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An Integrated Approach with AR-DEA and Fuzzy DEMATEL for Technology Selection

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Abstract: Selecting the right technology is always a difficult task for decision-makers. Technology selection models help decision makers choose between evolving technologies. The objective of this paper is to present a new methodology for selecting technology by integration of fuzzy decision-making trial and evaluation laboratory (DEMATEL) and assurance region-data envelopment analysis (AR-DEA). A numerical example demonstrates the application of the proposed method.

Key words: Assurance region . fuzzy set . data envelopment analysis . DEMATEL and technology selection

INTRODUCTION

Selecting the right technology is always a difficult task for decision-makers. Technologies have varied strengths and weaknesses which require careful assessment by the purchasers. Technology selection models help decision makers choose between evolving technologies. The reason for a special focus on technology selection is due to the complexity of their evaluation which includes strategic and operational characteristics [1]. Tools that consider a wide range of dimensions have been developed for evaluating these many characteristics, which include cost, quality, flexibility, time, etc. Some mathematical programming approaches have been used for technology selection in the past. Chan *et al*. [2] presented a fuzzy GP approach to model the machine tool selection and operation allocation problem of flexible manufacturing systems (FMSs). Khouja [3] proposed a decision model for technology selection problems using a two-phase procedure. In phase 1, DEA is used to identify technologies that provide the best combinations of vendor specifications on the performance parameters of the technology. In phase 2, a MADM model is used to select a technology from those identified in phase 1. To select the best technologies in the existence of both cardinal and ordinal data, Farzipoor Saen [4] proposed an innovative approach, which is based on IDEA. To select the best advanced manufacturing technologies, Karsak and Ahiska [5] introduced a multi-criteria decision methodology that can integrate multiple outputs such as various technical characteristics and qualitative factors with a single input such as cost. Their model is derived from the cross-efficiency analysis, which is one of the branches of DEA model. Farzipoor Saen [1] used imprecise data and weight restrictions for technology selection. The objective of this paper is to propose a new method that integrates assurance region-data envelopment analysis (AR-DEA) with fuzzy DEMATEL for selecting the best technology. This paper proceeds as follows. The following section describes the methodology of this paper and explains the principle of fuzzy DEMATEL and AR-DEA methods. Numerical example and concluding remarks are discussed in Section 3 and 4, respectively.

RESEARCH METHODOLOGY

The integrated approach, composed of Fuzzy DEMATEL and AR-DEA methods, for the Technology selection problem consists of 6 stages: (1) determine the inputs and outputs for technology selection, (2) collect the data for inputs and outputs, (3) derive ordinal ranking of inputs and outputs weights via Fuzzy DEMATEL, (4) transform the weights of inputs and outputs into interval scales, (5) incorporate interval scales as weight restrictions to DEA model and (6) solve AR-DEA model. Various stages of research and data analysis are shown in Fig. 1.

In this section; we present a concise treatment of the basic concepts of fuzzy set theory and we present the methodology of fuzzy DEMATEL and AR-DEA model.

FUZZY SETS AND FUZZY NUMBERS

Fuzzy set theory, which was introduced by Zadeh [6] to deal with problems in which a source of vagueness is involved, has been utilized for

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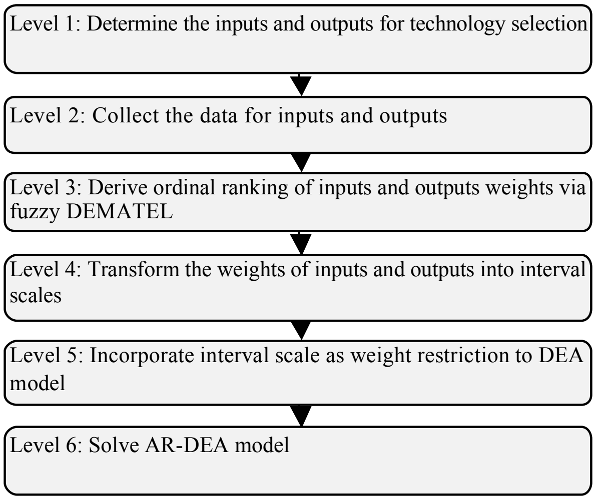

Fig. 1: Algorithm of the proposed model

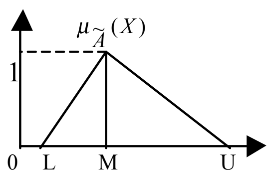

Fig. 2: A triangular fuzzy number $\tilde{A}$

incorporating imprecise data into the decision framework. A fuzzy set $\tilde{A}$ can be defined mathematically by a membership function $\mu_{\tilde{A}}(X)$, which assigns each element x in the universe of discourse X a real number in the interval [0, 1]. A triangular fuzzy number $\tilde{A}$ can be defined by a triplet (a, b, c) as illustrated in Fig. 2.
The membership function $\mu_{\tilde{A}}(X)$ is defined as

$$\mu_{\tilde{A}}(X) = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{x-c}{b-c} & b \le x \le c \\ 0 & \text{otherewise} \end{cases} \quad (1)$$

Basic arithmetic operations on triangular fuzzy numbers $A_1 = (a_1,b_1,c_1)$, where $a_1 \le b_1 \le c_1$ and $A_2 = (a_2,b_2,c_2)$, where $a_2 \le b_2 \le c_2$, can be shown as follows:

Addition:

$$A_1 \oplus A_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (2)$$

Subtraction:

$$A_1 \theta A_2 = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \quad (3)$$

Multiplication: if k is a scalar

$$k \otimes A_1 = \begin{cases} (ka1 \;\; kb1 \;\; kc1), & k > 0 \\ (kc1 \;\; kb1 \;\; ka1), & k < 0 \end{cases}$$

$$A_1 \otimes A_2 \sim (a_1 a_2, b1b2, c1c2), \text{ if } a_1 \ge 0, a_2 \ge 0 \quad (4)$$

$$\text{Division: } A_1 \oslash A_2 \sim \left(\frac{a1}{c2}, \frac{b1}{b2}, \frac{c1}{a2}\right), \text{ if } a_1 \ge 0, a_2 \ge 0 \quad (5)$$

Although multiplication and division operations on triangular fuzzy numbers do not necessarily yield a triangular fuzzy number, triangular fuzzy number approximations can be used for many practical applications [7]. Triangular fuzzy numbers are appropriate for quantifying the vague information about most decision. The primary reason for using triangular fuzzy numbers can be stated as their intuitive and computational-efficient representation [8]. A linguistic variable is defined as a variable whose values are not numbers, but words or sentences in natural or artificial language. The concept of a linguistic variable appears as a useful means for providing approximate characterization of phenomena that are too complex or ill defined to be described in conventional quantitative terms [9].

THE FUZZY DEMATEL METHOD

The Decision Making Trial and Evaluation Laboratory (DEMATEL) method is presented in 1973 [10], as a kind of structural modeling approach about a problem. DEMATEL is an extended method for building and analyzing a structural mo del for analyzing the influence relation among complex criteria. However, making decisions is very difficulty in fuzzy environment to segment complex factors. The current study uses the fuzzy DEMATEL method to obtain a more accurate analysis. The steps of Fuzzy DEMATEL as follow:

Step 1: Set up fuzzy matrix which is shown by $\tilde{z}_b$ and called Assessment Data Fuzzy Matrix.

For forming fuzzy matrix, we use fuzzy linguistic variables as shown in Table 1.

Next [11], it must acquire and average the assessment of executives' preferences using

Table 1: The fuzzy linguistic scale

Linguistic terms	Triangular fuzzy numbers
No influence (No)	(0.00, 0.00, 0.25)
Very low influence (VL)	(0.00, 0.25, 0.50)
Low influence (L)	(0.25, 0.50, 0.75)
High influence (H)	(0.50, 0.75, 1.00)
Very high influence (VH)	(0.75, 1.00, 1.00)

$$\tilde{z} = \frac{\left(\tilde{z}^1 \oplus \tilde{z}^2 \oplus \ldots \oplus \tilde{z}^p\right)}{p} \quad (6)$$

Then, fuzzy matrix $\tilde{z}$ is produced which is shown as

$$\tilde{z} = \begin{bmatrix} 0 & \tilde{z}_{12} & \cdots & \tilde{z}_{1n} \\ \tilde{z}_{21} & 0 & \cdots & \tilde{z}_{2n} \\ \tilde{z}_{n1} & \tilde{z}_{n2} & \cdots & 0 \end{bmatrix} \quad (7)$$

which is called initial direct-relation fuzzy matrix. In this matrix, $\tilde{z}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ are triangular fuzzy numbers and $\tilde{z}_{ij}$ = (i = 1,2,…,n) will be regarded as triangular fuzzy number (0, 0, 0) whenever is necessary. Then, by normalizing initial direct-relation fuzzy matrix, we acquire normalized direct-relation fuzzy matrix $\tilde{x}$ by using

$$\tilde{x} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{11} & \tilde{x}_{22} & 0 & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & \tilde{x}_{nn} \end{bmatrix} \quad (8)$$

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij},}{r}, \frac{m_{ij},}{r}, \frac{u_{ij},}{r}\right) \quad (9)$$

$$R = \max_{1 \le i \le n}\left(\sum_{j=1}^{n} u_{ij}\right) \quad (10)$$

It is assumed at least one i such that

$$\sum_{j=1}^{n} u_{ij} < 1$$

After computing the above matrices, the total-relation fuzzy matrix $\tilde{T}$ is computed. Total-relation fuzzy matrix is defined as [11]

$$\tilde{T} = \lim_{k \to \infty}\left(\tilde{x}^1 + \tilde{x}^2 + \ldots + \tilde{x}^n\right) \quad (11)$$

Then,

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \tilde{t}_{12} & \cdots & \tilde{t}_{1n} \\ \tilde{t}_{11} & \tilde{t}_{22} & 0 & \tilde{t}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{t}_{n1} & \tilde{t}_{n2} & \cdots & \tilde{t}_{nn} \end{bmatrix} \quad (12)$$

In which

$$\tilde{t}_{ij} = \left(l''_{ij}, m''_{ij}, u''_{ij}\right)$$

and

$$\left[l''_{ij}\right] = X_1 \times \left(I - X_l^{-1}\right), \left[m''_{ij}\right] = X_1 \times \left(I - X_m^{-1}\right)$$
$$\left[u''_{ij}\right] = X_1 \times \left(I - X_u^{-1}\right) \quad (13)$$

By producing matrix $\tilde{T}$ then it is calculated $(\tilde{D}_i + \tilde{R}_i)$ and $(\tilde{D}_i - \tilde{R}_i)$ in which $\tilde{D}_i$ and $\tilde{R}_i$ are the sum of row and the sum of columns of $\tilde{T}$ respectively. To finalize the procedure, all calculated $(\tilde{D}_i + \tilde{R}_i)$ and $(\tilde{D}_i - \tilde{R}_i)$ are defuzified through suitable defuzification method. Then, there would be two sets of numbers: $(\tilde{D}_i + \tilde{R}_i)_{def}$ which shows how important the strategic objectives are and $(\tilde{D}_i - \tilde{R}_i)_{def}$ which shows which strategic objective is cause and which one is effect. Generally, if the value $(\tilde{D}_i - \tilde{R}_i)_{def}$ is positive, the objectives belong to the cause group and if the value $(\tilde{D}_i - \tilde{R}_i)_{def}$ is negative, the objectives belong to the effect group.

AR-DEA MODEL

DEA proposed by Charnes [12] (Charnes-Cooper-Rhodes (CCR) model) and developed by Banker [13] (Banker-Charnes-Cooper (BCC) model) is an approach for evaluating the efficiencies of DMUs. One serious drawback of DEA applications in technology selection has been the absence of decision maker judgment, allowing total freedom when allocating weights to input and output data of technology under analysis. This allows technologies 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 [14] and assurance region models [15]. Both methods constrain the domain of feasible solutions in the space of the virtual multipliers. To introduce the method for technology 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 [12] 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 DMUo relative to a set of peer DMUs:

Table 2: Nomenclature

Problem parameters
$(\sigma_i, \tau_i, \rho_r, \eta_r \alpha_i, \psi_r, \theta_r, \xi_r, \varphi_i)$ User-specified constants
j = 1,...,n collection of suppliers (DMUs)
r = 1,...,s the set of outputs
i = 1,...,m the set of inputs
y_{rj} = the rth output of jth DMU
x_{ij} = the ith input of jth DMU
y_{ro} = rth outputs of the DMUo under investigation
X_{1o} = ith inputs of the DMUo under investigation
u_r = weight of the rth output
v_1 = weight of the ith input

$$E_o = \max \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}},$$
$$\text{s.t:} \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad j=1,\ldots,n, \tag{14}$$
$$v_i \quad u_r \geq 0 \quad \forall i \text{ and } r,$$

where there is a set of n peer DMUs, $\{DMU_j: j=1,2,\ldots,n\}$, which produce multiple outputs $y_{rj}(r=1,2,\ldots,s)$, by utilizing multiple inputs $x_{rj}(i=1,2,\ldots,m)$. DMUo is the DMU under consideration. u_r is the weight given to output r and v_i is the weight given to input i. e is a positive non-Archimedean infinitesimal. DMUo is said to be efficient (Eo = 1) if no other DMU or combination of DMUs can produce more than DMUo 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 (14) is as follows:

$$E_o = \max \sum_{r=1}^{s} u_r y_{ro},$$
$$\text{s.t:} \sum_{i=1}^{m} v_i x_{io},$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 1 \quad ,\forall j \tag{15}$$
$$v_i \geq 0 \quad \forall i,$$
$$u_r \leq 0 \quad \forall r.$$

In (16, 17, 18) the various types of weight restriction that can be applied to multiplier models are shown [16].

Absolute weight restrictions

$$\begin{aligned} \sigma_i \leq v_i \leq \tau_i \quad (g_i), \\ \rho_r \leq u_r \leq \eta_r \quad (g_o). \end{aligned} \tag{16}$$

Assurance region of type I (relative weight restrictions)

$$\begin{aligned} \alpha_i \leq v_i \leq \psi_i \quad (h_i), \\ \theta_r \leq u_r \leq \xi_r \quad (h_o). \end{aligned} \tag{17}$$

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

$$\varphi_i v_i \geq u_r \quad (l). \tag{18}$$

The Greek letters $(\sigma_i, \tau_i, \rho_r, \eta_r \alpha_i, \psi_r, \theta_r, \xi_r, \varphi_i)$ 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 (g) and (h) in (16, 17) relate on the left hand side to input weights and on the right hand side to output weights. Constraint (l) 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.

In this paper, we propose a new type of weight restriction which is called ordinal weight restriction. Imagine that there are three inputs and outputs. Using fuzzy DEMATEL, we can obtain the following weight restriction regarding the weights of inputs and outputs:

$$v1 \geq v2 \geq \cdots \geq vi. \tag{19}$$

$$ul \geq u2 \geq \cdots \geq ur. \tag{20}$$

In order to incorporate 19 and 20 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 [17] 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 19 and 20 into cardinal scale. Suppose weights of V_i and U_r 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:

$$ur \in \left[\delta\chi^{n-r}, \chi^{1-r}\right] \quad r = 1,\cdots,n \quad \text{with} \quad \delta \le \chi^{1-n}, \tag{21}$$

$$vi \in \left[\delta\chi^{n-i}, \chi^{1-i}\right] \quad r = i,\cdots,n \quad \text{with} \quad \delta \le \chi^{1-n}, \tag{22}$$

where χ is a preference intensity parameter satisfying $\chi>1$ 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≤B if and only if aL≤bL and aU≤bU, where A = [aL, aU] and B = [bL, bU] are two interval numbers, the transformed interval data still reserve the original ordinal preference relationships [17]. Finally, the output of restriction (21) and (22) like a restriction (16) are an absolute numbers that indicate the lower and upper bounds for input and output weights but with this difference that reflects the priorities weight of inputs and outputs. So we have a special kind of restriction (16) that reflects the priorities weight of inputs and outputs. So we have introduced the third type of AR model. Now, instead of restricts of linear programming equivalent of (15), weighted restricts of Eq.16 is add and model (23) is obtain as follows:

$$\begin{aligned} E_o &= \max \textstyle\sum_{r=1}^{s} u_r y_{ro}, \\ \text{s.t:} & \textstyle\sum_{i=1}^{m} v_i x_{io}, \\ & \textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 1, \forall j \\ & \sigma_i \le v_i \le \tau_i \quad \forall i, \\ & \rho_r \le u_r \le \eta_r \quad \forall r. \end{aligned} \tag{23}$$

Adding the weighted restricts are also make broblems. 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 [18]. Podinovski [18] proved that by adding these variables, all of the problems will be solved. By adding p and q variables to the model (23), model (24) is obtained as follows:

$$\begin{aligned} E_o &= \max \textstyle\sum_{r=1}^{s} u_r y_{ro}, \\ \text{s.t:} & \textstyle\sum_{i=1}^{m} v_i x_{io}, \\ & \textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 1, \forall j \\ & \sigma_i p \le v_i \le \tau_i p \quad \forall i, \\ & \rho_r q \le u_r \le \eta_r q \quad \forall r. \end{aligned} \tag{24}$$

Table 3: Inputs and outputs for robot selection

Input:	Outputs:
x_1 = Cost (10000$)	y_{1j} = Repeatability(mm) y_{2j} = Load capacity (kg) y_{3j} = Velocity (m/s) y_{4j} = Amount of know-how transfer

Table 4: Related attributes for 20 robots

(DMU)	x_1 = Cost (10000$)	y_{1j} = Repeatability (mm)	y_{2j} = Load capacity (kg)	y_{3j} = Velocity (m/s)	y_{4j} = Amount of know-how transfer
1	3.0	0.35	55	1.20	4
2	2.0	0.65	24	1.30	3
3	3.5	1.19	26	1.30	2
4	5.0	0.65	30	0.70	2
5	4.5	0.43	30	0.90	5
6	1.9	0.53	21	0.75	5
7	2.2	0.62	25	0.92	2
8	3.0	0.72	28	1.00	3
9	4.7	0.17	26	1.30	3
10	2.3	0.88	26	1.10	5
11	3.0	0.47	30	0.97	4
12	5.0	1.00	12	0.82	2
13	3.3	0.75	18	1.76	1
14	3.5	0.75	32	1.88	3
15	3.5	0.82	27	0.71	4
16	4.8	1.10	46	0.71	2
17	3.65	1.74	10	1.89	5
18	2.87	0.48	19	1.25	4
19	3.21	0.64	18	1.04	2
20	3.16	0.80	22	0.80	3

A NUMERICAL APPLICATION OF PROPOSED APPROACH

In this paper, the proposed methodology that may be applied to a wide range of technology selection problems is used for robot selection. We considered cost as an input and Repeatability, Load capacity, Velocity and Amount of know-how transfer as outputs for Technology selection. These inputs and outputs are taken from Farzipoor saen [1, 4].These inputs and outputs are shown in Table 3.

After that we collect data for inputs and outputs. Data about inputs and outputs for each robot is shown in Table 4.

After that we rank outputs separately by using of Fuzzy DEMATEL. At the next step, subject to the fuzzy linguistic scale, everyone should make pair wise relationships between each output. Then, we will have a lot of assessment data fuzzy matrix in hand. Using (6) to average all these assessments matrices, we will have initial-direct fuzzy matrix $\tilde{z}$ for outputs. Our partial results are shown in Table 5. Then, using (9), the normalized direct-relation fuzzy matrix $\tilde{x}$ will be produced. The partial results are depicted in Table 6.

Following (13), we will acquire the total-relation fuzzy matrix which will be the last step for transforming crisp data into the fuzzy environments. Our matrix partially depicted on Table 7.

To access the casual relationships between outputs, we will calculate $(\tilde{D}_i + \tilde{R}_i)$ and $(\tilde{D}_i - \tilde{R}_i)$ in which $\tilde{D}_i$ and $\tilde{R}_i$ are the sum of row and the sum of columns of our total-relation fuzzy matrix respectively. Our partial results and the result of ranking are shown in Table 8.

Using of Eq. (14) outputs which are ranked and transformed into interval scale. These intervals identify the range of outputs. For example, interval scale of U_1 with ($\chi = 1.5, \sigma = 0.1$) is calculated as below:

$$ul \in \left[(0.1)1.5^{4-1}, \chi^{1-1}\right] = [0.338,1]$$

Similar to U_1, the interval weight of other outputs are calculated and shown in the Table 9.

Table 5: The Initial direct-relation fuzzy matrix $\tilde{z}$ for outputs

Z	O_1	O_2	O_3	O_4
O_1	(0,0,0.25)	(0.44,0.69,0.81)	(0.31,0.56,0.81)	(0.44,0.69,0.88)
O_2	(0.56,0.81,1)	(0,0,0.25)	(0.38,0.63,0.88)	(0.19,0.44,0.69)
O_3	(0.13,0.38,0.63)	(0.13,0.38,0.63)	(0,0,0.25)	(0.19,0.44,0.69)
O_4	(0.19,0.44,0.69)	(0.31,0.56,0.75)	(0.25,0.5,0.75)	(0,0,0.25)

Table 6: The normalized initial direction-relation fuzzy matrix $\tilde{x}$ for outputs

X	O_1	O_2	O_3	O_4
O_1	(0,0,0.21)	(0.37,0.58,0.68)	(0.26,0.47,0.68)	(0.37,0.58,0.74)
O_2	(0.47,0.68,0.84)	(0,0,0.21)	(0.32,0.53,0.74)	(0.16,0.37,0.58)
O_3	(0.11,0.32,0.53)	(0.11,0.32,0.53)	(0,0,0.21)	(0.16,0.37,0.58)
O_4	(0.16,0.37,0.58)	(0.26,0.47,0.63)	(0.21,0.42,0.63)	(0,0,0.21)

Table 7: The total-relation fuzzy matrix $\tilde{T}$

T	O_1	O_2	O_3	O_4
O_1	(0.74,1.32,1.74)	(0.39,0.95,0.99)	(0.46,0.97,1.04)	(0.39,0.92,0.95)
O_2	(0.37,0.89,1.04)	(0.73,1.3,1.71)	(0.45,0.99,0.99)	(0.48,0.82,0.99)
O_3	(0.37,0.41,0.69)	(0.34,0.41,0.69)	(0.64,0.96,1.33)	(0.33,0.43,0.64)
O_4	(0.4,0.63,0.82)	(0.35,0.69,0.78)	(0.41,0.69,0.83)	(0.67,1.08,1.45)

Table 8: The value of ($\tilde{D}_i + \tilde{R}_i$), ($\tilde{D}_i - \tilde{R}_i$) and the result of ranking

Ranking	R+C	R-C	C	R	RANK R
O_1	10.98	0.07	5.45	5.52	2
O_2	10.96	-0.03	5.50	5.46	4
O_3	11.11	0.27	5.42	5.69	1
O_4	10.93	0.02	5.45	5.47	3

Table 9: Ordinal scale and interval scale for U_r

Outputs:	Ordinal scale	Interval scale for its ur with $\chi=1.5$ $\sigma=0.1$ L	U
U_1	2	0.225	0.667
U_2	4	0.100	0.296
U_3	1	0.338	1.000
U_4	3	0.150	0.444

Table 10: Efficiency scores with weight restrictions and without weighted restrictions

DMU	Score CCR	Rank CCR	Score new AR-CCR	Rank new AR-CCR
1	1.000000	1	1.000000	1
2	1.000000	1	0.941314	4
3	0.831904	7	0.568178	12
4	0.440585	19	0.353476	19
5	0.500906	17	0.490411	16
6	1.000000	1	0.983235	2
7	0.881059	6	0.748216	5
8	0.731976	11	0.644385	8
9	0.440480	20	0.393231	18
10	1.000000	1	0.974498	3
11	0.710946	13	0.695737	6
12	0.446652	18	0.246284	20
13	0.820513	9	0.508067	15
14	0.826374	8	0.686111	7
15	0.649328	15	0.569936	11
16	0.730280	12	0.544743	13
17	1.000000	1	0.591760	10
18	0.758762	10	0.629637	9
19	0.548241	16	0.445845	17
20	0.650454	14	0.530371	14

Then model (21) for the first Technology will be solved. The solution of two models for the first Technology and other Technology are provided in the Table 10:

As it can be seen in the second column of Table 10, by solving an input oriented CCR model (model 15) without weight restrictions, five DMUs are efficient and in model 15, the opinion of managers and consultants are not considered, therefore, this model is completely free to determine the weights of inputs and outputs. In this paper, the opinion of managers and consultants are considered but the domains specified for the weight of input and output are not efficient as seen in the third column of Table 10 and the efficiency score for DMU is not changed and this matter is occurred in AR-CCR model but in spite of other papers, this problem did not occur in our method. In this way, by increasing the amount of parameters σ, χ, we can increase the influence of Manager's opinion. As you can see in the fourth column of Table 10, technology 1 is the most efficient technology between other technologies and the technology 12 has the lowest efficiency. The results of this paper show that the method provided by the authors is completely flexible and by increasing the opinions of managers and consultants, the power of differentiation this model will increase.

CONCLUSIONS

DEA models without weight restrictions will evaluate the efficiency of DMU in the best conditions and input and output weights are set up so that the efficiency of DMU will be maximum (The results of solving CCR problem is provided in the Table 10). In some cases, we may want to give weights for input and output, so the use of weight restrictions is the proper way for these cases. In this paper, in order to reach the weight restrictions, the opinions of managers and experts about the importance of indicators have been identified by using of questionnaire. After that the rating scale transformed to interval scale and then these interval data added to DEA model and solved. Then the efficiency of technology is calculated. According to new method, technology 1 is the most efficient technology between other technologies. As a future direction, other decision-making methods such as fuzzy ELECTRE and Fuzzy TOPSIS can be used in this area. Fuzzy TOPSIS method is used by Momeni *et al*. [19] in other area that can be used in Technology selection.

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