A new AR-Interval Data Envelopment Analysis Model for Supplier Selection

Ali Mohaghar [1], Abdol Hossein Jafarzadeh [2], Mohammad Hosein Soleimani-Sarvestani [3], Mohsen Moradi-Moghadam [3]

[1] Associated Professor, Department of Management, University of Tehran, Tehran, Iran
[2] M.S. Candidate of Industrial Management, University of Tehran
[3] M.S. of Industrial Management, University of Tehran, Tehran, Iran
Email: moradi_mohsen@alumni.ut.ac.ir

Abstract: Traditionally, supplier-selection models have been based on quantitative data with less emphasis on qualitative data. However, with the expansion of manufacturing philosophies such as the just-in-time production, emphasis has shifted to the simultaneous consideration of quantitative and qualitative data in the supplier-selection process. Considering the supplier selection problem is a Complex and multi-criteria problem, one of the efficient models for selecting the best suppliers is Data envelopment analysis (DEA). Weight restrictions allow for the integration of expert opinion and controlling the range of weight changes in Data Envelopment analysis.So in this paper a new model with interval data envelopment analysis with considering the weight restrictions is presented.
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1. Introduction

Economic developments, market requirements, intensity of competition, new technologies, changing customer expectations and variety of sources, and many other categories provides areas for creation of value in an economy based on network . Share profits and share value in the value chain of activities leading to the development of strategic concepts in a chain system. Supply Chain is a network of facilities that convert raw materials to finished products and distribution of tasks among their customers [1]. A supply chain, as well as alignment the companies that offer a product or service to the market [2]. In other words, supply chains are included directly and indirectly in the completion of customer requests. Supply chain is not only for manufacturers and suppliers, but also includes transport, warehouses, retail and even customers [3]. Therefore, Supply Chain Management (SCM) includes all management activities that satisfy the needs of customers with minimal costs for all companies involved in the production and delivery of products [4]. Supply chain management is the integration of organizational units throughout the supply chain and coordinating Flows of material, information and the term of SCM was coined by consultant Oliver and Weber in 1982 [5]. Suppliers play an important role in achieving the objectives of supply management [6]. As far as suppliers have a substantial effect on the success or failure a company [7] .Target of companies to manage their suppliers throughout the supply chain to deliver a faster, lower latency production, reduce costs and improve quality [8]. Supplier selection decisions determine who the suppliers should be chosen as the resource to buy or how to order quantities should be allocated among the selected suppliers [9]. Choosing the best supplier is a critical decision for wide range of conclusions in a supply chain [6]. Supplier selection process requires a systematic and effective method that will help the buyer to help obtain the most effective decision [10]. Gaballa is the first research that has been applied a mathematical programming to vendor selection in a real case. He has used a mixed programming model to formulate the problem of decision making in the post office of Australia. The objective function of this model was minimum discount off the price of items allocated to transmitters by capacity constraints and satisfies the demand of the seller [11]. Weber (1996) and Easton et al. (2002) proposed Data Envelopment Analysis (DEA) method to measure the performance of suppliers [12,13] and Then the DEA with its unique capabilities and features in recent decades has been considered one of the most applicable techniques in the evaluation and choice of suppliers. In applying classical DEA models, two problems often occur, the weakness of distinction and another unrealistic distribution weight between the inputs and output. The weakness of distinction when accrued that the total number of units under assessment is not sufficiently larger than number of inputs and outputs. In this case the classical models of many decision units are identified as efficient. The problem of the weight of non-logical model occurs when a model assigned very small weight to input or assigned large weight to output [14]. Freedom in selecting of weights is useful in determining the inefficient units. Because of inefficient at best for the most amounts of weight and performance, it is ineffective. But it may be a single or multiple functional units in a scenario maximize performance is selected Zero-weights for inputs and outputs and are known as best units. It may ignored by decision makers and analysts who spend the time to choose the most appropriate inputs and outputs to be realized. Some of the criteria are normally not be accepted by the unit under review. For controlling the range of inputs and outputs weight in the optimal solution, we need to define the range. Also if certain indicators are important in terms of management and decision makers, they can be changed according to weight range and limited control inputs and outputs. This result would be consistent with managers and adding the weight constraints of the causes of the relative importance of input and output data. Also Traditional DEA models as CCR and BBC models**,** the value of all data inputs and outputs must be known; but, this assumption is not always true in real world [15]. Due to the existence of uncertainty in the data, DEA sometimes faces the situation of imprecise data, especially when a set of DMUs contains judgment data, forecasting data or ordinal preference information. When some inputs and outputs are unknown variables the DEA model becomes an Imprecise Data Envelopment Analysis (IDEA) is called. In 1999, Cooper et al. were the first to study how to deal with imprecise data such as cardinal data, ordinal data and ratio bounded data in DEA [15]. The resulting DEA model was called IDEA, which transformed a nonlinear programming problem into a linear programming problem equivalent through a series of scale transformations and variable alternations. In 1999, Kim et al. use an analogous scale transformation and variable alternation method, but they did not take the cardinal data situation into account [16]. In 2002, Lee et al. extended the idea of IDEA to the additive model. Their scale transformations also make both the exact data and imprecise information including preference data and interval data into constraints, which leads to a rapid increase in computation burden[17]. Despotis and Smirlis in 2002 also introduced a method to deal with imprecise data. Their approach was to transform a nonlinear Data Envelopment Analysis model to a Liner Programming equivalent by applying transformations only on the variables. The resulting efficiency scores were defined to be intervals [18]. In 2002 Entani et al. proposed a DEA model with interval efficiencies measured from both the pessimistic and the optimistic viewpoints. Their model was developed for crisp, interval and fuzzy data. Weakness of the model was that only one input and one output can be measured with qualitative data [19]. All models are presented for the measures of the efficiency in data envelopment analysis models with imprecise data (or IDEA) have suffered two major weaknesses: First, most of these methods were usually a nonlinear optimization problem with the need of extra variable alternations or scale transformations that using this causes an increase in computation and its complexity. And second, they needed utilizes variable production frontiers (i.e. different constraint sets) to measure interval efficiencies. For more discussions on their method, please refer to Wang et al. [20]. To solve this problem, a pair of models was constructed by Wang et al. in 2005 on the basis of interval arithmetic and the CCR model without the need of extra variable alternations and uses a fixed and unified production frontier to measure the efficiencies of decision making units with qualitative, ordinal and cardinal input and output data [20]. Farzipoor Saen in 2006 proposed a pair of model based on Wang's method for technology selection in Management of Technology Transfer Area. That it can use the expert opinion for measuring efficiency. [21]. Thus, in this paper provides a new model for dealing with imprecise data in the presence of weight restrictions is developed. The paper is organized as follow: the first part described a comprehensive and concise overview of supplier selection problem. In the second part have been reviewed imprecise data envelopment analysis and weight restrictions. In the third section, a new model for dealing with imprecise data in the presence of a new weight limits has been introduced. The fourth section presents an example of this model and the results have been evaluated, and finally in the last section summarizes and conclusion has been made.

2- Background

2-1-Interval data Envelopment Analysis

A pair of input-oriented model is reviewed to measure the interval efficiency based on Wang model [20]. Consider the following model:

$$\theta_j = \sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij}, \quad j = 1, \dots, n \qquad (1)$$

which θ_j represents the efficiency of jth DMU . The concept of spatial data is follows:

$$\theta_j = \frac{\sum_{r=1}^{s} u_r \left[y_{rj}^L, y_{rj}^U\right]}{\sum_{i=1}^{m} v_i \left[x_{ij}^L, x_{ij}^U\right]} = \frac{\left[\sum_{r=1}^{s} u_r y_{rj}^L, \sum_{r=1}^{s} u_r y_{rj}^U\right]}{\left[\sum_{i=1}^{m} v_i x_{ij}^L, \sum_{i=1}^{m} v_i x_{ij}^U\right]} = \left[\frac{\sum_{r=1}^{s} u_r y_{rj}^L}{\sum_{i=1}^{m} v_i x_{ij}^L}, \frac{\sum_{r=1}^{s} u_r y_{rj}^U}{\sum_{i=1}^{m} v_i x_{ij}^U}\right], \quad j = 1, \dots, n \tag{2}$$

θ_j also included a form of interval numbers that is shown $\left[\theta_j^L, \theta_j^U\right]$. Therefore,

$$\theta_j = \left[\theta_j^L, \theta_j^U\right] = \left[\frac{\sum_{r=1}^{s} u_r y_{rj}^L}{\sum_{i=1}^{m} v_i x_{ij}^U}, \frac{\sum_{r=1}^{s} u_r y_{rj}^U}{\sum_{i=1}^{m} v_i x_{ij}^L}\right] \subseteq (0,1], \quad j = 1, \dots, n \tag{3}$$

Therefore:

$$\theta_j^L = \sum_{r=1}^{s} u_r y_{rj}^L \Big/ \sum_{i=1}^{m} v_i x_{ij}^U > 0 \tag{4}$$

And

$$\theta_j^U = \sum_{r=1}^{s} u_r y_{rj}^U \Big/ \sum_{i=1}^{m} v_i x_{ij}^L \leq 1 \tag{5}$$

The following models for computing upper and lower bounds of the efficiency the jth unit are used:

$$\begin{aligned} &\text{Max}\theta_{jo}^L = \sum_{r=1}^{s} u_r y_{rj}^L \Big/ \sum_{i=1}^{m} v_i x_{ij}^U, \quad j = 1, \dots, n \, s.t. \\ &\theta_j^U = \sum_{r=1}^{s} u_r y_{rj}^U \Big/ \sum_{i=1}^{m} v_i x_{ij}^L \leq 1, \quad j = 1, \dots, n \\ &u_r, v_i \geq 0; \ \forall r, i \end{aligned} \tag{6}$$

And

$$\begin{aligned} &\text{Max}\theta_{jo}^U = \sum_{r=1}^{s} u_r y_{ro}^U \Big/ \sum_{i=1}^{m} v_i x_{io}^L, \quad j = 1, \dots, n \\ &s.t. \\ &\theta_j^U = \sum_{r=1}^{s} u_r y_{rj}^U \Big/ \sum_{i=1}^{m} v_i x_{ij}^L \leq 1, \ j = 1, \dots, n \\ &u_r, v_i \geq 0; \ \forall r, i \end{aligned} \tag{7}$$

Using Charnes–Cooper transformation, the above pair of fractional programming models can be simplified as the following equivalent LP models: [22]:

$$\begin{aligned} &\text{Max } \theta_{jo}^L = \sum_{r=1}^{s} u_r y_{ro}^L \\ &s.t. \\ &\sum_{i=1}^{m} v_i x_{io}^U = 1 \\ &\sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \leq 0, \ j = 1, \dots, n \\ &u_r, v_i \geq \varepsilon; \ \forall r, i \end{aligned} \tag{8}$$

And

$$\begin{aligned} &\text{Max } \theta_{jo}^L = \sum_{r=1}^{s} u_r y_{ro}^U \\ &\text{s.t.} \\ &\sum_{i=1}^{m} v_i x_{io}^L = 1 \\ &\sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \leq 0, \ j = 1, \dots, n \\ &u_r, v_i \geq \varepsilon; \ \forall r, i \end{aligned} \tag{9}$$

x_{ij}^{L} And x_{ij}^{U} represent the lower and upper limit of ith input , Respectively. y_{rj}^{L} and y_{rj}^{U} also represent the Low and High limit of rth output , Respectively . θ_{ij}^{L} And θ_{ij}^{U} Order to show the worst and best possible relative efficiency of the unit under evaluation. Addition, u_r and v_i represent weights of the rth output and ith input, respectively.

2.2. Assurance Region

In (10, 11, 12) the various types of weight restriction that can be applied to multiplier models are shown [23].

Absolute weight restrictions

$\sigma_i \le v_i \le \tau_i(g_i)$

$\rho_r \le u_r \le \eta_r(g_o)$ (10)

$\alpha_i \le \frac{v_i}{v_{i+1}} \le \psi_i(h_i)$

$\theta_r \le \frac{u_r}{u_{r+1}} \le \xi_r(h_o)$ (11)

Assurance regions of type II (input-output weight restrictions)

$\varphi_i v_i \ge u_r$ (*l*) (12)

The Greek letters $(\sigma_i, \tau_i, \rho_r, \eta_r, \alpha_i, \psi_i, \theta_r, \xi_r, \varphi_i)$ are user-specified constants (upper and lower bounds of weights determined by the expert)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 (*g*) and (*h*) in (10, 11) relate on the left hand side to input weights and on the right hand side to output weights. Constraint (l2) 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 (h_i) or only output weights (h_o). The relationship between input and output weights are termed assurance region of type II.

2.3. A Minimax Regret-Based Approach for Comparing and Ranking Interval Permanent

In interval permanent assessment, since the final permanent score for each alternative is characterized by an interval, a simple yet practical ranking approach is thus needed for comparing and ranking the permanents of different alternatives. Here we use the minimax regret approach (MRA) developed by Wang et al. The approach has some attractive features and can be used to compare and rank the intervals permanent of alternatives. Interested readers may refer to Wang et al (2005) for more discussions on the existing approaches [20]. The approach is summarized as follows.

Let $A_i = [a_i^L, a_i^U] = \langle m(A_i), w(A_i)\rangle (i = 1, \ldots, n)$ be the intervals permanent of n alternatives, where $m(A_i) = \frac{1}{2}(a_i^L + a_i^R)$ and $w(A_i) = \frac{1}{2}(a_i^R - a_i^L)$ are their midpoints (centers) and widths. Suppose $A_i = [a_i^L, a_i^U]$ is chosen as the best interval permanent. Let $b = \max_{j\ne i}\{a_j^U\}$. Obviously, if $a_i^L < b$, the DM might suffer the loss of permanent (also called the loss of opportunity or regret) and feel regret. The maximum loss of permanent he/she might suffer is given by

$\max(r_i) = b - a_i^L = \max_{j\ne i}(a_j^U) - a_j^L$ (13)

If $a_i^L \ge b$, the DM will definitely suffer no loss of permanent and feel no regret. In this situation, his/her regret is defined to be zero, i.e. $r_i = 0$. Combining the above two situations, we have

$\max(r_i) = \max[\max_{j\ne i}(a_j^U) - a_j^L, 0]$ (14)

Thus, the minimax regret criterion will choose the interval permanent satisfying the following condition as the best (most desirable) interval permanent:

$\min_i\{\max(r_i)\} = \min_i\{\max[\max_{j\ne i}(a_j^U) - a_j^L, 0]\}$ (15)

Based on the analysis above, the following eliminating approach with following steps is suggested for comparing and ranking intervals permanent.

Step 1: Calculate the maximum loss of permanent of each interval permanent and choose a most desirable interval permanent that has the smallest maximum loss of permanent (regret). Suppose A_{i1} is selected, where $1 \le i_i \le n$.

Step 2: Eliminate A_{i1} from the consideration, recalculate the maximum loss of permanent of every interval permanent and determine a most desirable interval permanent from the remaining $(n-1)$ intervals permanent. Suppose A_{i2} is chosen, where $1 \le i_2 \le n$ but $i_1 \ne i_2$.

Step 3: Eliminate A_{i2} from the further consideration, re-compute the maximum loss of permanent of each interval permanent and determine a most desirable interval permanent A_{i3} from the remaining $(n-2)$ intervals permanent.

Step 4: Repeat the above eliminating process until only one interval permanent A_{i3} is left. The final ranking is $A_{i1} > A_{i2} > A_{i3} > \cdots >$, where the symbol '>' means 'is superior to'.

The above ranking approach is referred to as the MRA.

3. Proposed method

At this juncture we propose a new type of weight restriction which is called ordinal weight restriction. Imagine that there are i inputs and r out puts. Using MCDM (or other way), we can obtain the following weight restriction regarding the weights of inputs and outputs:

$V_1 > V_2 > \cdots > V_i$ (16)
$U_1 > U_2 > \cdots > U_r$ (17)

In order to incorporate 16 and 17 into the DEA model, we transform them into cardinal (interval) scale .To this end, there are some transformation methods which are not all discussed here. Wang et al [20] proposed a method to deal with both cardinal and ordinal data in DEA models. Wang used an innovative method to transform the ordinal inputs or outputs into cardinal scale ,and then solved the DEA model with only cardinal data .one of the main contributions of our paper is to use Wang's strategy to translate ordinal weight restrictions 16 and 17 into cardinal scale. Suppose weights of inputs and outputs for DMUs are given in the form of ordinal preference information. Usually, there may exist three types of ordinal preference information: (1) strong ordinal preference information such as $U_j > U_k$ or $V_j > V_k$ which can be further expressed as $U_j \geq \chi U_k$ and $V_j \geq \chi V_k$, where $\chi > 1$ and is the parameters on the degree of preference intensity provided by decision maker (DM); (2) weak ordinal preference information such as $U_p \geq U_q$ or $V_p \geq V_q$; (3) indifference relationship such as $U_l = U_t$ or $V_l = V_t$.We can conduct a scale transformation to ordinal input and output index so that its best ordinal datum is less than or equal to unity and then give an interval estimate for each ordinal datum. For transforming ordinal scale to interval scale, we use the following formula:

$U_r \in [\sigma\eta^{n-r}, \eta^{1-r}],\ r = 1, \dots, n$ whit $\sigma \leq \chi^{1-n}$ (18)

$V_i \in [\sigma\chi^{n-i}, \chi^{1-i}], i = 1, \dots, n$ whit $\sigma \leq \chi^{1-n}$ (19)

Where χ is a preference intensity parameters satisfying $\chi, \eta > 1$ provided by the DM and σ is the ratio parameter also provided by the DM. According to the simplest order relation between two interval numbers, i.e. $A \leq B$ if and only if $aL \leq bL$ and $aU \leq bU$, where $A = [aL, aU]$ and $B = [bL, bU]$ are two interval numbers, the transformed interval data still reserve the original ordinal preference relationships [20].Restrictions 18 and 19 can be converted as follows:

$\sigma\eta^{n-r} \leq U_r \leq \eta^{1-r},\ r = 1, \dots, n\ whit\ \ \sigma \leq \eta^{1-n}$ (20)

$\sigma\chi^{n-i} \leq V \leq \chi^{1-i}, i = 1, \dots, n\ whit\ \ \sigma \leq \chi^{1-n}$ (21)

Adding the weighted restricts are also make problems. First, the problem may not be solved. Second, relative efficiency may not be calculated. For solving these problems, we should multiply the fix numbers of restricts in p and q variables. This idea is presented and demonstrated by Podinovski (1999). Podinovski [24] proved that by adding these variables, all of the problems will be solved [24]: By adding p and q variables to the 20 and 21,22 and 23are obtained as follows:

$(\sigma\eta^{n-r})P \leq U_r \leq (\eta^{1-r})P,\ r = 1, \dots, n$ whit $\sigma \leq \eta^{1-n}$ (22)
$(\sigma\chi^{n-i})Q \leq V \leq (\chi^{1-i})Q, i = 1, \dots, n$ whit $\sigma \leq \chi^{1-n}$ (23)

By adding 22 and 23cardinal weight restrictions to the (8) model and (9) model, (24) and (25) models are obtained as follows:

$$\text{Min } \theta_{jo}^L = \sum_{i=1}^m v_i x_{io}^U$$
$$\text{s.t.}$$
$$\sum_{r=1}^s u_r y_{ro}^L = 1$$
$$\sum_{r=1}^s u_r y_{rj}^U - \sum_{i=1}^m v_i x_{ij}^L \leq 0\ , j = 1, \dots, n \qquad (24)$$
$$(\sigma\eta^{n-r})P \leq U_r \leq (\eta^{1-r})P, \quad r = 1, \dots, n\ whit\ \sigma \leq \eta^{1-n};\ \forall r$$
$$(\sigma\chi^{n-i})Q \leq V_i \leq (\chi^{1-i})Q\ ,\ i = 1, \dots, n\ whit\ \ \sigma \leq \chi^{1-n};\ \forall i$$

and

$$\text{Min } \theta_{jo}^L = \sum_{i=1}^m v_i x_{io}^L$$
$$\text{s.t.}$$
$$\sum_{r=1}^s u_r y_{ro}^U = 1$$

$$\sum_{r=1}^{s} u_r y_{rj}^{U} - \sum_{i=1}^{m} v_i x_{ij}^{L} \le 0 \,, j = 1, \dots, n \quad (25)$$
$$(\sigma\eta^{n-r})P \le U_r \le (\eta^{1-r})P, \quad r = 1, \dots, n \quad \text{whit} \quad \sigma \le \eta^{1-n};\ \forall\, r$$
$$(\sigma\chi^{n-i})Q \le V_i \le (\chi^{1-i})Q\,, \quad i = 1, \dots, n \quad \text{whit} \quad \sigma \le \chi^{1-n};\ \forall\, i$$

4. Numerical example

In order to investigate the importance of this model in selecting suppliers, the article of Talluri and Banker [25] is reviewed, which contains data quality, spatial precision. The Variables of this model is shown as follow:

Table 1. Inputs and outputs for supplier selection

Inputs:	Outputs:
x_{1j} = Total Cost of shipments (TC) (1000$)	y_{1j} = Number of Shipments to arrive on time (NB)
x_{2j} = Price (P)	y_{2j} = Number of bills received from supplier without errors (NOT)
x_{3j} = Distance (D) (KM)	y_{3j} = Supply Variety (SV)

Table 2. Related attributes for 18 suppliers

supplier	TC(1000$)	Price	D(KM)	NB	NOT	SV
1	253	[950,2000]	249	[50,65]	187	2
2	268	[800,1800]	643	[60,70]	194	13
3	259	[1000,2100]	714	[40,50]	220	3
4	180	[8200,2150]	1809	[100,160]	160	3
5	257	[735,1900]	238	[45,55]	204	24
6	248	[650,2500]	241	[85,115]	192	28
7	272	[450,2200]	1404	[70,95]	194	1
8	330	[400,1900]	984	[100,180]	195	24
9	327	[607,2040]	641	[90,120]	200	11
10	330	[455,1890]	588	[50,80]	171	53
11	321	[830,2000]	241	[250,300]	174	10
12	329	[650,1950]	567	[100,150]	209	7
13	281	[960,2350]	567	[80,120]	165	19
14	309	[1200,2300]	967	[200,350]	199	12
15	291	[880,2000]	635	[40,55]	188	33
16	334	[655,2010]	795	[75,85]	168	2
17	249	[800,1990]	689	[90,180]	177	34
18	216	[645,2153]	913	[90,150]	167	9

The Ranking of input and output and the value of χ, η and σ are obtained from Mohaghar et al [26] that shows in Table 3:

Table 3. Ordinal scale and Interval Scale for V_i and U_r

Input	Ordinal scale	Interval Scale for its V_i	Output	Ordinal scale	Interval Scale for its U_r
		$\chi = 1.5$ $\sigma = 0.1$			$\eta = 1.5$ $\sigma = 0.1$
TC	1	$[0.225Q, 1Q]$	NOT	1	$[0.225P, 1P]$
D	2	$[0.150Q, 0.667Q]$	SV	2	$[0.150P, 0.667P]$
P	3	$[0.100Q, 0.444Q]$	NB	3	$[0.100P, 0.444P]$

Then models (24, 25) for the first supplier will be solved. The solution of new model for the first supplier and other suppliers are provided in the Table 4:

Table 4. Efficiency scores with weight restrictions for suppliers

supplier	θ_j^L	θ_j^U	Rank based on MRA
1	0.592486	0.796139	4
2	0.564549	0.763505	8
3	0.570114	0.776972	6
4	0.448427	0.728199	16
5	0.662352	0.920833	2
6	0.594716	1	3
7	0.461346	0.866121	14
8	0.512219	1	10
9	0.523468	0.873434	13
10	0.493202	0.973812	11
11	0.707458	1	1
12	0.565361	0.929141	7
13	0.44399	0.688056	17
14	0.581187	0.934309	5
15	0.505907	0.69602	14
16	0.425872	0.660908	18
17	0.552952	0.945625	9
18	0.49589	0.896824	12

As you can see in the second and third columns of Table 4, the efficiency of suppliers are obtained in the range. So for ranking supplier MRA method is used that proposed By Wang In 2005. Results are presented in the fourth column of Table 4 as follow:

$$A_{11} > A_5 > A_6 > A_1 > A_{14} > A_3 > A_{12} > A_2 > A_{17} > A_8 > A_{10} > A_{18} > A_9 > A_7 > A_{15} > A_4 > A_{13} > A_{16}$$

As you can see, the best supplier is supplier number 11 and other suppliers in ranked and presented in the last column of Table 4.

5. Conclusion

One of the best methods for selection and evaluation of suppliers in supply chain is a DEA model. According to the DEA method calculates the weight of their decision variables without any change is important. However, an important issue in the use of this method is that the traditional model did not consider the opinion of experts and qualitative data. In 1999 Cooper introduced AR-IDEA Model to correct the problems. After that, other researchers have developed this model. As you can see, this paper introduced the new form of AR-IDEA.

Corresponding Author:
Mohsen Moradi-Moghadam
M.S. of Industrial Management, University of Tehran, Tehran, Iran
Email: moradi_mohsen@alumni.ut.ac.ir

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