

# International Journal of Sciences: Basic and Applied Research (IJSBAR)



ISSN 2307-4531  
(Print & Online)

<http://gssrr.org/index.php?journal=JournalOfBasicAndApplied>



---

## Supplier Selection and Evaluation Using Restricting Weights Method in Presence of Dual Factor under Fuzzy Environment.

Abid Hussain Nadeem<sup>a</sup>, Juiping Xu<sup>\*b</sup>, Muhammad Nazim<sup>c</sup>, Muhammad Hashim<sup>d</sup>,  
Muhammad Kashif Javed<sup>e</sup>

*Uncertainty Decision-Making Laboratory, Sichuan University, Chengdu 610064, P. R. China*

<sup>a</sup> e-mail: [abidnadeem.iub@gmail.com](mailto:abidnadeem.iub@gmail.com)

<sup>b</sup> e-mail: [xujiuping@scu.edu.cn](mailto:xujiuping@scu.edu.cn)

<sup>c</sup> e-mail: [nazimscu@gmail.com](mailto:nazimscu@gmail.com)

<sup>d</sup> e-mail: [hashimscu@gmail.com](mailto:hashimscu@gmail.com)

<sup>e</sup> e-mail: [mkjaved3@gmail.com](mailto:mkjaved3@gmail.com)

### Abstract

As businesses grow more complex, so do their supply chains. Data envelopment analysis (DEA) is a useful method for supplier selection. Weight restrictions allow for the integration of managerial preferences in terms of relative importance levels of various inputs and outputs. In some situations there are some factors which play both input and output roles as well. The purpose of this research is to propose a method for selecting the best suppliers in the presence of weight restrictions and dual-role factors. This study shows the supplier selection process through a DEA model, while allowing for the incorporation of decision maker's preferences and considers multiple factors which simultaneously play both input and output roles. The proposed model does not demand exact weights from the decision maker. This study presents a robust model to solve the multiple-criteria problem. A numerical example certifies the application of the proposed method.

Keywords: Data envelopment analysis; Supplier selection; Weight restrictions; Dual-role factors

---

Corresponding author. Tel: +86-028-85418191, Fax: +86-28-85415143.

E-mail address: [xujiuping@scu.edu.cn](mailto:xujiuping@scu.edu.cn)

## **1. Introduction**

Supplier selection is a key operational task for developing sustainable supply chain partnerships. Currently, due to outsourcing initiatives, organizations have become more dependent on suppliers making it more critical to choose and evaluate their supplier performance. Supplier evaluation and selection requires the consideration of multiple objectives and criteria [1].

Supplier selection is the process by which suppliers are reviewed, evaluated, and chosen to become part of the company's supply chain. Shin et al. [2], Farzipoor Saen [3], Farzipoor Saen and Zohrehbandian [4], argue that several important factors have caused the current shift to single sourcing or a reduced supplier base.

First, multiple sourcing prevents suppliers from achieving the economies of scale based on order volume and learning curve effect. Second, multiple supplier system can be more expensive than a reduced supplier base. For instance, managing a large number of suppliers for a particular item directly increases costs, including the labor and order processing costs to managing multiple source inventories. Meanwhile multiple sourcing lowers overall quality level because of the increased variation in incoming quality among suppliers. Third, a reduced supplier base helps eliminate mistrust between buyers and suppliers due to lack of communication. Fourth, worldwide competition forces firms to find the best suppliers in the world.

The supplier selection process has only recently (within the last decade) started to integrate various environmental dimensions. The decision models will necessarily become more complex due to the many new dimensions brought in by green supply chain efforts, where the tradeoffs become more evident and numerous. The decisions will also include more intangible dimensions such as reputation, supply chain risk, business continuity, and social impact. These new criteria and dimensions required rethinking some of the more established approaches and models. In addition, decision makers, or agents that influence the decisions, continue to grow when environmental factors come into play[5]. Models for supplier selection represent only one of over a dozen supply chain management areas (a comprehensive review of supply chain modeling literature).[6] Thus, it is easy to see that a strategic direction in supplier management practices requires the ability to take multiple criteria and measures in order to arrive at a clear and straightforward prioritization or final selection [7]. The extensive nature and modeling complexity of the regular supplier selection process makes the problem heavily reliant on multiple criteria decision models. This real world complexity in the outsourcing and vendor selection process generated the need to help organizations make more thoughtful and simplified decisions. Simplifying complex managerial decision making is the role of many pragmatic theories and models [8].

Supply chain management has become a key aspect that has implications for effective and efficient management of industrial relations. It has also become an important focus for firms and organizations to obtain a competitive advantage [9].

One of the uses of data envelopment analysis (DEA) is supplier selection. In original DEA formulations the

assessed decision making units (DMUs) can freely choose the weights or values to be assigned to each input and output in a way that maximizes its efficiency, subject to this system of weights being feasible for all other DMUs. This freedom of choice shows the DMU in the best possible light, and is equivalent to assuming that no input or output is more important than any other. The free imputation of input–output values can be seen as an advantage, especially as far as the identification of inefficiency is concerned. If a DMU (supplier) is free to choose its own value system and some other supplier uses this same value system to show that the first supplier is not efficient, then a stronger statement is being made. The advantages of full flexibility in identifying inefficiency can be seen as disadvantages in the identification of efficiency. An efficient supplier may become so by assigning a zero weight to the inputs and/or outputs on which its performance is worst. This might not be acceptable by decision makers as well as by the analyst, who after spending time in a careful selection of inputs and outputs sees some of them being completely neglected by suppliers. Decision makers may have in supplier selection problems value judgments that can be formalized a priori, and therefore should be taken into account in supplier selection. These value judgments can reflect known information about how the factors used by the suppliers behave, and/or “accepted” beliefs or preferences on the relative worth of inputs, outputs or even suppliers. For example, in supplier selection problem in general, one input (material price) usually overwhelms all other inputs, and ignoring this aspect may lead to biased efficiency results. Suppliers might also supply some outputs that require considerably more resources than others and this marginal rate of substitution between outputs should somehow be taken into account when selecting a supplier. To avoid the problem of free (and often undesirable) specialization, input and output weights should be constrained in DEA. In some situations there is a strong argument for permitting certain factors to simultaneously play the role of both inputs and outputs. In supplier selection context, the research and development cost can be considered as both an input and an output. Remembering that the simple definition of efficiency is the ratio of output to input, an output can be defined as anything whose increase will cause an increase in efficiency. Similarly, an input can be defined as anything whose decrease will cause an increase in efficiency. If the research and development cost is considered as an output, then the increase in the research and development cost will increase the efficiency of the supplier. Likewise, if the research and development cost is considered as an input, then any decrease in the research and development cost without a proportional decrease in the outputs will increase efficiency. So, depending on how one looks at it, either increasing or decreasing the research and development cost can increase efficiency [10].

Generally speaking, the criteria for supplier selection highly depend on individual companies and industries. On the one hand, different companies have different organizational structure, management strategy, enterprise culture and others. All of these influence the determination of supplier selection criteria. On the other hand, industry background causes huge difference and greatly impacts the selection of suppliers. Therefore, the identification of supplier selection criteria are on the basis of specific environments, and largely requires domain experts’ assessment and judgment [11]. Supplier selection highly depends on large amounts of domain knowledge, where experts’ assessments play an important role. However, various uncertainties are present in domain experts’ subjective and qualitative judgment, such as imprecision, fuzziness, incompleteness and so on. Therefore it is necessary to develop a more effective method for supplier selection, which should be able to handle various types of uncertainties [12].

## **2. Literature review:**

Some mathematical programming approaches have been used for supplier selection in the past. With the increased emphasis on manufacturing and organizational philosophies such as total quality management and just in time, all companies are faced with quality assurance issues in design, manufacturing, purchasing, and delivery. The performance of suppliers has become a crucial element in a company's quality success or failure, and clearly influences the responsiveness of the company [13].

When relative weight of purchased product feature, relationship measure between purchased product feature and supplier assessment criteria and ratings of suppliers with respect to each supplier assessment criteria are represented as fuzzy numbers, computation of the weights of supplier assessment criteria and the ratings of suppliers fall into the category of fuzzy weighted average [14].

A ranking method based on area measurement that attempts to alleviate the drawbacks of the existing fuzzy number ranking methods is employed to rank the potential suppliers. Most ranking methods observe the order of fuzzy numbers and do not measure the degree of difference between them. Furthermore, some of the ranking methods can only be applied when membership functions are known. This issue can be problematic when one considers that fuzzy numbers to be ranked are generally the output of fuzzy number aggregation operations and their exact membership functions are unknown. Moreover, the inclusion or omission of fuzzy numbers to or from the comparison may alter the original ranking [15].

Previous studies have identified some criteria for evaluating suppliers. Based on the relationships between suppliers and manufacturers, summarized 23 criteria, which fell into four categories: quality, deliverability, performance, and warranty policy [16]. In order to increase a company's competitive advantage in supply chain management, enterprises have to maintain long-term relationships with their most reliable suppliers. When companies select the right suppliers, cost is not the only criterion to be considered; companies also need to consider quality, deliverability, and service [17].

US manufacturing company assessed its supply chain risk and made its offshore sourcing decisions. The case company adopted the AHP method to evaluate the weights of its main objectives (such as product, partner, and environment) and sub-objectives (such as quality, cost, service, and management capabilities). Based on the weights of the 16 factors, the case company could evaluate several offshore alternatives: finished goods from China; finished goods from Mexico; parts from China, Maquiladora, no investment; parts from China, Maquiladora, with investment; and parts from China, with assembly in the US. The results showed that sourcing finished goods from China would be the best offshore strategy for the case company [18].

A fuzzy-based mathematical programming approach to account for multiple criteria and vagueness within the supplier selection procedure. Recently, a weighted max–min fuzzy multi- objective model developed to deal with the vagueness of input data and criteria weights effectively in supplier selection [19, 20].

A two phase decision model for supplier management including supplier selection, evaluation, and development. In the first phase, QFD model was integrated with a quantitative model to select the appropriate internet service providers. In the second phase, the selected internet service providers were evaluated from customer, performance, and competition perspectives [21].

Forker and Mendez proposed an analytical method for benchmarking using DEA that can help companies identify their most efficient suppliers, the suppliers among the most efficient with the most widely applicable total quality management (TQM) programs, and those suppliers who are not on the efficient frontier but who could move toward it by emulating the practices of their “best peer” supplier (s) [22].

Although previously reported studies developed approaches for supplier selection process, further studies are necessary to integrate imprecise information concerning the importance of purchased product features, relationship between purchased product features and supplier assessment criteria, and dependencies between supplier assessment criteria into the analysis.

### **3. Proposed method for supplier selection:**

DEA proposed by Charnes et al. [23] (Charnes–Cooper–Rhodes (CCR) model) and developed by Banker et al. [24] (Banker– Charnes–Cooper (BCC) model) is an approach for evaluating the efficiencies of DMUs. One serious drawback of DEA applications in supplier selection has been the absence of decision maker judgment, allowing total freedom when allocating weights to input and output data of supplier under analysis. This allows suppliers to achieve artificially high efficiency scores by indulging in inappropriate input and output weights.

The most widespread method for considering judgments in DEA models is, perhaps, the weight restrictions inclusion. Weight restrictions allow for the integration of managerial preferences in terms of relative importance levels of various inputs and outputs. The idea of conditioning the DEA calculations to allow for the presence of additional information arose first in the context of bounds on factor weights in DEA’s multiplier side problem. This led to the development of the cone-ratio [25] and assurance region models [26]. Both methods constrain the domain of feasible solutions in the space of the virtual multipliers. To introduce the method for supplier selection, Table 2 lists the nomenclature used to formulate the problem under consideration. The discussions in this paper are provided with reference to the original DEA formulation by Charnes et al. [23] below, which assumes constant returns to scale and that all input and output levels for all DMUs are strictly positive. The CCR model measures the efficiency of DMU<sub>o</sub> relative to a set of peer DMUs:

$$e_o = \max \frac{\sum_{q=1}^t g_q u_{qo}}{\sum_{r=1}^k h_r v_{ro}}, \tag{1}$$

$$s.t. \quad \frac{\sum_{q=1}^t g_q u_{pq}}{\sum_{r=1}^k h_r v_{pr}} \leq 1, \quad p = 1, \dots, n,$$

$$g_q, h_r \geq \zeta \quad \forall q \quad \text{and} \quad r$$

3.1. Problem parameters:

$\lambda_r, \gamma_r, \varepsilon_q, \mu_q, \Omega_r, \Phi_r, \beta_q, \vartheta_q, \varpi_r, d_q, c_q, a_r, b_r$  User-specified constants

$P = 1, \dots, n$  collection of suppliers (DMUs)

$Q = 1, \dots, t$  the set of outputs

$R = 1, \dots, k$  the set of inputs

$F = 1, \dots, F$  the set of dual-role factors

$U_{qp} =$  the  $q$ th output of  $p$ th DMU

$V_{pr} =$  the  $r$ th input of  $p$ th DMU

$U_{qo} =$   $q$ th outputs of the DMUo under investigation

$V_{ro} =$   $r$ th inputs of the DMUo under investigation

$Z_j =$  the factor that plays the role of both an input and output

$Z_{fp} =$  the  $f$ th dual-role factor of  $p$ th DMU Decision variables

$g_q =$  weight of the  $q$ th output

$h_r =$  weight of the  $r$ th input

Where there is a set of  $n$  peer  $DMU_t, \{DMU_p : p = 1, 2, \dots, n\}$ , which produce multiple outputs  $U_{qp} (q = 1, 2, \dots, t)$ , by utilizing multiple inputs  $V_{pr} (i = 1, 2, \dots, m)$ .  $DMU_o$  is the  $DMU$  under

consideration.  $g_q$  is the weight given to output  $q$  and  $h_r$  is the weight given to input  $r$ .  $\zeta$  is a positive non-Archimedean infinitesimal.  $DMU_o$  is said to be efficient. ( $e_o = 1$ ) if no other  $DMU$  or combination of  $DMU$ s can produce more than  $DMU_o$  on at least one output without producing less in some other output or requiring more of at least one input. The linear programming equivalent of (1) is as follows:

$$\begin{aligned}
 e_o &= \max \sum_{q=1}^t u_{qo} g_q, \\
 \text{s.t. } &\sum_{r=1}^k v_{ro} h_r = 1, \\
 &\sum_{r=1}^k v_{pr} h_r - \sum_{q=1}^t u_{pq} g_q \geq 0 \quad \forall p, \\
 &h_r \geq \zeta \quad \forall r, \\
 &g_q \geq \zeta \quad \forall q
 \end{aligned} \tag{2}$$

In (3) the various types of weight restriction that can be employed to multiplier models are shown [32].

Absolute weight restrictions

$$\lambda_r \leq h_r \leq \gamma_r \quad (a_r) \quad \varepsilon_q \leq g_q \leq \mu_q \quad (a_o),$$

Assurance region of type I

(3)

$$\Omega_r \leq \frac{h_r}{h_{r+1}} \leq \phi_r \quad (b_r) \quad \beta_q \leq \frac{g_q}{g_{q+1}} \leq \vartheta_q \quad (b_o),$$

Assurance regions of type II

$$\omega_r h_r \geq g_q \quad (c),$$

These letters  $(\lambda_r, \gamma_r, \varepsilon_q, \mu_q, \Omega_r, \Phi_r, \beta_q, \vartheta_q, \varpi_r)$  are user-specified constants to reflect value judgments the decision maker wishes to incorporate in the assessment. They may relate to the perceived importance or worth of input and output factors. The restrictions (a) and (b) in (3) relate on the left hand side to input weights and on the right hand side to output weights. Constraint (c) links directly input and output weights. Absolute weight restrictions are the most immediate form of placing restrictions on the weights as they simply restrict them to vary within a specific range. Assurance region of type I, link either only input weights  $(b_r)$  or only output weights  $(b_o)$ . The relationship between input and output weights are termed assurance region of type II. Weights restrictions may be applied directly to the DEA weights or to the product of these weights with the respective input or output level, referred to as virtual input or virtual output. The virtual inputs and outputs can be seen as normalized weights reflecting the extent to which the efficiency rating of a DMUqt understood by a given input or output variable. Restrictions on virtual inputs/virtual outputs assume the form in (4), where the proportion of the total virtual output of DMUp accounted for by output q is restricted to lie in the range  $[c_q, d_q]$  and the proportion of the total virtual input of DMUp accounted for by input r is restricted to lie in the range  $[b_r, a_r]$ .

$$\begin{aligned}
 c_q &\leq \frac{g_q h_{pq}}{\sum_{q=1}^t g_q h_{pq}} \leq d_q, & q=1, \dots, t. \\
 b_r &\leq \frac{h_r v_{pr}}{\sum_{r=1}^k h_r v_{pr}} \leq a_r, & r=1, \dots, k.
 \end{aligned}
 \tag{4}$$

The range is normally determined to reflect prior views on the relative ‘‘importance’’ of the individual outputs and inputs. Constraints such as (5) are DMU specific meaning that the DEA model with such constraints may become computationally expensive. Wong and Beasley [27] suggest some methods for implementing restrictions on virtual values:

- Method 1: Add the restrictions only in respect of DMUo being assessed leaving free the relative virtual values of the comparative DMUt;
- Method 2: Add the restrictions in respect of all the DMUt being compared. This is computationally expensive as the constraints added will be of the order of  $2n(t + k)$ ;
- Method 3: Add the restrictions (4) only in relation to the assessed DMU, and add constraints (5) with respect to the ‘‘average’’

DMU, which has an average level of the qth output equal to  $\sum_{p=1}^n u_{pq} / n$  and has an average level of the rth input equal to  $\sum_{p=1}^n v_{rp} / n$ .

$$c_q \leq \frac{g_q \sum_{p=1}^n u_{pq} / n}{\sum_{q=1}^t g_q \left( \sum_{p=1}^n u_{pq} / n \right)} \leq d_q, \quad q = 1, \dots, t,$$

$$b_r \leq \frac{h_r \sum_{p=1}^n v_{rp} / n}{\sum_{r=1}^m h_r \left( \sum_{p=1}^n v_{rp} / n \right)} \leq a_r, \quad r = 1, \dots, m.$$
(5)

Restrictions on the virtual input–output weights represent indirect absolute bounds on the DEA weights of the type shown in (a) in (3). The imposition of restrictions on virtual inputs or outputs is sensitive to the model orientation. The multipliers formulation, with the virtual weights restrictions applying to DMUo (method 1), is as below2, 3, 4:

$$e_o = \max \sum_{q=1}^t u_{qo} g_q,$$

$$\text{s.t.} \quad \sum_{r=1}^k v_{ro} h_r = 1,$$

$$\sum_{r=1}^k v_{pr} h_r - \sum_{q=1}^t u_{pq} g_q \geq 0 \quad \forall p,$$

$$b_r \left( \sum_{r=1}^m v_{ro} h_r \right) - v_{ro} h_r \leq 0,$$

$$v_{ro} h_r - b_r \left( \sum_{r=1}^m v_{ro} h_r \right) \leq 0,$$

$$h_r \geq \zeta \quad \forall r,$$

$$g_q \geq \zeta \quad \forall q$$
(6)

In summary, Model (6) proposes a method for selecting the best suppliers in the presence of weight restrictions. Now, to consider dual-role factors and weight restrictions, a new model is proposed. Consider a situation where

members p of a set of n DMU<sub>t</sub> are to be evaluated in terms of t outputs  $u_p = (u_{pq})_{q=1}^t$  and m inputs  $v_p = (v_{rp})_{r=1}^m$ . In addition, assume that a particular factor is held by each DMU in the amount  $z_p$ , and serves as both an input and output factor. The proposed model for considering single dual-role factor is as follows [28].

$$\begin{aligned}
 & \max \frac{\left( \sum_{q=1}^t g_q u_{qo} + \Theta z_o - \Upsilon z_o \right)}{\sum_{r=1}^m h_r v_{ro}}, \\
 \text{s.t.} \quad & \sum_{q=1}^t g_q u_{pq} + \Theta z_p - \Upsilon z_p - \sum_{r=1}^m h_r u_{rp} \leq 0, \quad p = 1, \dots, n \quad (7) \\
 & g_q, h_r, \Theta, \Upsilon \geq 0
 \end{aligned}$$

At this point, to demonstrate how to consider multiple dual-role factors in the model, the following new model is presented. Assume that some factors are held by each DMU in the amount  $z_{fp} (f = 1, \dots, F)$ , and serve as both an input and output factors. The proposed model for considering multiple dual-role factors is as follows:

$$\begin{aligned}
 & \max \frac{\left( \sum_{q=1}^t g_q u_{qo} + \sum_{f=1}^F \Theta_f z_{fo} - \sum_{f=1}^F \Upsilon_f z_{fo} \right)}{\sum_{r=1}^k h_r v_{ro}}, \\
 \text{s.t.} \quad & \sum_{q=1}^t g_q u_{pq} + \sum_{f=1}^F \Theta_f z_{fp} - \sum_{f=1}^F \Upsilon_f z_{fp} - \sum_{r=1}^k h_r v_{pr} \leq 0, \quad p = 1, \dots, n \quad (8) \\
 & g_q, h_r, \Theta, \Upsilon \geq 0
 \end{aligned}$$

The linear programming form of Model (8) is as follows:

$$\begin{aligned}
 & \max \quad \sum_{q=1}^t g_q u_{qo} + \sum_{f=1}^F \Theta_f z_{fo} - \sum_{f=1}^F \Upsilon_f z_{fo} \\
 \text{s.t.} \quad & \sum_{r=1}^k h_r v_{ro} = 1 \\
 & \sum_{q=1}^t g_q u_{pq} + \sum_{f=1}^F \Theta_f z_{fp} - \sum_{f=1}^F \Upsilon_f z_{fp} - \sum_{r=1}^k h_r v_{pr} \leq 0, \quad p = 1, \dots, n \quad (9) \\
 & g_q, h_r, \Theta, \Upsilon \geq 0
 \end{aligned}$$

At this stage, the model that considers both dual-role factors and weight restrictions is introduced.

$$\begin{aligned}
 \max \quad & \sum_{q=1}^t g_q u_{qo} + \sum_{f=1}^F \Theta_f z_{fo} - \sum_{f=1}^F \Upsilon_f z_{fo} \\
 \text{s.t.} \quad & \sum_{r=1}^k h_r v_{ro} = 1 \\
 & \sum_{q=1}^t g_q u_{pq} + \sum_{f=1}^F \Theta_f z_{fp} - \sum_{f=1}^F \Upsilon_f z_{fp} - \sum_{r=1}^k h_r v_{pr} \leq 0, \quad p = 1, \dots, n \\
 & g_q, h_r, \Theta, \Upsilon \geq 0 \\
 & b_r \left( \sum_{r=1}^m v_{ro} h_r \right) - v_{ro} h_r \leq 0, \\
 & v_{ro} h_r - b_r \left( \sum_{r=1}^m v_{ro} h_r \right) \leq 0, \\
 & h_r \geq \zeta \quad \forall r, \\
 & g_q \geq \zeta \quad \forall q \\
 & \Theta, \Upsilon \geq 0
 \end{aligned} \tag{10}$$

#### 4. Numerical example:

The data set for this example is partially taken from Talluri and Baker [29] and contains specifications on 18 suppliers. The supplier inputs considered are Total Cost of shipments (TC), 5 Number of Shipments per month (NS), and Research and Development cost (R&D). The outputs utilized in the study are Number of shipments to arrive On Time (NOT), Number of Bills received from the supplier without errors (NB), and R&D. R&D plays the role of both input and output. According to the decision of decision maker, the importance of TC, as expressed by the weight  $h_r$ , must be as follows (method 1):

$$0.5 \leq \frac{h_r v_{1o}}{\sum_{r=1}^m h_r v_{ro}} \leq 3$$

Table 1 reports the results of efficiency assessments in the presence of virtual weight restriction and dual-role factor and their input/output behavior for the 18 suppliers obtained by using Model (10).

Supplier no.	Efficiency score in the presence of virtual weight restriction and dual-role factor (applying Model (10))	$\hat{\Theta}_1$	$\hat{Y}_1$	$\hat{\Theta}_1 - \hat{Y}_1$
1	.934	.002354147	0	.002354147
2	.9695	.002213107	0	.002213107
3	1	.002267565	0	.002267565
4	1	.003359652	0	.003359652
5	.9705	.00228148	0	.00228148
6	1	.007130057	0	.007130057
7	1	0	.9176708	-.9176708
8	.8842	.001762005	0	.001762005
9	.8859	.001780101	0	.001780101
10	.7653	.001767251	0	.001767251
11	.7628	.001824056	0	.001824056
12	.9053	.003981494	0	.003981494
13	.9228	.005004239	0	.005004239
14	.9132	.001989893	0	.001989893
15	.9775	.00466217	0	.00466217
16	.8169	.0017675	0	.0017675
17	1	.019386	0	.019386
18	1	.005784615	0	.005784615

Table 1: Efficiency scores in the presence of virtual weight restriction and dual-role factor, and input/output behavior [10]

$\zeta$  has been set to be 0.0001. Model (10) identified suppliers 3, 4, 6, 7, 17, and 18 to be efficient with a relative efficiency score of 1. The remaining 12 suppliers with relative efficiency scores of less than 1 are considered to be inefficient. Therefore, decision maker can choose one or more of these efficient suppliers. The supplier 7 is the DMU that R&D is behaving like an input.

Using T the null hypothesis that the two groups have the same population at a level of significance  $\alpha$  can be checked. In this example, there is  $T = -1.0757$ . If  $\alpha = 0.05$  (5%) is chosen, then it holds that  $T_{0.025} = 1.96$ . Since  $T = -1.0757$

$<_{1.96} =_{T0.025}$ , the null hypothesis at the significance level 5% is not rejected. Consequently, the differences among the efficiency scores obtained by Model (2) and efficiency scores obtained by Model (10) are not statistically significant.

## **5. Conclusion:**

Strong competitive pressure impels many organizations to deliver their products and services to customers faster, cheaper and better than others. Managers have come to know that it is not possible to do it alone without responsible suppliers. Hence the selection of suppliers has received considerable attention in the purchasing literature, because of the increasing importance of supplier selection decisions is forcing organizations to rethink their purchasing and selection strategies.

This paper provided a model for supplier selection in the presence of dual-role factors and weight restriction. Notice that, whatever we propose any possible process to improve DEA model, there always is a result that shows the best DMUs as efficient so that their efficiency scores equal to one. The reason is that DEA measures the relative efficiency of DMUs. Each DEA model has a specific assumption which should be considered beforehand. In real world, decision makers should consider these assumptions. As a result, the proposed model is only a possible way to achieve better supplier selection but not sufficient. In other words, the proposed model assumes that weight restrictions and dual-role factors are present. It is understood that if these assumptions are not relevant, the proposed model cannot be used.

One of the limitations of this paper is that the proposed model assumes all suppliers are completely homogeneous. As Farzipoor Saen [30] discussed, the assumption of classical supplier selection models is based on the principle that suppliers consume common inputs to supply common outputs. In spite of this assumption in many applications some suppliers do not comprehensively consume common inputs to comprehensively supply common outputs. In other words, different industrial suppliers may have many differences between them. To evaluate the relative efficiency of suppliers, all the suppliers may not have identical functions. For instance, to select a supplier most of inputs and outputs (selection criteria) of suppliers are common, but there are a few input (s) and/or output (s) for some suppliers that may not be common to all. In a supplier evaluation example that buyer consumes two types of materials such as type X and type Y. X supplier may not supply type Y. To evaluate this supplier, considering cost as an input, cost of type Y for the supplier is meaningless. It is clear that zero value allocation for this type of input, causes relative efficiency of the supplier, to increase unrealistically.

In this case, it is not satisfactory saying that the suppliers which do not supply material of type Y, are not comparable with the suppliers which supply material of type Y. Meanwhile, allocating zero value to suppliers that do not supply material of type Y, is not fair. Generally, zero allocation to outputs and inputs of some suppliers, makes the efficiency evaluation unfair. That is zero allocation to output, may make a supplier inefficient, on the other hand, zero allocation to input, may make a supplier efficient, unrealistically. Farzipoor Sean [31] proposes a

model for selecting slightly non-homogeneous suppliers. However, he did not consider weight restrictions and dual-role factors. A potential extension to the methodology includes the case that some of the suppliers are slightly non-homogeneous in the presence of both weight restrictions and dual-role factors.

## **6. Reference:**

- [1] K.S, Bhutta, F, Huq. "Supplier selection problem: a comparison of total cost of ownership and analytic hierarchy process approaches". *Supply Chain Management: An International Journal* 7 (3), 126e135, 2002.
- [2] H. Shin, D.A. Collier, D.D. Wilson, "Supply management orientation and supplier/buyer performance", *J. Oper. Manage.* 18 (3) 317–333, (2000).
- [3] R. F. Saen, "Suppliers selection in the presence of both cardinal and ordinal data", *Eur. J. Oper. Res.* 183 (2) 741–747, (2007).
- [4] R. F. Saen, M. Zohrebandian, "A data envelopment analysis approach for supplier selection in volume discount environments" *Int. J. Procur. Manage.* 1 (4) 472–488, (2008).
- [5] M. Herva, E. Roca. "Ranking municipal solid waste treatment alternatives based on ecological footprint and multi-criteria analysis". *Ecological Indicators* 25, 77e84, 2013.
- [6] C.M. Badole, D.R. Jain, D.A.Rathore. "Research and opportunities in supply chain modeling: a review" *International Journal of Supply Chain Management* 1 (3), 63e86, Nepal, D.B., 2013.
- [7] W. Ho, X. Xu, P.K. Dey. "Multi-criteria decision making approaches for supplier evaluation and selection: a literature review" *European Journal of Operational Research* 202 (1), 16e24, 2010.
- [8] O.E. Williamson, "Outsourcing: transaction cost economics and supply chain management" *Journal of Supply Chain Management* 44 (2), 5e16, 2008.
- [9] D.A. Carrera, R.V. Mayorga, "Supply chain management: a modular fuzzy inference system approach in supplier selection for new product development" *J. Intell. Manuf.* 19 1–12, (2008).
- [10] R F. Saen, "Restricting weights in supplier selection decisions in the presence of dual-role factors" *Applied Mathematical Modelling* 34 2820–2830, (2010).
- [11] X. Deng, Y. Hu, Y. Deng, "Sankaran Mahadevan c. Supplier selection using AHP methodology extended by D numbers". *Expert Systems with Applications* 41 156–167, (2014).
- [12] S. S. Kara, "Supplier selection with an integrated methodology in unknown environment". *Expert Systems with Applications*, 38(3), 2133–2139, (2011).
- [13] S.H. Ghodsypour, C. O'Brien, "The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint", *Int. J. Prod. Econ.* 73 15–27, (2001).
- [14] S.T. Liu, "Rating design requirements in fuzzy quality function deployment via a mathematical programming approach", *Int. J. Prod. Res.* 43 497– 513, (2005).
- [15] C.B. Chen, C.M. Klein, "A simple approach to ranking a group of aggregated fuzzy utilities", *IEEE Trans. Syst. Man Cybern. Part B: Cybern.* 27 26–35, (1997).

- [16] G. Dickson, "An analysis of supplier selection systems and decisions". *Journal of Purchasing*, 2(1), 5–17, (1966).
- [17] W. Ho, X. Xu, P. K. Dey, "Multi-criteria decision making approaches for supplier evaluation and selection: A literature review". *European Journal of Operational Research*, 202(1), 16–24, (2010).
- [18] T. Schoenherr, V. M. R. Tummala, T. P. Harrison, "Assessing supply chain risks with the analytic hierarchy process: Providing decision support for the off shoring decision by a US manufacturing company" *Journal of Purchasing and Supply Management*, 14(2), 100–111, (2008).
- [19] L.Y. Chen, T.C. Wang, "Optimizing partners' choice in IS/IT outsourcing projects: the strategic decision of fuzzy VIKOR" *Int. J. Prod. Econ.* 120 233– 242, (2009).
- [20] A. Amid, S.H. Ghodsypour, C. O'Brien, "A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain", *Int. J. Prod. Econ.* 131 139–145, (2011).
- [21] S.H. Amin, J. Razmi, "An integrated fuzzy model for supplier management: a case study of ISP selection and evaluation", *Expert Syst. Appl.* 36 8639–8648, (2009).
- [22] L.B. Forker, D. Mendez, "An analytical method for benchmarking best peer suppliers", *Int. J. Oper. Prod. Manage.* 21 (1/2) 195–209, (2001).
- [23] A. Charnes, W.W. Cooper, E. Rhodes, "Measuring the efficiency of decision making units", *Eur. J. Oper. Res.* 2 (6) 429–444, (1978).
- [24] R.D. Banker, A. Charnes, W.W. Cooper, "Some methods for estimating technical and scale inefficiencies in data envelopment analysis", *Manage. Sci.* 30 (9) 1078–1092, (1984).
- [25] A. Charnes, W.W. Cooper, Q.L. Wei, Z.M. Huang, "Cone-ratio data envelopment analysis and multi-objective programming, *Int. J. Syst. Sci.* 20 (7) (1989) 1099–1118.
- [26] R.G. Thompson, L.N. Langemeier, C.T. Lee, E. Lee, R.M. Thrall, "The role of multiplier bounds in efficiency analysis with application to kansas farming", *J. Econ.* 46 (1/2) 93–108, (1990).
- [27] Y.H.B. Wong, J.E. Beasley, "Restricting weight flexibility in data envelopment analysis", *J. Oper. Res. Soc.* 41 (9) 829–835, (1990).
- [28] W.D. Cook, R.H. Green, J. Zhu, "Dual-role factors in data envelopment analysis", *IIE Trans.* 38 (2) 105–115, (2006).
- [29] S. Talluri, R.C. Baker, "A multi-phase mathematical programming approach for effective supply chain design", *Eur. J. Oper. Res.* 141 (3) 544–558, (2002).
- [30] R. F. Saen, "A new mathematical approach for suppliers selection: accounting for non-homogeneity is important", *Appl. Math. Comput.* 185 (1) 84–95, (2007).
- [31] R. F. Saen, "A new approach for selecting slightly non-homogeneous vendors", *J. Adv. Manag. Res.* 6 (2) 144–153, (2009).
- [32] W.W. Cooper, L.M. Seiford, J. Zhu, "Handbook on Data Envelopment Analysis, Kluwer Academic Publishers", 2004.