geq mi(\mu_{\widetilde{A}}(x_1), \mu_{\widetilde{A}}(x_2)) \tag{2}$$

Definition 3. $\widetilde{A}$ is defined to be a triangular fuzzy number represented by a triplet (a,b,c), where, $a < b < c$. Its membership function is defined as:

$$\begin{cases} 0, & x < a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x > c \end{cases} \tag{3}$$

Fuzzy Scale for Measuring the Importance of Each Criterion

Efficiency is typically calculated by optimizing output over input, which implies that for increasing the efficiency, either the output should increase or the input should decrease (Ozcan, 2008). Table 1 is used for weighting the inputs and outputs. In order to evaluate supplier's performance, decision-makers (experts) assign a linguistic value to each criterion of the suppliers based on their judgment, varying from Very Low (VL) to Very High (VH). Since in DEA (or any model), the outputs affect the efficiency directly, the fuzzy linguistic numbers are assigned to the outputs. On the other hand, the inputs affect the efficiency inversely; therefore, the fuzzy numbers can still be considered from VL to VH, provided that they are assigned a reversed value, that is, (7, 9, 10) and (0, 1, 3) respectively. It should also be noticed that the specific scales for the linguistic judgments depend on the real application systems and the domain of experts' opinions.

Table 1. Fuzzy Linguistic Variables

Linguistic values	Outputs	Inputs
Very low (VL)	(0, 1, 3)	(7, 9, 10)
Low (L)	(1, 3, 5)	(5, 7, 9)
Medium (M)	(3, 5, 7)	(3, 5, 7)
High (H)	(5, 7, 9)	(1, 3, 5)
Very high (VH)	(7, 9, 10)	(0, 1, 3)

DEA

DEA, developed by Charnes et al. (1978), is a mathematical programming approach for evaluating the relative efficiency of homogenous decision-making units with multiple inputs and outputs. DEA is a non-parametric method that calculates efficiency without introducing specific weights for inputs and outputs or specifying a production function. Also, DEA is a leading method for performance analysis in many areas, because it provides a better way to organize and analyze data. It allows efficiency to change over time and requires no prior specification of the best practice frontier. DEA can be used to measure efficiency analysis of alternative suppliers. In supplier selection area, suppliers are assessed on benefit criteria (outputs) and cost criteria (inputs). The efficiency of a supplier is defined as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. In practice there are n suppliers indexed by j, and $j = 1,2,3,...,n$ to be evaluated. The jth supplier (denoted as s_j) has m different inputs (x_{ij}) and s different outputs (y_{rj}). Let the observed input and output vectors of s_j be $X_j = (x_{1j}, x_{2j}, ..., x_{mj})^T \succ 0 \;\; j = 1,2,...,n$ and $Y_j = (y_{1j}, y_{2j}, ..., y_{sj})^T \succ 0 \;\; j = 1,2,...,n$ respectively. Therefore, the relative efficiency of s_j is calculated as:

$$s_j = \frac{\sum_{r=1}^{s} u_r y_{kj}}{\sum_{i=1}^{m} v_i x_{ij}} = \frac{U^T Y_j}{V^T X_j}, \;\; j = 1,2,...,n \tag{4}$$

Where $V = (v_1, v_2, ..., v_m)^T$ and $U = (u_1, u_2, ..., u_s)^T$ are input and output vectors, respectively. The Charnes Cooper Rhodes (CCR)-DEA model can be written as:

$$minimize \qquad \theta - \varepsilon\left(\sum_{i=1}^{m} s_{i^-} + \sum_{r=1}^{s} s_{r^+}\right)$$

subject to

$$0 = \theta x_{i0} - \sum_{j=1}^{n} x_{ij}\lambda_j + s_{i^-} \quad i = 1,2,....,m \quad and \quad y_{r0} = \sum_{j=1}^{n} y_{ij}\lambda_j - s_r^{\ r} \tag{5}$$

$$r = 1,2,...,s \, and \quad 0 \le s_i^{\ -}, s_r^{\ +}, \lambda_j \;\; \forall i, j, r$$

The CCR model assumes Constant Returns to Scale (CRS) for the inputs and outputs. To take into account Variable Returns to Scale (VRS), a model introduced by Banker et al. (1984), with the abbreviation name (BCC-DEA) is utilized. The BCC model aids in determining the efficiency scale of a set of units (which is a technically efficient unit for the VRS model). The BCC-DEA model evaluates whether increasing, constant, or decreasing returns to scale would boost the observed efficiency. In the case of CRS, the output changes proportionately to input, as it also does in the CCR-DEA model. In the case of CRS, a change in the input leads to a disproportional change in the output (da Silva et al., 2017). The efficiency of a specific DMU can be evaluated by BCC model of DEA which is as follows (Banker et al., 2016; da Silva et al., 2017):

$$\textit{minimize} \qquad \theta_0 - \varepsilon\left(\sum_{i=1}^{m} s_{i^-} + \sum_{r=1}^{s} s_{r^+}\right)$$

subject to

$$\theta_0 x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_{i^-} \quad i = 1,2,....,m \quad \textit{and} \quad y_{r0} = \sum_{j=1}^{n} y_{ij}\lambda_j - s_{r^+} \tag{6}$$

$$r = 1,2,...,s \;\; \textit{and} \quad 1 = \sum_{j=1}^{n} \lambda_j \qquad \textit{and} \;\; 0 \le s_{i^-}, s_{r^+}, \lambda_j \;\; \forall i, j, r$$

SVM

SVMs are a group of supervised learning methodologies that can be employed for classification or regression. SVMs illustrate an extension to non-linear models of the generalized portrait algorithm developed by Vapnik in 1995. The SVM algorithm is based on the statistical learning theory and the Vapnik-Chervonenkis dimension introduced by Vladmir and Alexey Chervonenkis (Nurwaha & Wang, 2011). A SVM performs classification by constructing an N-dimension hyper-plane that optimally separates data into two categories.

SVM models are closely related to neural networks. Using a kernel function, SVM is an alternative training method for polynomial, radial basis function and multi-layer perceptron classifiers in which the weights of the network are obtained by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard NN training (Lee & To, 2010).

The optimal plane classifier uses only dot products between vectors in input space. So, the goal of SVM modeling is to find the optimal hyper-plane that separates clusters of vector in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other side of the plane (Rejani & Selvi, 2009). The vectors near the hyper-plane are the support vectors. The hyper-plane can be constructed by solving a convex optimization problem that minimizes a quadratic function under linear inequality constraints. The optimization problem employed to get the optimal hyper-plane and the decision function used for the actual classification of vectors can be expressed in dual form which depends only on dot products between vectors. The dual representation of the decision function is:

$$f(X) = sgn\left[\sum_{i=1}^{l} Y_i \alpha_i \prec X.X_{i \succ + b}\right] \tag{7}$$

Where $\alpha_i \in R$ is a real-valued variable that can be considered as a measure of how much information all value X_i has. Thus, for vectors that do not lie on the margin, this value will be zero. The optimal hyper-plane classifier uses only dot products vectors in input space. In feature space, this will be translated to $\prec \phi(X), \succ \phi(X)$. A kernel function $K(X, X')$, which gives two vectors in input and returns the dot product of their images in feature space, is given by:

$$K(X, X') = \prec \phi(X), \phi(X') \succ \tag{8}$$

With the help of the decision function for the optimal hyper-plane classifier in dual form and applying the mapping ϕ to each vector, we get:

$$f(x) = sgn\left[\sum_{i=1}^{l} Y_i \alpha_i \prec \phi(X).\phi(X_i) \succ + b\right] \tag{9}$$

We will use kernels which will give a non-linear decision function of the form:

$$f(X) = sgn\left[\sum_{i=1}^{l} Y_i \alpha_i K(X, X_i) + b\right] \tag{10}$$

The SVM algorithm is based on statistical learning theory, which is practical since it reduces optimization problem with a unique solution. A generalization to regression that is having $y \in R$ can be given. In this case, the algorithm tries to build a linear function in the feature space such that the training point lies at a distance of $\varepsilon \succ 0$. Similar to the pattern-recognition case, this can be written as a quadratic programming problem in terms of kernels. The kernel approach is employed to address the curse of dimensionality. The support vector regression solution, using an ε insensitive loss function, is given by:

$$maxW(\alpha,\alpha^*)max\sum_{i=1}^{l}\alpha_i^*(y_i-\varepsilon)-\alpha_i(y_i+\varepsilon)-1/2\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i^*-\alpha_i)(\alpha_j^*-\alpha_j)K(X_i,X_j) \quad (11)$$

With constraints: $0 \le \alpha_i, \alpha_i^* \ge C, i = 1,....,l.$ α_i *and* α_i^* are the Lagrange multipliers.

$$\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0 \quad (12)$$

The regression equation is given by:

$$f(X)=\sum_{SVs}\alpha_i^- -\alpha_l^-)K(X,X_i)+b^- \quad (13)$$

where

$$\prec w^-,X \succ = \sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(X,X_i) \quad (14)$$

and

$$b^- = 1/2\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(X_i,X_r)+K(X_i,X_s) \quad (15)$$

The equality constraint may be dropped if the kernel contains a bias term, b being accommodated with the kernel functions; in that case, the regression function is given by:

$$f(X)=\sum_{i=1}^{l}(\alpha_i^- -\alpha_i^{*-})K(X,X_i) \quad (16)$$

The quadratic loss function produces a solution which is equivalent to a ridge regression, zero order. Regularization parameter is $\lambda = 1/2C$ where λ and C are optimization parameters (Ghosh & Chatterjee, 2010). Kernel functions can have various forms such as polynomial, Gaussian radial basis, exponential radial basis which have the following forms (Geng et al., 2016):

$$Polynomial\,kernel:\ K(x,z) = \prec x,z \succ^{p} \tag{17}$$

$$Gaussian\ radial\ basis\ kernel:\ K(x,z) = e^{\left[-\frac{|x-z|^2}{2\sigma^2}\right]} \tag{18}$$

$$Exponential\ radial\ basis\ kernel:\ K(x,z) = e^{\left[-\frac{|x-z|}{2\sigma^2}\right]} \tag{19}$$

Where p in equation specifies the degree of polynomial kernel and σ indicates the width of the kernels.

The Developed Integrated DEA-SVM Model under Fuzzy Environment

Figure 2 depicts the conceptual model for supplier selection using DEA and SVM. The hybrid model can function as both classification and regression models, including three modules. In Module 1, by using GMIR method, linguistic variables are changed to crisp data as initial dataset for DEA. Module 2 uses DEA and sorts suppliers into efficient and inefficient groups based on the computed efficiency scores. Module 3 is a classification or regression module based on the AI-based models and presents the supplier performance-related information to train the AI model and employs the trained predictor on new suppliers. In Module 3, the objective is to address the classification or the regression problem, which involves the development of a relationship between the classes and the criteria. To establish such a functional relationship, it is necessary that the prediction error between the previous efficiency and predicted efficiency values is minimized.

Results and Discussion

Data collection and DEA Inputs–Outputs

Data used in this study have been collected from a spinning and weaving factory located in Iran. Production of this company is cotton and cotton-polyester blended spun yarn. This firm has more than 600 employees and a monthly production capacity of 150,000 kilograms of yarn and 120,000 meters of woven fabric, respectively. Commercial manager was selected as the expert to consult about the suppliers' performance and criteria for supplier selection. The selected expert has a PhD degree in fiber spinning, and totally has more than 15 years of experience in the textile industry.

The first step in the assessment of the suppliers' performance involves defining the evaluation criteria. In this study, based on the literature and the expert's opinion, six criteria were selected and applied to the garment company. The criteria were Quality of the Material (QM), Cost (C), Delivery (D), Service (S), Flexibility (F) and Customer satisfaction (Cs). In terms of DEA, S, D and QM are outputs and C, F and Cs are inputs. Table 2 defines each criterion. The expert was asked to deliver his judgment related to all the suppliers' criteria using fuzzy linguistic variables, due to imperfect information and uncertainty affecting the assessment. His evaluation over the selected criteria in linguistic preferences is shown in Table 3.

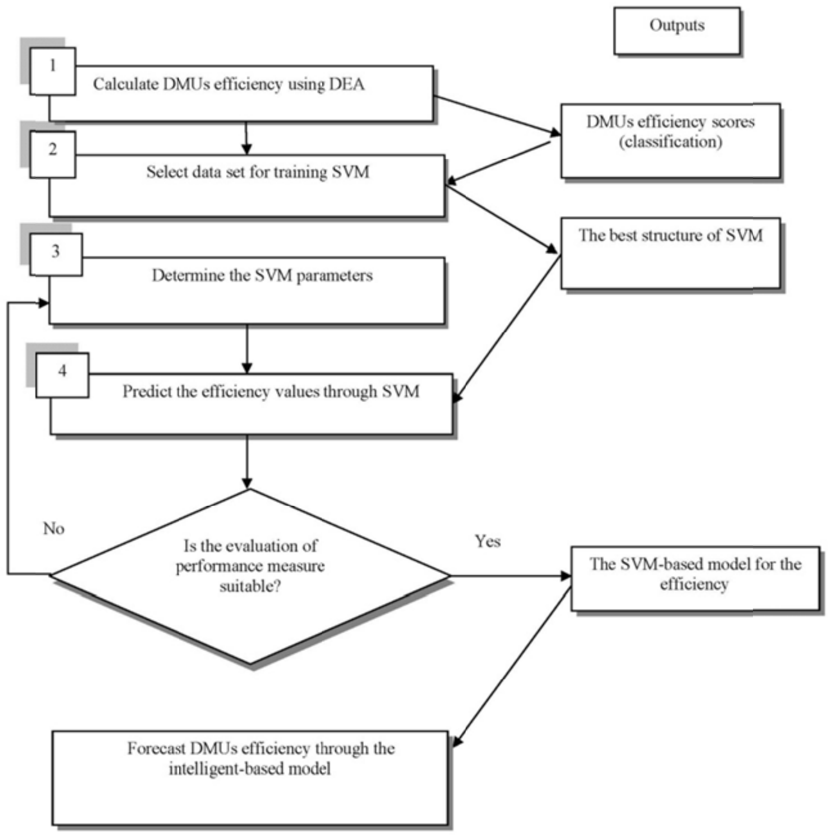

Figure 2. The hybrid model for supplier selection

Table 2. Selection Criteria for Evaluating the Suppliers' Performance (Çelebi & Bayraktar, 2008; Lima et al., 2013; Mukherjee, 2016)

Criteria	Definition
Quality of Material (QM)	The ability of supplied materials to meet or exceed purchasers' expectations. In order to evaluate this criterion, quality certification and standards are very important. This attribute has positive impact on the suppliers' efficiency: with QM increasing, the suppliers' efficiency increases too.
Service (S)	This refers to the after sales responsibility borne by the supplier and the motivation to share skills for problem solving. It also looks at the efficiency of scheduling and ability to handle changing orders. This attribute affects directly the supplier's efficiency.
Delivery (D)	This looks at the on-time delivery. As the performance against this criterion increases, supplier's profile is better.
Flexibility (F)	This factor shows the level of the flexibility of supplier in supplying material, price of the supplied material, etc.
Cost (C)	This covers the final cost of the goods purchased, the ordering cost (the cost of preparing a purchase order and cost of receiving the goods ordered) and the transportation cost. A supplier is termed as "more efficient" if its total cost is lower than that of the competing suppliers.
Customer satisfaction (Cs)	The level of satisfaction of the customer.

Table 3. Assessment Result of Suppliers with Respect to the Defined Criteria

Criteria	Input for DEA model			Output for DEA model			
Supplier	Material quality	Transportation cost	Material price	Delivery time	Flexibility	Satisfaction	Revenue
S1	(7,9,10)	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)
S2	(1,3,5)	(7,9,10)	(3,5,7)	(7,9,10)	(7,9,10)	(3,5,7)	(3,5,7)
S3	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)
S4	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)
S5	(3,5,7)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
S6	(0,1,3)	(5,7,9)	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)	(3,5,7)
S7	(0,1,3)	(5,7,9)	(1,3,5)	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)
S8	(0,1,3)	(5,7,9)	(1,3,5)	(7,9,10)	(7,9,10)	(5,7,9)	(7,9,10)
S9	(3,5,7)	(5,7,9)	(3,5,7)	(1,3,5)	(3,5,7)	(7,9,10)	(7,9,10)
S10	(0,1,3)	(0,1,3)	(3,5,7)	(7,9,10)	(3,5,7)	(5,7,9)	(1,3,5)
S11	(3,5,7)	(5,7,9)	(1,3,5)	(7,9,10)	(7,9,10)	(3,5,7)	(3,5,7)
S12	(3,5,7)	(7,9,10)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,10)
S13	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
S14	(0,1,3)	(5,7,9)	(3,5,7)	(1,3,5)	(3,5,7)	(7,9,10)	(5,7,9)
S15	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)	(5,7,9)	(7,9,10)	(7,9,10)
S16	(5,7,9)	(7,9,10)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,10)
S17	(1,3,5)	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
S18	(1,3,5)	(5,7,9)	(7,9,10)	(3,5,7)	(3,5,7)	(7,9,10)	(3,5,7)
S19	(5,7,9)	(0,1,3)	(3,5,7)	(1,3,5)	(0,1,3)	(1,3,5)	(1,3,5)
S20	(3,5,7)	(3,5,7)	(7,9,10)	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)
S21	(3,5,7)	(7,9,10)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)
S22	(1,3,5)	(5,7,9)	(7,9,10)	(3,5,7)	(7,9,10)	(5,7,9)	(3,5,7)
S23	(3,5,7)	(0,1,3)	(7,9,10)	(0,1,3)	(1,3,5)	(5,7,9)	(1,3,5)
S24	(7,9,10)	(5,7,9)	(3,5,7)	(7,9,10)	(1,3,5)	(5,7,9)	(7,9,10)
S25	(5,7,9)	(1,3,5)	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,10)	(5,7,9)
S26	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)
S27	(7,9,10)	(0,1,3)	(7,9,10)	(7,9,10)	(3,5,7)	(7,9,10)	(3,5,7)
S28	(7,9,10)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)	(3,5,7)	(7,9,10)

Criteria	Input for DEA model			Output for DEA model			
Supplier	Material quality	Transportation cost	Material price	Delivery time	Flexibility	Satisfaction	Revenue
S29	(5,7,9)	(3,5,7)	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(7,9,10)
S30	(7,9,10)	(3,5,7)	(5,7,9)	(1,3,5)	(7,9,10)	(3,5,7)	(5,7,9)
S31	(5,7,9)	(5,7,9)	(1,3,5)	(0,1,3)	(5,7,9)	(1,3,5)	(3,5,7)
S32	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)
S33	(3,5,7)	(3,5,7)	(1,3,5)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)
S34	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)
S35	(5,7,9)	(0,1,3)	(5,7,9)	(7,9,10)	(7,9,10)	(5,7,9)	(7,9,10)
S36	(1,3,5)	(7,9,10)	(1,3,5)	(5,7,9)	(5,7,9)	(7,9,10)	(1,3,5)
S37	(5,7,9)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,10)
S38	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(7,9,10)	(7,9,10)	(3,5,7)
S39	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)	(7,9,10)
S40	(5,7,9)	(5,7,9)	(7,9,10)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)
S41	(1,3,5)	(7,9,10)	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(5,7,9)
S42	(0,1,3)	(3,5,7)	(7,9,10)	(1,3,5)	(7,9,10)	(7,9,10)	(1,3,5)
S43	(0,1,3)	(7,9,10)	(7,9,10)	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)
S44	(7,9,10)	(3,5,7)	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)
S45	(5,7,9)	(7,9,10)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
S46	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)
S47	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
S48	(7,9,10)	(3,5,7)	(5,7,9)	(7,9,10)	(0,1,3)	(7,9,10)	(7,9,10)

In supplier selection problems, all criteria are evaluated by linguistic judgements received from experts. However, it is easier for decision experts to use crisp values instead of fuzzy ones. After receiving the expert’s opinion in terms of linguistic variables for each criterion, the fuzzy numbers were converted into crisp values through a defuzzification rule as Table 4 shows. In this work, defuzzification is applied with GMIR of the triangular fuzzy numbers, introduced by Chen and Hsieh (1999) for three input and four output criteria. Chen and Hsieh (1999) proved that GMIR of triangular fuzzy numbers $\widehat{A}(a_1, a_2, a_3)$ becomes (Chen & Hsieh, 1999):

$$\partial\widehat{\mathrm{A}} = \frac{(\mathrm{a} + 4\mathrm{b} + \mathrm{c})}{6} \tag{20}$$

Thereafter, expert’s judgment is arranged based on Table 4 and crisp values were used for DEA efficiency measurement. The linguistic variables in Table 4 were also used for the importance of each criterion and their relevant triangular fuzzy numbers.

Table 4. Linguistic Variables for the Importance Weight of Each Criterion and Their Relevant Fuzzy Numbers and Crisp Values (Awasthi & Kannan, 2016)

Linguistic variables	Triangular fuzzy numbers	Crisp values
Very Bad	(0,1,3)	1.167
Bad	(1,3,5)	3.000
Fair	(3,5,7)	5.000
Good	(5,7,9)	7.000
Very Good	(7,9,10)	8.333

Calculating Suppliers' Efficiency

In the CCR model, each DMU designs its own optimal weights and achieves its best efficiency (Zuo & Guan, 2017; Kwon, 2017; Paradi et al., 2018; Hosseinzadeh-Bandbafha et al., 2018). In DEA, CCR model is believed to be more powerful than BCC model (Sarkar & Sarkar, 2017; Liu & Lim, 2017; Azadi et al., 2017; Yoon et al., 2017; Jauhar & Pant, 2017). In this paper, efficiency scores of the suppliers were calculated according to CCR-DEA model using LINGO (13.0 X64) software. Table 5 shows efficiency scores calculated for the suppliers. It is necessary to note that the efficiency scores of only 12 suppliers are provided in the table due to space limitation.

Table 5. Efficiency Score Calculated by CCR-DEA for Each Supplier

Supplier	CCR-DEA	Supplier	CCR-DEA	Supplier	CCR-DEA	Supplier	CCR-DEA
S1	0.784	S13	0.975	S25	0.734	S37	0.884
S2	0.984	S14	1.000	S26	0.611	S38	0.575
S3	0.588	S15	0.671	S27	0.953	S39	0.865
S4	0.788	S16	0.938	S28	0.881	S40	0.537
S5	0.734	S17	0.911	S29	0.842	S41	0.739
S6	0.444	S18	0.868	S30	0.709	S42	0.778
S7	0.857	S19	0.976	S31	0.769	S43	0.937
S8	0.794	S20	1.000	S32	0.619	S44	0.691
S9	0.846	S21	0.941	S33	0.800	S45	1.000
S10	0.810	S22	0.822	S34	0.565	S46	0.774
S11	0.956	S23	1.000	S35	0.810	S47	0.850
S12	0.933	S24	0.867	S36	0.703	S48	0.913

Estimating the Suppliers' Efficiency

At this stage, the crisp values of the determined criteria (obtained from Table 4) and the efficiency scores related to the efficiency (Table 5) are considered as independent and dependent variables, respectively, for estimating the suppliers' efficiency using SVM. To develop the intelligent-based model, 75% of the dataset is selected for training the SVM-model and the remaining 25% of the dataset is used for testing the model (Mousavi et al., 2014; Tavana et al., 2016a; Armaghaniet al., 2017a; Shirazi & Mohammadi, 2017; Karkevandi-Talkhooncheh et al., 2017). There is no exact rule to find the best structure for the AI-based models, and this is always a trial and error process (Sgurev et al., 2017; Armaghani et al., 2017b; Zhou & Yao, 2017; Yu et al., 2017; Kaboli et al., 2016 ; Raut et al., 2017; Raut et al., 2017). To find the best SVM model, different structures are examined, specified in Table 6. In case of SVM model, all the Radial Basis Function (RBF), polynomial, sigmoid and linear kernel functions were used to map the data (Xu et al., 2016; Wan et al., 2016; Cao & Zhang, 2016). The penalty term (C) and regularization factor (γ) are optimized on trial and error basis (Vahdani et al., 2016; Pan et al., 2017). For developing the SVM model, the DTREG software is used. It is worth noting that the average statistical metrics namely Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are employed to evaluate the accuracy of the proposed model. These metrics are defined by:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - \hat{P_i}\right| \qquad MSE = \frac{1}{N}\sum^{N}(P_i - \hat{P_i})^2 \qquad RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \hat{P_i})^2} \tag{21}$$

The mean square errors of testing and training data were measured by presenting them to the trained network. Then, the average of these statistical merits of testing subsets was considered to compare the models. Table 6 shows the results of training processes for the optimal developed model.

Table 6. Performance and Characteristics of SVM-DEA with the Best Architecture on Training and Testing Data

Model	(C and γ)	Training function	Training data			Testing data		
			MAE	MSE	RMSE	MAE	MSE	RMSE
SVM-DEA	(12670,0.026)	sigmoid	0.037	0.003	0.060	0.051	0.004	0.068
	(12670,0)	linear	0.13	0.013	0.001	0.074	0.062	0.250
	(11026,0.0421)	Polynomial	0.010	0.009	0.098	0.046	0.006	0.080
	(10489,0.0749)	RBF	0.104	0.018	0.137	0.461	0.36	0.190

As can be seen, the SVM model with polynomial training function and C=11026 and γ=0.0421 is the best model in both training and testing. Figure 3 (a and b) shows the accuracy of the model in comparison with the real efficiency.

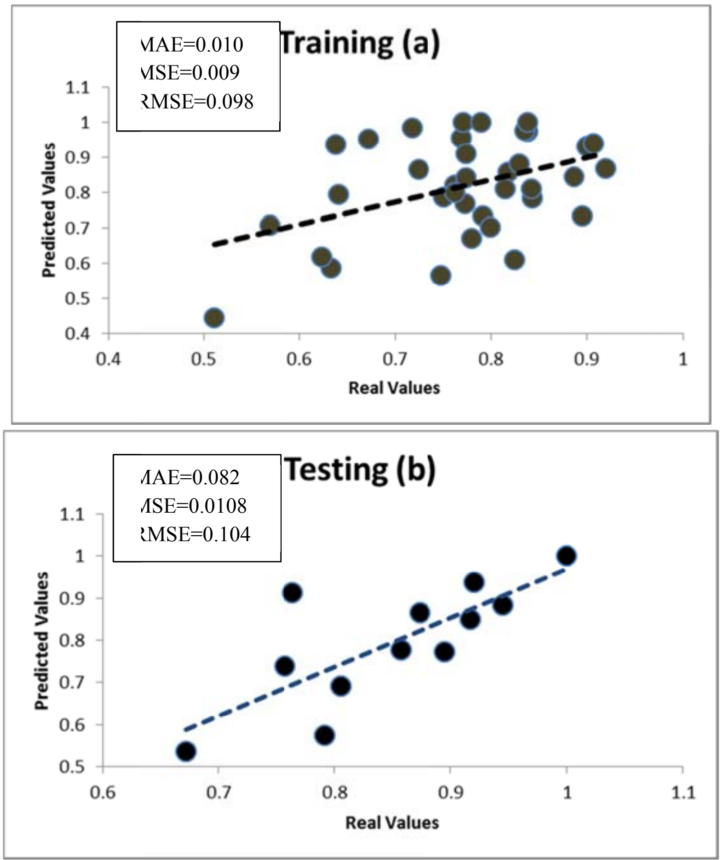

Figure 3. The training and testing results

Furthermore, the obtained results of average MSE, RMSE and MAE of six subsets of testing data are provided in Table 7. As it can be seen from the table, the performance of SVM-DEA model is satisfactory.

Table 7. Performance of SVM-DEA Architecture with the Best Architecture on Training and Testing Datasets

Data set	SVM-DEA model					
	Training data			Testing data		
	MSE	RMSE	MAE	MSE	RMSE	MAE
1	0.017	0.132	0.100	0.001	0.037	0.030
2	0.012	0.108	0.078	0.034	0.185	0.160
3	0.091	0.124	0.091	0.102	0.015	0.123
4	0.012	0.110	0.084	0.031	0.177	0.137
5	0.017	0.132	0.099	0.031	0.177	0.137
6	0.012	0.113	0.084	0.001	0.037	0.302
Ave	0.027	0.120	0.089	0.033	0.105	0.148

Conclusion

In this study, a new integrated model was developed to help in selecting efficient suppliers in textile industry by using DEA and SVM as an AI-based methodology. This model can function as both a classification model and a regression model. To make the decision making process more easier, linguistic scores received from experts were transformed to crisp values by using the GMIR method of the triangular fuzzy numbers. Then, an efficiency score (CCR-DEA) was calculated for each decision making unit using DEA, which performed as a new output for AI-based model. Then, SVM was utilized to execute decision making process for supply chain as a powerful and accurate tool in estimation function. Finally, the developed model was applied for estimating the suppliers' efficiency. The finding illustrates that the developed DEA-SVM is a robust and powerful tool for predicting the efficiency of suppliers, and can be used as a tool for supplier selection process.

There are several opportunities to extend this study in the future. The emphasize of the recent studies has been on sustainable SSP using economic, environmental and social attributes (Malviya & Kant, 2015; Dubey et al., 2017; Johnsen et al., 2017). So, using sustainability criteria is recommended for suppliers' performance evaluation and selection, which can be considered as an immediate extension of this study. Another room for future research that would be of interest is using other AI-based techniques such as Simulated Annealing, Gene Expression Programming, and ANFIS, allowing to compare the result of other methods with the ones of this study. Furthermore, future studies can take into account the relationships among criteria and develop the current models based on the interdependencies among the criteria.

References

Amin, G. R., Toloo, M., & Sohrabi, B. (2006). An improved MCDM DEA model for technology selection. *International Journal of Production Research, 44*(13), 2681-2686.

Andre, F. J., Herrero, I., & Riesgo, L. (2010). A modified DEA model to estimate the importance of objectives with an application to agricultural economics. *Omega, 38*(5), 371-382.

Armaghani, D. J., Mohamad, E. T., Narayanasamy, M. S., Narita, N., & Yagiz, S. (2017a). Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition. *Tunnelling and Underground Space Technology, 63*, 29-43.

Armaghani, D. J., Raja, R. S. N. S. B., Faizi, K., & Rashid, A. S. A. (2017b). Developing a hybrid PSO–ANN model for estimating the ultimate bearing capacity of rock-socketed piles. *Neural Computing and Applications, 28*(2), 391-405.

Awasthi, A., & Kannan, G. (2016). Green supplier development program selection using NGT and VIKOR under fuzzy environment. *Computers & Industrial Engineering, 91*, 100-108.

Azadeh, A., Ghaderi, S., & Izadbakhsh, H. (2008). Integration of DEA and AHP with computer simulation for railway system improvement and optimization. *Applied Mathematics and Computation, 195*(2), 775-785.

Azadeh, A., Zarrin, M., & Salehi, N. (2016). Supplier selection in closed loop supply chain by an integrated simulation-Taguchi-DEA approach. *Journal of Enterprise Information Management, 29*(3), 302-326.

Azadi, M., Mirhedayatian, S. M., Saen, R. F., Hatamzad, M., & Momeni, E. (2017). Green supplier selection: a novel fuzzy double frontier data envelopment analysis model to deal with undesirable outputs and dual-role factors. *International Journal of Industrial and Systems Engineering, 25*(2), 160-181.

Banker, R., Chen, J. Y., & Klumpes, P. (2016). A trade-level DEA model to evaluate relative performance of investment fund managers. *European Journal of Operational Research, 255*(3), 903-910.

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.

Cao, W., & Zhang, X. (2016). Supply chain risk assessment based on support vector machine. *RISTI (Revista Iberica de Sistemas e Tecnologias de Informacao),* (E5), 310-323.

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.

Chen, S. H., & Hsieh, C. H. (1999). Optimization of fuzzy simple inventory models. Proceedings from F*UZZ-IEEE'99: IEEE International Conference of the Fuzzy Systems.*

Chou, S., & Chen, C.-W. (2017). Supply chain coordination: an inventory model for single-period utility product under fuzzy demand. *The International Journal of Advanced Manufacturing Technology, 88*(1-4), 585-594.

Da Silva, A. F., Marins, F. A. S., Tamura, P. M., & Dias, E. X. (2017). Bi-Objective Multiple criteria data envelopment analysis combined with the overall equipment effectiveness: An application in an automotive company. *Journal of Cleaner Production, 157*, 278-288.

De Boer, L., & de Boer, L. (2017). Procedural rationality in supplier selection: Outlining three heuristics for choosing selection criteria. *Management Decision, 55*(1), 32-56.

De, S. K., & Mahata, G. C. (2017). Decision of a fuzzy inventory with fuzzy backorder model under cloudy fuzzy demand rate. *International Journal of Applied and Computational Mathematics, 3*(3), 2593-2609.

Demirtas, E. A., & Üstün, Ö. (2008). An integrated multiobjective decision making process for supplier selection and order allocation. *Omega, 36*(1), 76-90.

Dubey, R., Gunasekaran, A., Papadopoulos, T., Childe, S. J., Shibin, K., & Wamba, S. F. (2017). Sustainable supply chain management: Framework and further research directions. *Journal of Cleaner Production, 142*, 1119-1130.

Ehsani, E., Kazemi, N., Olugu, E. U., Grosse, E. H., & Schwindl, K. (2017). Applying fuzzy multi-objective linear programming to a project management decision with nonlinear fuzzy membership functions. *Neural Computing and Applications*, 28(8), 2193–2206.

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.

Emrouznejad, A., & Yang, G.-l. (2017). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*.

Fallahpour, A., Amindoust, A., Antuchevičienė, J., & Yazdani, M. (2016). Nonlinear genetic-based model for supplier selection: a comparative study. *Technological and Economic Development of Economy*, 23(1), 178-195.

Fallahpour, A., Amindoust, A., Antuchevičienė, J., & Yazdani, M. (2017a). Nonlinear genetic-based model for supplier selection: a comparative study. *Technological and Economic Development of Economy, 23*(1), 178-195.

Fallahpour, A., Olugu, E. U., & Musa, S. N. (2017b). A hybrid model for supplier selection: integration of AHP and multi expression programming (MEP). *Neural Computing and Applications, 28*(3), 499-504.

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.

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.

Fallahpour, A., Olugu, E. U., Musa, S. N., Wong, K. Y., & Noori, S.

(2017). A decision support model for sustainable supplier selection in sustainable supply chain management. *Computers & Industrial Engineering, 105*, 391-410.

Geng, Y., Chen, J., Fu, R., Bao, G., & Pahlavan, K. (2016). Enlighten wearable physiological monitoring systems: On-body rf characteristics based human motion classification using a support vector machine. *IEEE Transactions on Mobile Computing, 15*(3), 656-671.

Ghasemi, M.-R., Ignatius, J., Lozano, S., Emrouznejad, A., & Hatami-Marbini, A. (2015). A fuzzy expected value approach under generalized data envelopment analysis. *Knowledge-Based Systems, 89*, 148-159.

Ghosh, A., & Chatterjee, P. (2010). Prediction of cotton yarn properties using support vector machine. *Fibers and Polymers, 11*(1), 84-88.

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.

Gupta, H., & Barua, M. K. (2017). Supplier selection among SMEs on the basis of their green innovation ability using BWM and fuzzy TOPSIS. *Journal of Cleaner Production, 152*, 242-258.

Hanafizadeh, P., Khedmatgozar, H. R., Emrouznejad, A., & Derakhshan, M. (2014). Neural network DEA for measuring the efficiency of mutual funds. *International Journal of Applied Decision Sciences, 7*(3), 255-269.

He, J., Ma, C., & Pan, K. (2017). Capacity investment in supply chain with risk averse supplier under risk diversification contract. *Transportation Research Part E: Logistics and Transportation Review, 106*, 255-275.

Hosseinzadeh-Bandbafha, H., Nabavi-Pelesaraei, A., Khanali, M., Ghahderijani, M., & Chau, K.-W. (2018). Application of data envelopment analysis approach for optimization of energy use and reduction of greenhouse gas emission in peanut production of Iran. *Journal of Cleaner Production*, 172, 1327-1335.

Ignatius, J., Ghasemi, M.-R., Zhang, F., Emrouznejad, A., & Hatami-Marbini, A. (2016). Carbon efficiency evaluation: An analytical framework using fuzzy DEA. *European Journal of Operational Research*, 253(2), 428-440.

Jauhar, S. K., & Pant, M. (2017). Integrating DEA with DE and MODE for sustainable supplier selection. *Journal of Computational Science*, 21, 299-306.

Johnsen, T. E., Miemczyk, J., & Howard, M. (2017). A systematic literature review of sustainable purchasing and supply research: Theoretical perspectives and opportunities for IMP-based research. *Industrial Marketing Management, 61*, 130-143.

Kaboli, S. H. A., Fallahpour, A., Kazemi, N., Selvaraj, J., & Rahim, N. (2016). An expression-driven approach for long-term electric power consumption forecasting, American Journal of Data Mining and Knowledge Discovery, 1(1), 16-28.

Kanal, L. N., & Lemmer, J. F. (2014). *Uncertainty in artificial intelligence* (Vol. 4). Elsevier.

Karkevandi-Talkhooncheh, A., Hajirezaie, S., Hemmati-Sarapardeh, A., Husein, M. M., Karan, K., & Sharifi, M. (2017). Application of adaptive neuro fuzzy interface system optimized with evolutionary algorithms for modeling CO 2-crude oil minimum miscibility pressure. *Fuel, 205*, 34-45.

Karsak, E. E., & Dursun, M. (2016). Taxonomy and review of non-deterministic analytical methods for supplier selection. *International Journal of Computer Integrated Manufacturing, 29*(3), 263-286.

Kazemi, N., Abdul-Rashid, S. H., Shekarian, E., Bottani, E., & Montanari, R. (2016a). A fuzzy lot-sizing problem with two-stage composite human learning. *International Journal of Production Research, 54*(16), 5010-5025.

Kazemi, N., Ehsani, E., & Glock, C. H. (2014). Multi-objective supplier selection and order allocation under quantity discounts with fuzzy goals and fuzzy constraints. *International Journal of Applied Decision Sciences, 7*(1), 66-96.

Kazemi, N., Ehsani, E., Glock, C. H., & Schwindl, K. (2015a). A mathematical programming model for a multi-objective supplier selection and order allocation problem with fuzzy objectives.

International Journal of Services and Operations Management, 21(4), 435-465.

Kazemi, N., Ehsani, E., & Jaber, M. (2010). An inventory model with backorders with fuzzy parameters and decision variables. *International Journal of Approximate Reasoning, 51*(8), 964-972.

Kazemi, N., Olugu, E. U., Abdul-Rashid, S. H., & Ghazilla, R. A. B. R. (2015b). Development of a fuzzy economic order quantity model for imperfect quality items using the learning effect on fuzzy parameters. *Journal of Intelligent & Fuzzy Systems, 28*(5), 2377-2389.

Kazemi, N., Olugu, E. U., Abdul-Rashid, S. H., & Ghazilla, R. A. R. (2016b). A fuzzy EOQ model with backorders and forgetting effect on fuzzy parameters: An empirical study. *Computers & Industrial Engineering, 96*, 140-148.

Keshavarz Ghorabaee, M., Amiri, M., Zavadskas, E. K., & Antucheviciene, J. (2017). Supplier evaluation and selection in fuzzy environments: A review of MADM approaches. *Economic Research-Ekonomska Istraživanja, 30*(1), 1073-1118.

Kumar, D., Rahman, Z., & Chan, F. T. (2017). A fuzzy AHP and fuzzy multi-objective linear programming model for order allocation in a sustainable supply chain: A case study. *International Journal of Computer Integrated Manufacturing, 30*(6), 535-551.

Kuo, R., Wang, Y., & Tien, F. (2010). Integration of artificial neural network and MADA methods for green supplier selection. *Journal of Cleaner Production, 18*(12), 1161-1170.

Kwon, H.-B. (2017). Exploring the predictive potential of artificial neural networks in conjunction with DEA in railroad performance modeling. *International Journal of Production Economics, 183*, 159-170.

Lee, M.-C., & To, C. (2010). Comparison of support vector machine and back propagation neural network in evaluating the enterprise financial distress. *International Journal of Artificial Intelligence & Applications (IJAIA), 1*(3), 1007-5133.

Liao, C.-N., & Kao, H.-P. (2011). An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management. *Expert Systems with Applications, 38*(9), 10803-10811.

Lima, F. R., Osiro, L., & Carpinetti, L. C. R. (2013). A fuzzy inference and categorization approach for supplier selection using compensatory and non-compensatory decision rules. *Applied Soft Computing, 13*(10), 4133-4147.

Liu, Q., & Lim, S. H. (2017). Toxic air pollution and container port efficiency in the USA. *Maritime Economics & Logistics, 19*(1), 94-105.

Liu, T., Deng, Y., & Chan, F. (2017). Evidential supplier selection based on DEMATEL and game theory. *International Journal of Fuzzy Systems*, 20(4), 1321-1333.

Luthra, S., Govindan, K., Kannan, D., Mangla, S. K., & Garg, C. P. (2017). An integrated framework for sustainable supplier selection and evaluation in supply chains. *Journal of Cleaner Production, 140*, 1686-1698.

Malviya, R. K., & Kant, R. (2015). Green supply chain management (GSCM): A structured literature review and research implications. *Benchmarking: An International Journal, 22*(7), 1360-1394.

Misiunas, N., Oztekin, A., Chen, Y., & Chandra, K. (2016). DEANN: A healthcare analytic methodology of data envelopment analysis and artificial neural networks for the prediction of organ recipient functional status. *Omega, 58*, 46-54.

Modak, N. M., Panda, S., & Sana, S. S. (2016a). Pricing policy and coordination for a two-layer supply chain of duopolistic retailers and socially responsible manufacturer. *International Journal of Logistics Research and Applications, 19*(6), 487-508.

Modak, N. M., Panda, S., & Sana, S. S. (2016b). Two-echelon supply chain coordination among manufacturer and duopolies retailers with recycling facility. *The International Journal of Advanced Manufacturing Technology, 87*(5-8), 1531-1546.

Modhej, D., Sanei, M., Shoja, N., & Hosseinzadeh Lotfi, F. (2017). Integrating inverse data envelopment analysis and neural network to preserve relative efficiency values. *Journal of Intelligent &*

Fuzzy Systems(Preprint), 1-12, Journal of Intelligent & Fuzzy Systems, 32(6), 4047-4058.

Mohammady Garfamy, R. (2006). A data envelopment analysis approach based on total cost of ownership for supplier selection. *Journal of Enterprise Information Management, 19*(6), 662-678.

Mokhtari, M., Javanshir, H., Kamali, D., Tashakori, L., & Maadanchi, F. (2013). Supplier selection in texture industry by using fuzzy MIDM. *Research Journal of Applied Sciences, Engineering and Technology, 6*(3), 400-411.

Montanari, R., Bottani, E., Shekarian, E., & Kazemi, N. (2017). A model for the analysis of procurement strategies in the economic order interval environment. *Mathematics and Computers in Simulation, 134*, 79-98.

Mousavi-Nasab, S. H., & Sotoudeh-Anvari, A. (2017). A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems. *Materials & Design, 121*, 237-253.

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.

Mukherjee, K. (2016). Supplier selection criteria and methods: past, present and future. *International Journal of Operational Research, 27*(1-2), 356-373.

Nurwaha, D., & Wang, X. (2011). Prediction of rotor spun yarn strength using support vector machines method. *Fibers and Polymers, 12*(4), 546-549.

Önüt, S., Kara, S. S., & Işik, E. (2009). Long term supplier selection using a combined fuzzy MCDM approach: A case study for a telecommunication company. *Expert Systems with Applications, 36*(2), 3887-3895.

Opricovic, S. (2016). A comparative analysis of the DEA-CCR model and the VIKOR method. *Yugoslav Journal of Operations Research, 18*(2).

Oum, T. H., Pathomsiri, S., & Yoshida, Y. (2013). Limitations of DEA-based approach and alternative methods in the measurement and comparison of social efficiency across firms in different transport modes: An empirical study in Japan. *Transportation Research Part E: Logistics and Transportation Review, 57*, 16-26.

Ozcan, Y. A. (2008). Health care benchmarking and performance evaluation: an assessment using Data Envelopment Analysis (DEA). Berlin: Springer.

Pagell, M., & Wu, Z. (2017). Business implications of sustainability practices in supply chains *Sustainable Supply Chains*. Springer, 339-353.

Pant, Y., Xiao, Z., Wang, X., & Yang, D. (2017). A multiple support vector machine approach to stock index forecasting with mixed frequency sampling. *Knowledge-Based Systems, 122*, 90-102.

Panda, S., Modak, N. M., & Cárdenas-Barrón, L. E. (2017). Coordinating a socially responsible closed-loop supply chain with product recycling. *International Journal of Production Economics, 188*, 11-21.

Paradi, J. C., Sherman, H. D., & Tam, F. K. (2018). Bank branch productivity applications: Strategic branch management issues addressed with DEA *data envelopment analysis in the financial services industry*. Springer, 129-143.

PrasannaVenkatesan, S., & Goh, M. (2016). Multi-objective supplier selection and order allocation under disruption risk. *Transportation Research Part E: Logistics and Transportation Review, 95*, 124-142.

Raut, R. D., Kamble, S. S., Kharat, M. G., Joshi, H., Singhal, C., & Kamble, S. J. (2017). A hybrid approach using data envelopment analysis and artificial neural network for optimising 3PL supplier selection. *International Journal of Logistics Systems and Management, 26*(2), 203-223.

Rejani, Y., & Selvi, S. T. (2009). Early detection of breast cancer using SVM classifier technique. *arXiv preprint arXiv, 0912-2314*.

Saberi, M., Rostamia, M. R., Hamidianb, M., & Aghamic, N. (2016). Forecasting the profitability in the firms listed in Tehran Stock Exchange using data envelopment analysis and artificial neural network, Advances in Mathematical Finance & Applications, 1(2) , 95 - 104.

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.

Sarkar, S., & Sarkar, S. (2017). A modified multiplier model of BCC DEA to determine cost-based efficiency. *Benchmarking: An International Journal, 24*(6), 1508-1522.

Sgurev, V., Yager, R. R., Kacprzyk, J., & Atanassov, K. T. (2017). *Recent contributions in intelligent systems*. Springer.

Shekarian, E., Jaber, M. Y., Kazemi, N., & Ehsani, E. (2014). A fuzzified version of the economic production quantity (EPQ) model with backorders and rework for a single-stage system. *European Journal of Industrial Engineering, 8*(3), 291-324.

Shekarian, E., Kazemi, N., Rashid, S. H. A., & Olugu, E. U. (2017). Fuzzy inventory models: A comprehensive review. *Applied Soft Computing,* Applied Soft Computing, 55, 588-621.

Shirazi, A. Z., & Mohammadi, Z. (2017). A hybrid intelligent model combining ANN and imperialist competitive algorithm for prediction of corrosion rate in 3C steel under seawater environment. *Neural Computing and Applications, 28*(11), 3455-3464.

Tavana, M., Fallahpour, A., Di Caprio, D., & Santos-Arteaga, F. J. (2016a). A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection. *Expert Systems with Applications, 61*, 129-144.

Tavana, M., Li, Z., Mobin, M., Komaki, M., & Teymourian, E. (2016b). Multi-objective control chart design optimization using NSGA-III and MOPSO enhanced with DEA and TOPSIS. *Expert Systems with Applications, 50*, 17-39.

Vahdani, B., Iranmanesh, S., 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.

Vahdani, B., Razavi, F., & Mousavi, S. M. (2016). A high performing meta-heuristic for training support vector regression in performance forecasting of supply chain. *Neural Computing and Applications, 27*(8), 2441-2451.

Verma, M., & Puri, J. G. (2017). DEA-MCDM approach for ranking decision making units using OWA aggregation operators.

Vlahogianni, E. I., Kepaptsoglou, K., & Karlaftis, M. G. (2016). Modelling the performance of the Athens Bus Network using data envelopment analysis and neural network regression. *Journal of Transport Economics and Policy (JTEP), 50*(4), 369-383.

Wan, X. L., Zhang, Z., Rong, X.-x., & Meng, Q.-c. (2016). Exploring an interactive value-adding data-driven model of consumer electronics supply chain based on least squares support vector machine. *Scientific Programming, 2016*, 4.

Wetzstein, A., Hartmann, E., Benton Jr, W., & Hohenstein, N.-O. (2016). A systematic assessment of supplier selection literature–state-of-the-art and future scope. *International Journal of Production Economics, 182*, 304-323.

Wu, D. (2009). Supplier selection: A hybrid model using DEA, decision tree and neural network. *Expert Systems with Applications, 36*(5), 9105-9112.

Xu, Y., Zhang, X., & Zhang, H. (2016). Research on the e-commerce platform performance and green supply chain based on data mining and SVM. *International Journal of Database Theory and Application, 9*(12), 141-150.

Yayla, A. Y., Yildiz, A., & Ozbek, A. (2012). Fuzzy TOPSIS method in supplier selection and application in the garment industry. *Fibres & Textiles in Eastern Europe*.

Yoon, J., Talluri, S., Yildiz, H., & Ho, W. (2017). Models for supplier selection and risk mitigation: a holistic approach. *International Journal of Production Research*, 1-26.

Yousefi, A., & Hadi-Vencheh, A. (2016). Selecting Six Sigma projects: MCDM or DEA? *Journal of Modelling in Management, 11*(1), 309-325.

Yu, C., Wong, T., & Li, Z. (2017). A hybrid multi-agent negotiation protocol supporting supplier selection for multiple products with synergy effect. *International Journal of Production Research, 55*(1), 18-37.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338-353.

Zhou, J., & Yao, X. (2017). A hybrid artificial bee colony algorithm for optimal selection of QoS-based cloud manufacturing service composition. *The International Journal of Advanced Manufacturing Technology, 88*(9-12), 3371-3387.

Zimmer, K., Fröhling, M., & Schultmann, F. (2016). Sustainable supplier management–a review of models supporting sustainable supplier selection, monitoring and development. *International Journal of Production Research, 54*(5), 1412-1442.

Zuo, K., & Guan, J. (2017). Measuring the R&D efficiency of regions by a parallel DEA game model. *Scientometrics*, 112(1), 175-194..